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Bear Periods Amplify Correlation:

A GARCH BEKK Approach

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By

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Abstract

The aim of this paper is to see how correlation changes across time across different indices. We have used a sufficiently large benchmark period of 20 years to have a better understanding as to how correlations have changed. We compared the correlation in the 20 year period with 3 sub periods namely the Dot Com crisis (1999-2002), the Bullish period (2004-mid 2007) and the Financial Crisis (mid 2007-mid 2009). The results suggest that time varying correlation increases in bearish spells whereas bullish periods do not have a big 'statistical' impact on correlation. This will have implications for geographical equity diversification since the premise of diversification has been that it lowers risk but a high correlation would imply risk might not be reduced to a certain extent as expected. Therefore, fund managers should take this into account when coming up with equity allocations.

Keywords: GARCH-BEKK, volatility, covariance, correlation, ARCH, GARCH, emerging markets

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I. Introduction

In the last 20 years there has been a great amount of integration in the financial markets, especially in equity markets. This has given rise to the notion that international equity markets are interdependent and therefore significant events in some countries may have far-reaching and wide repercussions also in other countries even though they may not be directly affected. Examples of such events are the 1987 Crash on Wall Street, the East Asian Crisis in 1997, the Dot Com Bubble, the tragic September 11 events and the recent Financial Crisis. When we view the trend in most of the international equity indices we could observe that a lot of them move in synchrony and to the unsuspecting eye this may further the notion of interdependence amongst these markets.

The increased interdependence of markets over time suggests the possibility to diversify away that risk has decreased. If many markets behave in the same manner then this could lead to a magnification of risk, at least not that reduction of risk as expected by diversification. Does this mean that portfolio diversification via investing in other international markets is of little consequence in the face of increasing global integration in equity markets? Events such as the East Asian Currency Crisis and the Russian crisis, and their reverberations throughout the world (see Kaminsky and Reinhart, 1998; Edwards and Susmel, 2001; Bae, Karolyi and Stulz, 2003) strengthen this perception further. Gupta and Mollik (2008) state that correlations between markets do not remain constant over time, that they depend on the behaviour of the markets in general. Dilating further on this topic, when times are good then markets would appear less correlated and vice versa (Longin and Solnik, 2001; Ang and Bekaert, 2002). Therefore when markets are in a bear spell then diversification of equity portfolio may not be advisable (Baele, 2005).

The purpose of our study is to extend the literature on financial integration, by examining emerging markets in Asia. In particular we extend the literature by examining KSE 100, the main stock index in Pakistan, and BSE 30, the main Indian index. Earlier literature has focused on the major stock indices, such as S&P 500, the US index, Nikkei 225, the main Japanese Index, and FTSE 100, the main British Index. However, the literature on financial integration is quite vast and attempts to measure correlations from developed to emerging markets have been documented although to our knowledge for these two indices there are no comprehensive results available. In the analysis we focus on three sub periods; the dot com bubble of the 1999-2002 period, the financial crisis of the mid 2007- mid 2009 period and the boom market period of 2004- mid 2007 almost exclusively. This is a contribution since earlier research has focused on bear periods. Another reason for looking at these periods is that a lot of the markets showed great volatility in these periods, as measured by daily percentage returns. It is therefore interesting to examine if periods with high volatility impact correlation.

By following the methodology of earlier research we let S&P 500 be the "world market", Nikkei the "regional market" and Hang Seng, BSE 30 and Karachi 100 the "local markets". We motivate our choice of indices as follows. The US market is by far the largest in the world, in terms of market capitalisation, and it's generally accepted that what happens in US affects the rest of the world. Our choice to include Nikkei is to follow earlier research by Angela NG (2000) that assumed a regional market to have an impact on the local markets. Nikkei 225 is the largest Index in Asia and a lot of smaller indices take their direction from it. The reason to choose Hang Seng, the Hong Kong Index, also stems from this. The reasoning to choose BSE 30 and KSE 100 arises from the fact that these are indices not widely analyzed in the literature on correlation studies.

Our Research Question is:

How do Correlations change across different indices across time?

Based on the research question we construct the following hypothesis:

Hypothesis 1: *Correlations across time are not constant.*

Hypothesis 2: *Correlations increase in periods of market uncertainty either Bear spells or Bullish ones.*

Hypothesis 3: *Correlation between markets depend not only on their proximity but the size of the markets as well. We hypothesize the regional market to have a higher correlation to the local markets than the global one.This would imply BSE 30, the Bombay Index, would have a greater correlation to the Nikkei 225 than to the US S&P 500.*

Hypothesis 4: *Correlation over time has increased between markets due to increasing market integration.*

Regarding time varying volatility we have delimited our research to a bivariate Generalised Autoregressive Conditional Hetroscedasticity GARCH. Through using GARCH we would be able to model time varying correlations in a pair wise fashion. We should also point out that we are not interested in what the coefficients in the BEKK specification mean since we are more concerned with the end result, which being mean correlations.

We observed that correlation is unstable and fluctuates for all indices over time. Besides, we also find that correlation seem to increase over time between some indices but not for all of them. Nikkei 225 seems to correlate more over time with all indices except for KSE 100. Our main focus and the cornerstone of our research were to analyze how correlation behaves between different market conditions. In particular during the financial crisis we found that correlation amongst the indices increased profoundly, but we could not observe the same phenomena for the bull period during 2004-2007. The bull market rather resembled the normal times, when we compared the time-varying correlations.

Section 1.1: Review of studies on previous research

Many studies in the field of market co integration have adopted the autoregressive conditional heteroscedastic (ARCH) processes proposed by Engle (1982), where the assumption of a constant conditional variance is relaxed. Since being introduced, the ARCH model has been further developed and refined. Bollerslev (1986) in particular developed GARCH to include a fitted variance from the historical variance. Hong Li and Ewa Majerovska (2007) employed the bivariate GARCH when they found spillovers from developed markets (US and Germany) to emerging markets (Warsaw and Budapest), although the spillovers documented were quite small. Using a similar model Longin and Solnik (1995) found the correlation to be unstable and that it increased over time. They also found that correlation increased in periods of high volatility. Engle and Susmel (1994) examined hourly spillover between New York and London by using an ARCH-model where they managed to document minimal volatility spillover within duration of an hour. By applying a trivariate GARCH, Fratzer (2001) found that European markets had become more integrated after 1996 and this development was largely a result of the European Monetary Union, by the removal of exchange rate volatility. Research on volatility and financial contagion

(Kaminsky and Reinhart, 1998; Bae et al., 2003) suggests that in uncertain times the transmission of negative events from one market to another might gather more pace. It had been observed by Chan, Gup and Pan, (1992); Garrett and Spyrou, (1999); Maish and Maish, (1999); Ghosh, Saidi and Johnson, (1999); Darrat and Zhong, (2002) that a long run relationship existed between Asia Pacific and developed markets but other research seemed to debunk such a relationship. The work done by Yang, Kolari and Sutanto (2004) highlighted no long term relationships between emerging and developed markets but that some form of relationship existed when times were uncertain. In addition, there was some evidence suggesting that capital markets shared common trends over the long term. (Kasa, 1992; Garrett and Spyrou, 1999). Sharkasi, Ruskin and Crane (2003) observed the circle of impact to emanate from Europe to America to Asia and back to Europe. They also observed an increase in International spillovers since the 1990's.

Following the logic of Bekaert and Harvey (1997) by letting spillover be determined by the world market, and a local market, Angela Ng (2000) extended it to include a regional market as well. We follow the same logic and letting the world impact be determined by the US market (S&P 500), the regional impact by the Japanese market (Nikkei), and the local impact be determined among the local markets, which are Hang Seng (Hong Kong), KSE 100 (Karachi) and BSE 30 (Bombay).

II. Theoretical background and financial theory

The studies on spillovers between stock indices or different asset classes are important. Aside from the documentation and the added knowledge in research it's also of importance, for portfolio managers, for instance, who may be looking for better diversification in their portfolios. It has been documented that adding commodities, to say a portfolio composed of stocks can reduce the variance, since some commodities have shown to be negatively correlated to equity indices through time, or at least exhibit low positive correlation.[2]

In this paper we have limited our interest to stock indices, and the question remains whether investing in for instance the US market and some emerging markets in Asia increases the benefits of diversification. As already mentioned, and documented in many studies, during bear markets

[2] http://www.investopedia.com/articles/trading/05/021605.asp

the correlation amongst stock indices increases. During periods of contagion such as the East Asian Financial crisis, the financial crisis or the Dot Com bubble, most of the stock markets were affected although some of that exposure was related to local markets. If this is the case then in turbulent times the benefits of diversification would be that great from a relative point of view.

Risk is most often measured by the variability, which is the variance around an assets expected return, the mean. Often the standard deviation of an asset is used as measure for risk. Individual stocks often show a high standard deviation, especially during volatile times, such as the Dot Com Bubble and the financial crisis. Although individually stocks have high variance, the market portfolio does not reflect the average variance of all stocks. The reason is that by diversifying, we add stocks with different correlations and since stocks do not move synchronously, the variance of the market portfolio will be lower than the average of the individual variances. A two-asset portfolio will achieve the best diversification if the two assets are perfectly negatively correlated. The portfolio variance will be a function of the assets own variance but also how the assets move together, the covariance. Covariance is given by:

$$Cov_{xy} = \rho_{12}\sigma_x\sigma_y, \qquad \textbf{(1)}$$

where ρ is the correlation. The variance of a portfolio with two assets x and y is calculated by:

$$PortfolioVar = w_x^2\sigma_x^2 + w_y^2\sigma_y^2 + 2w_x w_y \sigma_x \sigma_y \rho_{xy} \qquad \textbf{(2)}$$

Even though we do not attempt to measure the magnitude of diversification the documentation of time-varying correlation gives us a hint whether it’s worthwhile to invest abroad, since we will get an idea of how variance is transmitted over the different markets. A low time-varying correlation between US and an emerging market in Asia could imply benefits of diversification. If the US market does not transmit variance to a specific emerging market, then investing in these two markets simultaneously can reduce the variance of them combined, instead of holding only one of the market portfolios.

III. Methodology

Section 3.1:GARCH

In conventional econometric models the conditional variance is typically assumed to be constant. Engle (1982) introduced the ARCH model where variance was not assumed to be constant. OLS for example relies on the assumption of homoscedasticity, the value of squared error terms is constant, an assumption not always plausible to make. GARCH models deal with this kind of issue, where the data series is heteroscedastic, and variance is of interest to be modelled. Heteroscedasticity implies that the variance of the errors are not equal at all times. This poses a problem for OLS since the standard errors might be wrongly estimated, and therefore not reliable. GARCH models do not treat heteroscedasticity as a problem but rather something to be modelled which makes this model suitable for use with financial data.

If we consider a random variable u_t, then the conditional variance, denoted as σ^2 can be described as:

$$\sigma^2 = var(u_t | u_{t-1}, u_{t-2\ldots}) \tag{3}$$

The ARCH model can in its simplest form be described as following:

$$\sigma_t^2 = \overline{\omega} + \alpha\varepsilon_{t-1}^2 \tag{4}$$

where $\overline{\omega}$ >0, is the constant, and $\alpha\sigma^2$ is the past variance.

The equation above states that the variance of the error term at time t, depends on the squared error term from previous periods. Described differently, in the ARCH process we let the conditional variance to depend on its previous value, which is the lag. Equation (4) is an example of ARCH (1) model, wherein the conditional variance depends on one lagged squared error. In a general case with α on the right side we get an ARCH (α) model. This model is appealing since it states that a big shock in the previous period is likely to result in a larger variance in the current period.

ARCH models have some weaknesses. For instance, there was no best way of determining how many lags to include, and sometimes a very large number of lags are required in order to capture dependence in the conditional variance. For this reason, ARCH models are rarely used. To overcome these problems, Bollerslev (1986) developed the GARCH model. The simplest GARCH is the GARCH(1,1), mathematically described as:

$$\sigma_t^2 = \varpi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad \textbf{(5)}$$

which can be generalized to q lags, the autoregressive term (past variance), and p lags, the amount of GARCH terms (fitted variance from previous periods). $\beta\sigma^2$ is added to the GARCH Model; which is the fitted variance from previous periods.

Before the introduction of ARCH and GARCH simpler methods to forecast variance such as rolling standard deviation were practiced. The rolling standard deviation assumed equal weights for each observation, even though the more recent should have had more influence in the forecast. In the ARCH and GARCH these weights are estimated. The question is how to estimate the parameters ϖ,α and β. In the GARCH estimation procedure maximum likelihood is used in estimating the parameters and the function is maximized subject to the constraints.

Due to leptokurtosis characteristics of financial data even large samples reproduces a non-normal and skewed distribution. The implication is that a normal distribution underestimates the occurrence of large positive and large negative returns, hence a shortcoming when working with financial data. Corrado and Su (1997) summarized monthly returns for S&P 500 for each decade between 1926 and 1995, and found for arithmetical returns a negative skew for five out of eight decades. Kurtosis was also found to be between three to nine during the period, where a kurtosis of three equals the tails of a normal distribution. The kurtosis is much higher than under normal distribution. In agreement with this William (2007) found in a study of S&P 500 during the period 1950-2006 that the distribution was non-normal.[3] The density at the extreme levels was much higher than a normal distribution predicts. This is why when we used the GARCH BEKK model to calculate the correlations we used the student t distribution instead of the regular normal distribution.

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[3] www.dailyspeculations.com/Egan_Dis.pdf

Section 3.2:GARCH-BEKK

Bollerslev et al. (1988) proposes a bivariate GARCH model that allows not only for time varying conditional variances but also for a time varying conditional covariance. What it means is that investors renew their estimates of means and covariance's generated by the new period's returns. However, this model is rather complex and is heavily parameterized. Also the earlier GARCH models failed to ensure positive definiteness of the conditional covariance matrix.

An appealing property of the GARCH-BEKK is that the model ensures positive definite conditional covariance matrix. In order to reduce the number of parameters estimated in the GARCH-BEKK model, restrictions are often imposed, such as symmetricity and diagonality. The GARCH BEKK can be expressed as:

$$H_t = C_0{}' C_0 + A_{11}' \varepsilon_{t-1}' \epsilon_{t-1} A_{11} + G_{11}' H_{t-1} G_{11} \qquad (6)$$

where Ht is the conditional variance and C is a triangular matrix. A and G are two unrestricted matrices (Kashif Saleem 2009). Furthermore A, B and C are N*N parameter matrices. In order to make Ht positive definite, matrix C (the constant) is decomposed into two triangular matrices (Teräsvirta and Silvennoinen 2008).

The model ensures positive definite conditional covariance matrices on the right hand side by its structure of quadratic forms. The amount of parameters to be estimated in (3.9) is N(5N+1)/2, thus in a bivariate setting 11 parameters should be estimated. A drawback of the GARCH-BEKK is that the parameters are not easily interpreted. In matrix form (3.9) can be expressed as follows:

$$H_t = C_0{}' C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \qquad (7)$$

The GARCH-BEKK model above estimates 11 parameters, which we then use to estimate the conditional covariance matrix. The initial step was to generate the residual series from the mean equations, which we obtained by running the VAR on pair wise indices. The residuals were tested for ARCH in the series to see if the residuals were autocorrelated. If so, then they cannot be used. We found the residuals not to be autocorrelated and then used them in the GARCH

BEKK model. The general GARCH model with arbitrary dependencies can lead to complex structures which make it difficult to deal in practice. Therefore a way was devised to reduce the dimension of the parameter space. The conditional covariance matrix was restricted to a positive definite matrix which simplifies the structure. Again, we do not interpret the GARCH-BEKK coefficients, only the variance covariance matrix is of interest The GARCH BEKK also allows for dependence of conditional variances of one variable on the lagged values of another variable, which makes it possible to model causalities in the variance. [4]

We also tested the pair wise indices to determine which way the returns spillover. This was done by using the Granger causality test. In a simplistic explanation of the test it might explain which way the causality flows. Using the Granger Causality test we were able to know which index was significant on the other. The results of the test further established that it was only bigger markets which impacted the smaller markets and not otherwise as the Granger Causality Test was not significant in all the cases when smaller markets were tested against the bigger ones whereas all the bigger ones were significant on the smaller ones. It should be mentioned that the Granger causality regresses the mean's returns and not the variance. However, in our thesis it is the correlation that is of interest, hence which way causality moves is of less importance.

IV. Data

The five international Stock Indices analyzed in this study are:

- **S&P 500**
- **Nikkei 225**
- **KSE 100**
- **BSE 30**
- **Hang Seng**

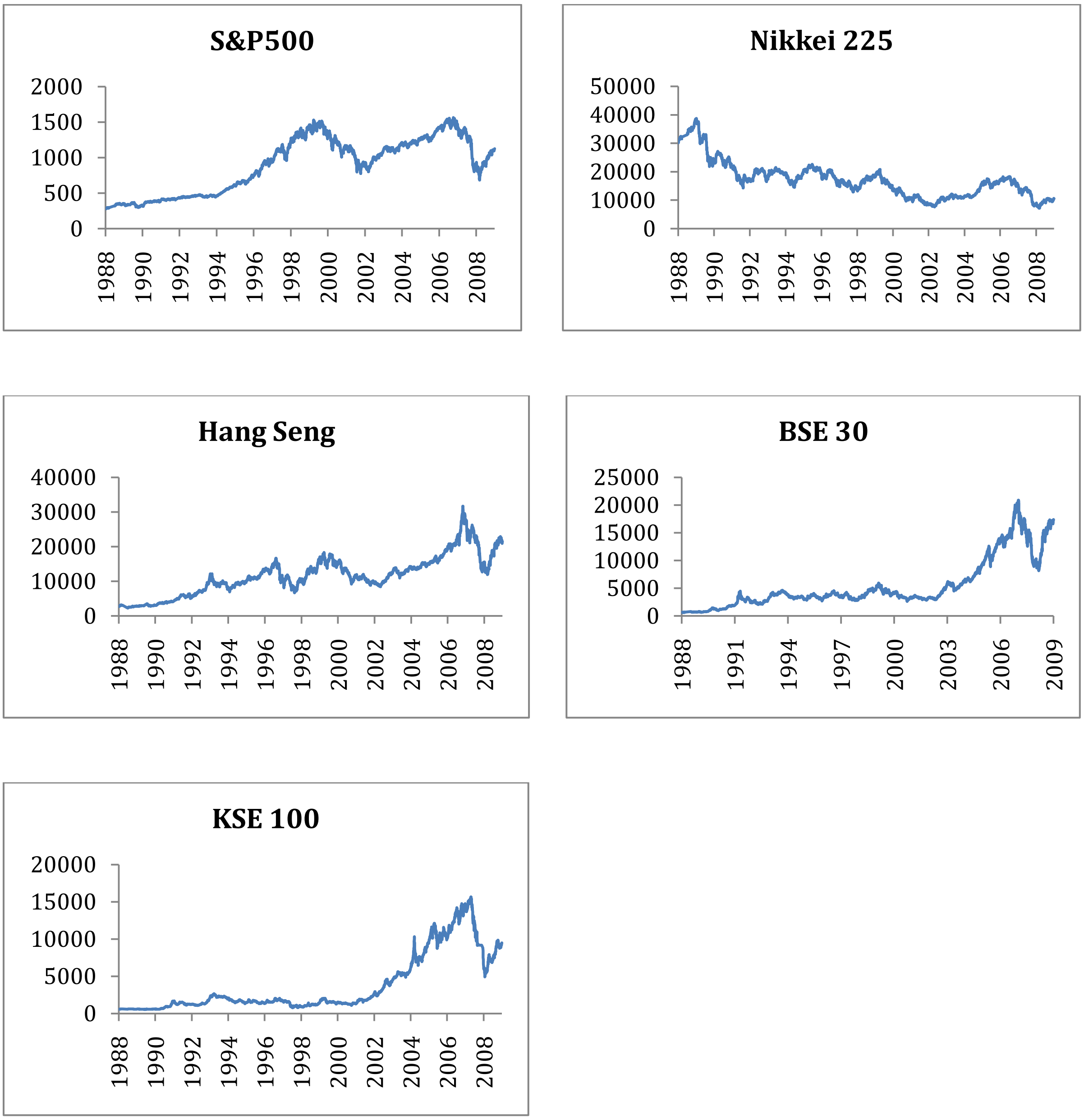
[4] http://fedc.wiwi.hu-berlin.de/xplore/tutorials/sfehtmlnode68.html

We have used daily closing index levels and the data covers the period from 4 January 1989 to 30 December 2009. The choice of time period was determined by availability of data. The 20 year time span captures periods of high volatility, such as during the financial crisis and the IT-bubble to name a few. All the data was obtained from the DataStream database. As the five indices had different holidays we took this into account too. Therefore when either of the markets was closed for a holiday we took all the markets to be closed that day following Sharkasi (2005). Some of the observations are therefore lost. The daily log returns are computed for the remaining observations.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \qquad \textbf{(8)}$$

We tested for stationarity using the Augmented Dickey Fuller test by testing the first difference of the log returns. We found that none of the indices had a unit root. The results are displayed in Appendix 9.

Figure 1 displays return series for S&P 500, Nikkei 225, Hang Seng, BSE 30 and KSE 100 (sample period 01/01/1988-12/31/2009)



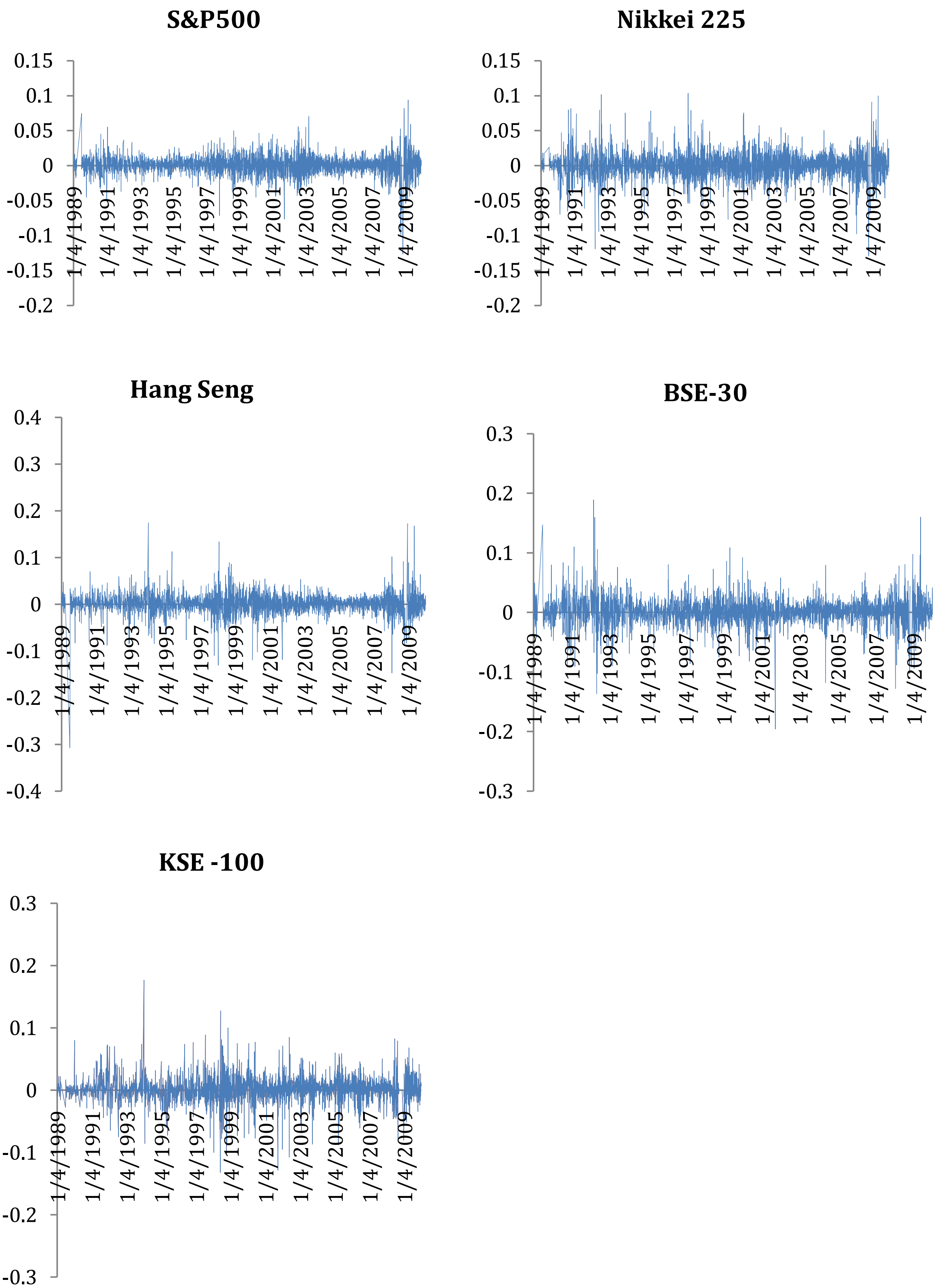
From the descriptive statistics in Table 1 it is evident that the returns of all the five indices exhibit high kurtosis, and that the Jarque-Bera test rejects normality. Thus as explained earlier in Section 3.1 all five indices seem to share the typical characteristics of financial data.

Table 1. Distributional characteristics for S&P 500, Nikkei 225, Hang Seng, BSE 30 and KSE 100 (sample period 01/01/1988-12/31/2009)

	S&P 500	Nikkei 225	Hang Seng	KSE 100	BSE 30
No obs	3837	3837	3837	3837	3837
Mean	0,00036	-0,00027	0,00054	0,00073	0,00085
Median	0,00071	-0,000053	0,00069	0,00089	0,0011
Max	0,094	0,1	0,17	0,17	0,19
Min	-0,13	-0,13	-0,31	-0,13	-0,19
Std. Dev.	0,013	0,017	0,019	0,018	0,021
Skewness	-0,39	-0,078	-0,78	-0,1	0,046
Kurtosis	11,35	8	26	10	11,7
Jarque-Bera	11240	4003	87113	8121	12211
Probability	0	0	0	0	0

The volatility clusters in figure 2 displays that periods of high volatility often evolves into periods of consolidation. The financial turmoil shows clearly up in all indices as a volatility cluster, especially in S&P 500.

Figure 2 displays the volatility clustering for S&P 500, Nikkei 225, Hang Seng, BSE 30 and KSE 100 (sample period 01/01/1988-12/31/2009)



V. Empirical results

We applied the GARCH-BEKK method. Earlier literature on this topic predominantly uses different types of GARCH methods which was also one of the reasons for us using GARCH. BEKK ensures a positive definite conditional variance matrix in the process of optimization (Engle and Kroner 1995). The GARCH-BEKK has shown to be successful in modelling variance, therefore good enough in our attempt to measure time-varying correlation.

Looking at figure 2 in descriptive statistics we observe volatility clustering for each index during the period 1988-2009. The volatility clusters are evidence of ARCH in the series. Some periods are more risky than others, or econometrically speaking the magnitude of the error terms is larger at some times than other (Engle 2001), i.e. feature of heteroscedasticity. As stated earlier it is unlikely to experience the features of homoscedasticity in financial data series. Because of the newsfeed, variance will most likely change over time. One of the better examples in recent times is the financial crisis where stock markets plummeted at the same time as their variance soared. Volatility clusters can capture herd behaviour when such movements in the financial markets occur. A closer look at figure 2 suggests that volatility clustering may not be random. Some degree of persistence in the variance seems to exist.

The first step was to run pair wise vector autoregressive regressions (VAR) with two lags between the indices to generate the mean equations. From the mean equations we generated the residual series. Before we used the GARCH model we had to make sure that the residuals were not autocorrelated since GARCH does not account for this see Appendix 1. GARCH assumes that the data is not autocorrelated so for the results to be meaningful this had to be accounted. For the VAR, we found that using more than two lags did not improve the model, since the Schwarz criterion did not show lower values at higher lags. A lower value for the Schwarz criterion suggests a better model.

In the final step we ran a bivariate GARCH-BEKK on the residual series to generate the conditional covariance matrix. The time-varying correlation between the indices were then calculated. One of the other reasons to choose GARCH BEKK was due to the fact that this limits variance to a positive value as the matrix happens to be positive definite which helps with the validity of the method. In the GARCH-BEKK estimates we applied the multivariate t-distribution. The reason for choosing the t-distribution was that our data set had a high Kurtosis which in common parlance means fatter tails as was stated earlier. T-distribution takes care of the fatter tails which is why it is preferred to a standard normal distribution especially when evaluating financial data.

In section 5.1 we present the time-varying correlation over the entire 20 year period while in Section 5.2, 5.3 and 5.4 we take a closer look at the 3 sub periods. The whole sample will then serve as a benchmark to our subsets. In the first section we will answer how correlation over time has evolved. As mentioned earlier we motivate the sub-periods by the fact that these are periods with high volatility. The sections 5.2 and 5.3 we will examine if bear periods compared to the whole sample show higher correlation. Finally section 5.4 investigates if correlation during the bull market has increased.

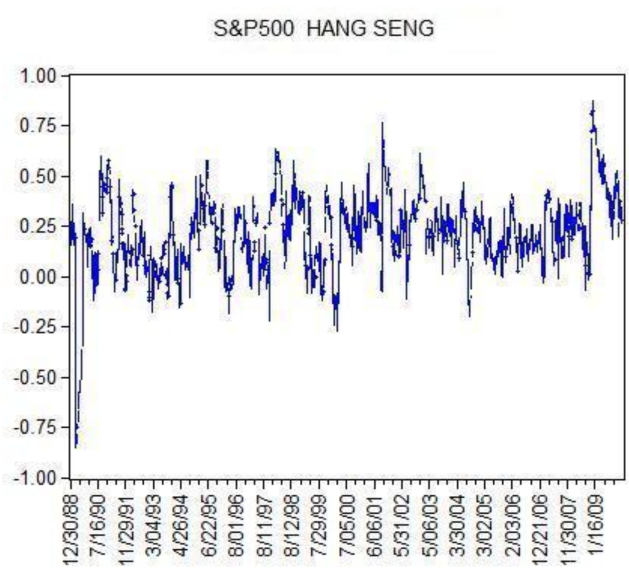
Section 5.1:GARCH-BEKK results for the whole sample period

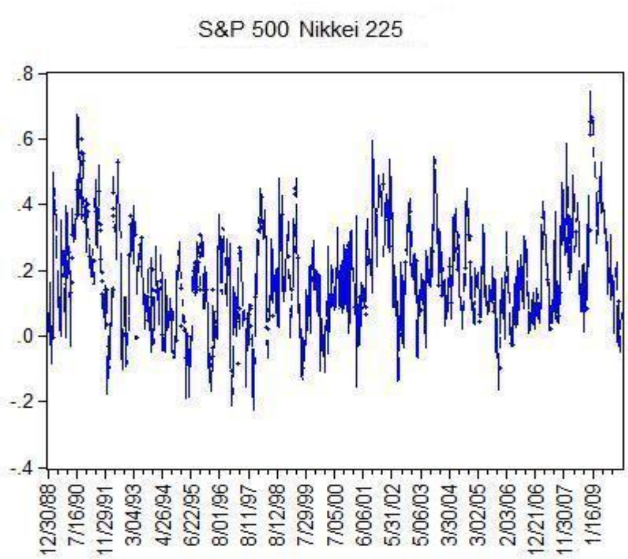
Table 2 displays the mean time-varying correlations for the sample period 01/01/1988-12/31/2009.

Table 2

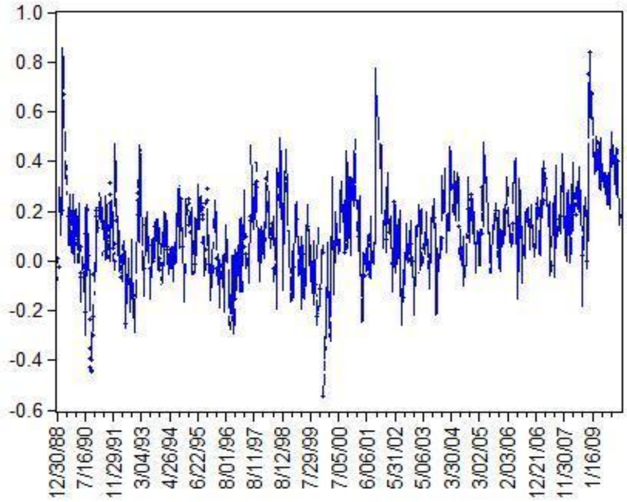
	Mean Correlation
S&P500 to Nikkei 225	0,177
S&P500 to Hang Seng	0,213
S&P500 to BSE 30	0,116
S&P500 to KSE 100	0,036
Nikkei 225 to Hang Seng	0,438
Nikkei 225 to BSE 30	0,206
Nikkei 225 to KSE 100	0,052
Hang Seng to BSE 30	0,275
Hang Seng to KSE 100	0,087
BSE 30 to KSE 100	0,079

Figure 3 shows the evolution of the time-varying correlation for the sample period 01/01/1988-12/31/2009.

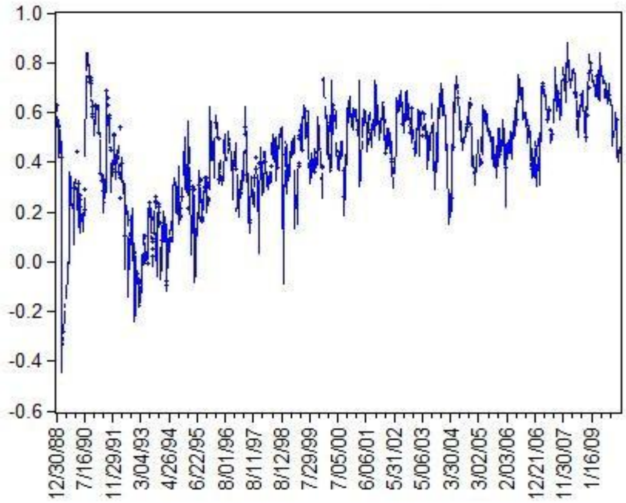


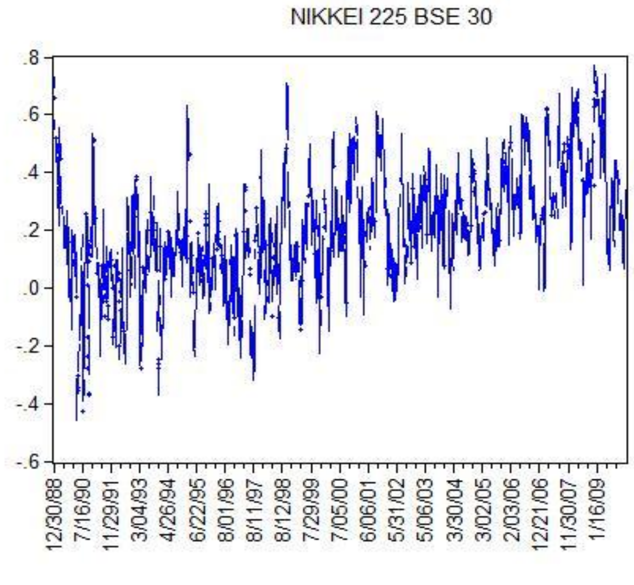


S&P500 BSE 30



Nikkei 225 HANG SENG




NIKKEI 225 BSE 30
.8
.6
.4
.2
.0
-.2
-.4
-.6
12/30/88
7/16/90
11/29/91
3/04/93
4/26/94
6/22/95
8/01/96
8/11/97
8/12/98
7/29/99
7/05/00
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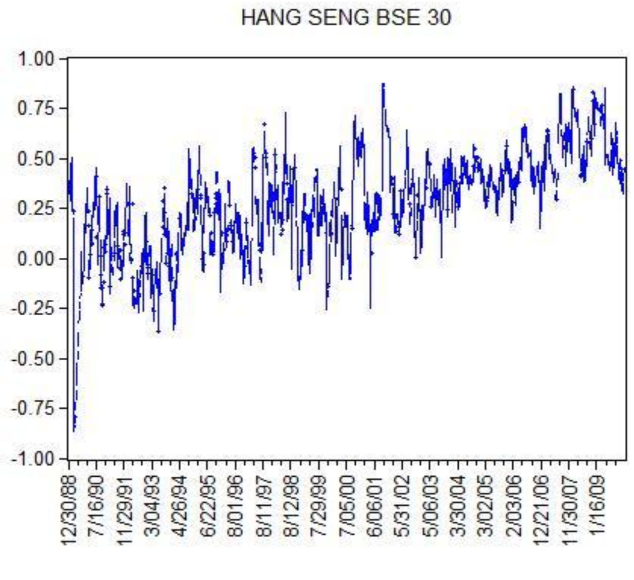
11/30/07
1/16/09


HANG SENG BSE 30
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00
12/30/88
7/16/90
11/29/91
3/04/93
4/26/94
6/22/95
8/01/96
8/11/97
8/12/98
7/29/99
7/05/00
6/06/01
5/31/02
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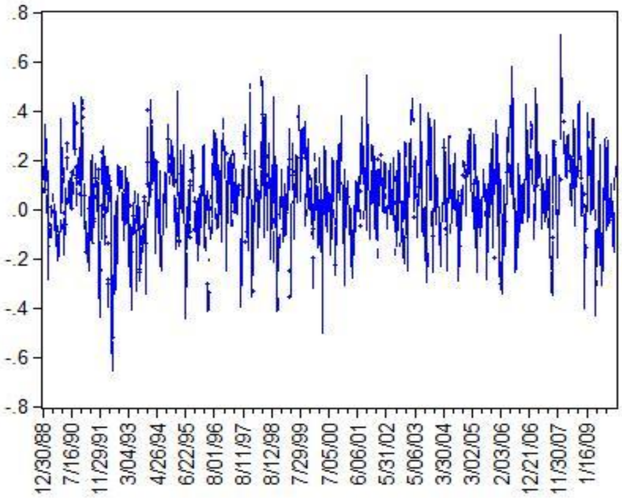
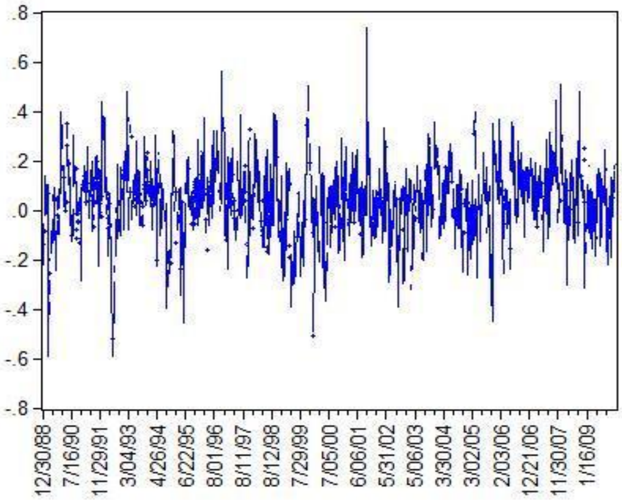
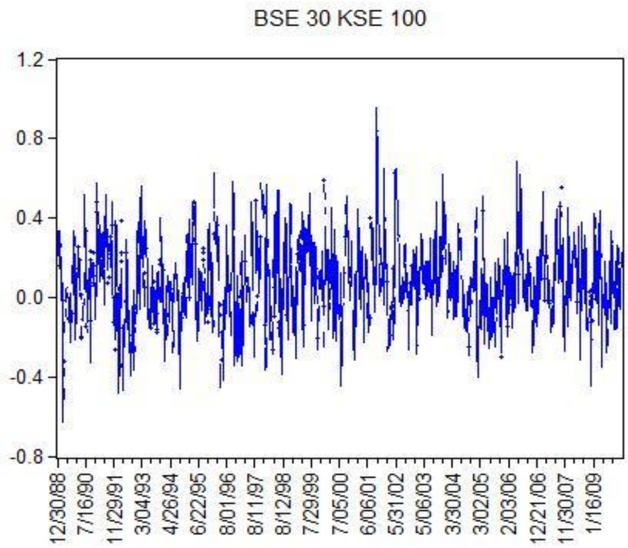
1/16/09

NIKKEI 225 KSE 100



S&P 500 KSE 100





The correlation between the developed markets is greater and it decreases as we move to smaller markets. S&P 500's correlation has the highest correlation with Nikkei 225 and Hang Seng reaching 0, 21 and decreasing to 0,036 against KSE. Table 2 portrays the time varying correlation effect of S&P 500, which as previously mentioned is our benchmark for the world index.

Looking at the regional correlations in table 2 we observe that the correlations have increased meaning the markets are impacted by regional effects to a greater degree than the global one. Moreover, the relationship of bigger markets having greater correlation is observed here as well. Correlation fluctuates between 0,43 for Hang Seng to 0,05 for KSE 100. In the bottom correlations among the local markets are displayed benchmarked to Hang Seng. BSE 30's mean correlation reaches 0,27. BSE 30's correlation to KSE 100 was not that high even though the two countries are close to each other with BSE 30 being the bigger market. The correlation was 0,08.

As we can see from the graphs above, the correlations are not stable. The correlation of Nikkei to BSE, Hang Seng to BSE and Nikkei to Hang Seng increase over time.

Section 5.2:GARCH-BEKK results for sample period 1999-2002

In this section we present our results of the time-varying correlations during the dot com bubble. When we compare S&P500 correlations for this subset to the whole sample period we observe that the correlation amongst the markets somewhat increased.

Table 3 shows the evolution of the time-varying correlation for the sample period 1999-2002.

Table 3

	Mean Correlation
S&P500 to Nikkei 225	0,218
S&P500 to Hang Seng	0,232
S&P500 to BSE 30	0,053
S&P500 to KSE 100	-0,023
Nikkei 225 to Hang Seng	0,516
Nikkei 225 to BSE 30	0,224
Nikkei 225 to KSE 100	0,065
Hang Seng to BSE 30	0,277
Hang Seng to KSE 100	0,067
BSE 30 to KSE 100	0,127

Appendix 5 displays the evolution of time-varying correlation for the sample Dot Com Period. During the IT bubble, most of the stock indices tanked registering significant losses. We observed that the correlations increased in the markets between the developed markets during this time. S&P 500's correlation increased to 0,21 from 0,17 to Nikkei 225 and so did its correlation to Hang Seng whereas to the BSE and KSE it decreased. As mentioned we are comparing with the benchmark 20 year period. The correlation from Nikkei 225 (table 3) onto the smaller indices had a greater effect where the correlation of Hang Seng to Nikkei increased to 0,516 and that of BSE 30 and KSE 100 went to 0,22 and 0,06. The regional markets had greater effect on the correlations, increasing when compared to our benchmark 20 year period lending credence to our observation that when bear spells follow markets become more correlated. Hang Seng's correlation onto BSE 30 was 0,27 and that of Hang Seng onto KSE 100 was 0,06. On the surprising note in this period we found a higher correlation coefficient of BSE 30 onto KSE 100 recorded at 0,12.

Section 5.3: GARCH-BEKK results for sample period 2007-2009

This section also illustrates a bear market, namely the financial crisis. When comparing table 4 to the whole sample period in table 2 we can see that markets become more correlated.

Table 4 shows the evolution of the time-varying correlation for the sample period 2007-2009.

Table 4

	Mean Correlation
S&P500 to Nikkei 225	0,374
S&P500 to Hang Seng	0,332
S&P500 to BSE 30	0,338
S&P500 to KSE 100	0,122
Nikkei 225 to Hang Seng	0,717
Nikkei 225 to BSE 30	0,518
Nikkei 225 to KSE 100	0,154
Hang Seng to BSE 30	0,713
Hang Seng to KSE 100	0,152
BSE 30 to KSE 100	0,143

Appendix 6 displays the evolution of time-varying correlations for the financial crisis. The financial crisis we feel impacted the correlations the greatest and it was during this period that S&P's correlation (Table 4) to the entire basket of our indices increased. S&P 500's correlation to Nikkei 225 went to 0,37, correlation of 0,33 with Hang Seng, correlation to BSE 30's of 0,33 and with KSE 100 to 0,12. We could also argue that during this time period most of the international indices became integrated with financial flows reaching record levels with globalization being increasingly responsible for these 'hot money flows in equity indices. It is beyond doubt that during bear periods correlation among equity markets increases which doesn't flow during bullish spells. The impact of Nikkei 225 onto Hang Seng went as high as 0,71 and to 0,51 for BSE 30.

Even its correlation to KSE 100 increased to 0,15. This was generally twice the correlations experienced in the benchmark 20 year period. Hang Seng's correlation to BSE 30 was 0,71 and with KSE was 0,15 quite the same when compared with Nikkei 225's. BSE 30's correlation to KSE 100 went to 0,14, which was again significantly higher than the benchmark 20 year period. We again noticed correlations increased from the global to the regional to the local markets and moreover they increased when looking at the other bear period being the dot com crisis.

Section 5.4: GARCH-BEKK results for sample period 2004-2007

Table 5 shows the evolution over the time-varying correlation for the sample period 2004-2007.

Table 5

	Mean Correlation
S&P500 to Nikkei 225	0,190
S&P500 to Hang Seng	0,204
S&P500 to BSE 30	0,184
S&P500 to KSE 100	0,027
Nikkei 225 to Hang Seng	0,537
Nikkei 225 to BSE 30	0,324
Nikkei 225 to KSE 100	0,091
Hang Seng to BSE 30	0,453
Hang Seng to KSE 100	0,078
BSE 30 to KSE 100	0,017

Appendix 7 displays the evolution of the time-varying correlation for the bull period.The correlation of S&P 500 to the other indices during this time was around the same as what was observed with the 20 year period; however the only exception being BSE 30 whose correlation increased significantly from 0,11 to 0,18. Nikkei 225's correlation increased to all the three indices by around a third with its correlation to Hang Seng being 0,53; to BSE being 0,32 and lastly to KSE being 0,09. Hang Seng's spillovers to the BSE 30 increased to 0,45. Its correlation to KSE-100 was around the same as in the 20 year benchmark period. The surprising result was the correlation of BSE 30 and KSE 30, which was recorded at only 0,01. Again correlation increased from the global to the regional to the local markets with the exception of BSE 30 onto KSE 100.

Section 5.5: Validation of the correlations

Looking at the computed time varying correlations one cannot make a judgement between the difference of the correlations between different time periods apart from just comparing the numerical values and making a judgement based on them. Therefore to add validity to our results we looked the correlations between the different time periods to see if the correlations were significantly different.

We divided our 20 year data set into 4 periods. The three 'abnormal' periods being the dot com bubble, the bull run and the financial crisis and the fourth period being the normal period, which includes all dates except the three periods.

To test the validity we introduced the three 'abnormal' periods as dummies. We regressed the time varying correlation coefficients against the three dummies. The fourth period forms the constant. The correlation coefficients are compared to the constant.

The ten pair correlations of the 5 indices $(C_2^5) = 10$ were all significant in the dot com and the financial crisis periods. In the Bull period there were instances when the results were not significant. It should be mentioned that when the dummies are significant it means that the correlations were impacted significantly at the 95% confidence interval. Hang Seng to S&P500 was not significant at the 5% level in the bull period. Some of the smaller indices also exhibited this result which we interpret to mean that during the bull period the correlations don't change to that a degree, as can also be observed from the numerical values which don't change by that much of a degree against the constant (the usual period) but during the bearish periods the relationships change significantly, numerically speaking. The higher numerical values of the correlation during both the dot com and financial crisis attest to this apart from being statistically significant too. Bearish markets therefore exhibit greater movement amongst markets than bullish periods.

VI. Conclusion

In our study we have examined the time-varying correlation between S&P 500, Nikkei 225, Hang Seng, BSE 30 and KSE 100 over the time period 1989-2009. We chose a time period which covered interesting developments on the stock exchanges world over, such as the recent financial crisis, the dot com bubble and also a bull market period. The reason to do this was to examine how correlations during these periods deviate from periods, which are more normal.

We find that correlation increases during bear periods, which is the cornerstone of our research, and also a common finding in previous research as well. Comparing the different sub-periods we find that during the financial crisis the correlation increased the most. It should also be mentioned that another reason for the increasing correlation was that during mid 2000's and onwards the pace of market integration increased dramatically. It seems that the financial crisis with its origin in the US has had immense repercussions on the stock markets worldwide. Noteworthy is the correlation for Nikkei 225 and Hang Seng, which reached 0.71 compared to the average correlation of 0.43.

Longin and Solnik (1995) and Kaminsky et al (1998) found the correlations to increase in uncertain periods which is what we have also observed. Our results therefore conform with these studies. Coming to our fourth hypothesis, our results generally follow the hypothesis. It is only on the second hypothesis that our results were not comprehensive especially in the bull period where some indices showed non-significant increase in correlations.

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VIII. APPENDIX

Appendix 1 displays the world correlogram statistics for S&P 500 pair wise together with Nikkei 225, Hang Seng, BSE 30 and KSE 100 (sample period 01/01/1988-12/31/2009). Since the p-values are all insignificant there is no presence of autocorrelation.

S&P500 and Hang Seng				
Lag	AC	PAC	Q-stat	Prob
1	-0,001	-0,001	0,0034	0,954
2	-0,001	-0,001	0,0105	0,995
3	-0,004	-0,004	0,0605	0,996
4	-0,018	-0,018	1,3692	0,85
5	-0,009	-0,009	1,6979	0,889
6	0,019	0,019	3,0462	0,803
7	-0,025	-0,026	5,5415	0,594
8	0,046	0,045	13,596	0,093
9	-0,002	-0,002	13,614	0,137
10	0,011	0,011	14,04	0,171

S&P500 and Nikkei 225				
Lag	AC	PAC	Q-stat	Prob
1	-0,001	-0,001	0,0028	0,958
2	-0,001	-0,001	0,0085	0,996
3	-0,006	-0,006	0,1646	0,983
4	-0,018	-0,018	1,4455	0,836
5	-0,009	-0,009	1,7747	0,879
6	0,019	0,019	3,2289	0,78
7	-0,025	-0,026	5,6998	0,575
8	0,045	0,045	13,611	0,092
9	-0,002	-0,002	13,625	0,136
10	0,011	0,012	14,119	0,168

S&P500 and BSE 30				
Lag	AC	PAC	Q-stat	Prob
1	-0,001	-0,001	0,0011	0,973
2	-0,001	-0,001	0,0065	0,997
3	-0,006	-0,006	0,1261	0,989
4	-0,02	-0,02	1,7301	0,785
5	-0,009	-0,009	2,0613	0,841
6	0,019	0,019	3,396	0,758
7	-0,024	-0,024	5,5609	0,592
8	0,044	0,043	12,86	0,117
9	-0,001	-0,001	12,865	0,169
10	0,011	0,012	13,347	0,205

S&P500 and KSE 100				
Lag	AC	PAC	Q-stat	Prob
1	-0,001	-0,001	0,003	0,956
2	-0,001	-0,001	0,0088	0,996
3	-0,004	-0,004	0,0645	0,996
4	-0,018	-0,018	1,2557	0,869
5	-0,009	-0,009	1,5854	0,903
6	0,019	0,019	2,9347	0,817
7	-0,025	-0,025	5,3339	0,619
8	0,046	0,045	13,37	0,1
9	-0,002	-0,002	13,379	0,146
10	0,011	0,012	13,841	0,18

Appendix 2 displays the regional correlogram statistics for Nikkei 225 pair wise together with, Hang Seng, BSE 30 and KSE 100 (sample period 01/01/1988-12/31/2009). Since the p-values are all insignificant there is no presence of autocorrelation.

Nikkei 225 and Hang Seng				
Lag	AC	PAC	Q-stat	Prob
1	-0,0001	-0,0001	-0,006	0,999
2	0,001	0,001	0,002	0,999
3	-0,008	-0,008	0,2223	0,974
4	0,026	0,026	2,7596	0,599
5	0,026	0,026	5,3618	0,373
6	-0,015	-0,015	6,1709	0,404
7	-0,031	-0,031	9,951	0,191
8	-0,006	-0,006	10,087	0,259
9	0,015	0,014	10,957	0,279
10	0,008	0,008	11,224	0,34

Nikkei 225 and BSE 30				
Lag	AC	PAC	Q-stat	Prob
1	0	0	0,0004	0,984
2	-0,001	-0,001	0,0049	0,998
3	-0,011	-0,011	0,4972	0,92
4	0,028	0,028	3,4187	0,49
5	0,026	0,026	5,9818	0,308
6	-0,013	-0,013	6,6128	0,358
7	-0,033	-0,032	10,723	0,151
8	-0,005	-0,005	10,806	0,213
9	0,015	0,014	11,695	0,231
10	0,009	0,008	11,997	0,285

Nikkei 225 and KSE 100				
Lag	AC	PAC	Q-stat	Prob
1	-0,001	-0,001	0,0019	0,966
2	0	0	0,0019	0,999
3	-0,008	-0,008	0,2469	0,97
4	0,026	0,026	2,8701	0,58
5	0,026	0,026	5,5364	0,354
6	-0,013	-0,013	6,2107	0,4
7	-0,029	-0,029	9,5436	0,216
8	-0,004	-0,005	9,6144	0,293
9	0,015	0,013	10,429	0,317
10	0,01	0,01	10,821	0,372

Appendix 3 displays the local pair wise correlogram statistics for Hang Seng, BSE 30 and KSE 100 (sample period 01/01/1988-12/31/2009). Since the p-values are all insignificant there is no presence of autocorrelation.

Hang Seng and BSE 30				
Lag	AC	PAC	Q-stat	Prob
1	-0,001	-0,001	0,0029	0,957
2	-0,001	-0,001	0,004	0,998
3	-0,026	-0,026	2,6006	0,457
4	-0,007	-0,007	2,7963	0,592
5	-0,004	-0,004	2,8594	0,722
6	-0,016	-0,017	3,8493	0,697
7	-0,013	-0,014	4,532	0,717
8	0,034	0,034	9,0695	0,336
9	0,03	0,03	12,641	0,18
10	0,015	0,014	13,525	0,196

Hang Seng and KSE 100				
Lag	AC	PAC	Q-stat	Prob
1	0	0	0,0003	0,966
2	0	0	0,0005	0,999
3	-0,024	-0,024	2,2895	0,97
4	-0,005	-0,005	2,3953	0,58
5	-0,002	-0,002	2,4133	0,354
6	-0,015	-0,015	3,2491	0,4
7	-0,009	-0,01	3,5881	0,216
8	0,036	0,036	8,6889	0,293
9	0,032	0,032	12,698	0,317
10	0,016	0,015	13,659	0,372

BSE 30 and KSE 100				
Lag	AC	PAC	Q-stat	Prob
1	-0,002	-0,002	0,0089	0,925
2	-0,001	-0,001	0,00118	0,994
3	-0,008	-0,008	0,2832	0,963
4	0,038	0,038	5,8046	0,214
5	-0,014	-0,014	6,5122	0,26
6	-0,008	-0,008	6,7493	0,345
7	0,043	0,044	13,86	0,054
8	0,02	0,018	15,384	0,052
9	-0,009	-0,008	15,723	0,073
10	-0,009	-0,008	16,061	0,098

Appendix 4 displays the validation results. The tests show whether the sub periods are significant.

Significance test: Hang Seng - BSE 30

	Coef.	Std. Dev.	t-stat	P-value
dot com	0.1206	0.0082	14.55	0.000
Bullmarket	0.2648	0.0087	30.41	0.000
Fincrisis	0.4649	0.0112	41.19	0.000
Constant	0.0648	0.0045	34.7	0.000

Significance test: Hang Seng - KSE 100

	Coef.	Std. Dev.	t-stat	P-value
dot com	-0.0173	0.0071	-2.41	0.016
Bullmarket	0.0094	0.0075	1.25	0.210
Fincrisis	0.0097	0.0097	1.00	0.316
constant	0.0884	0.0039	22.69	0.000

Significance test: KSE 100 - BSE 30

	Coef.	Std. Dev.	t-stat	P-value
dot com	0.0598	0.0081	7.39	0.000
bullmarket	-0.0126	0.0085	-1.49	0.137
fincrisis	0.0381	0.0110	3.45	0.001
constant	0.0648	0.0043	14.74	0.000

Significance test: S&P500 - Nikkei 225

	Coef.	Std. Dev.	t-stat	P-value
dot com	0.0209	0.0059	3.52	0.000
bullmarket	-0.0128	0.0062	-2.06	0.040
fincrisis	0.1509	0.0081	18.62	0.000
constant	0.1601	0.0032	49.50	0.000

Significance test: S&P500 - Hang Seng

	Coef.	Std. Dev.	t-stat	P-value
dot com	0.0289	0.0078	3.67	0.000
bullmarket	-0.0046	0.0082	-0.57	0.571
fincrisis	0.1448	0.0107	13.48	0.000
constant	0.1935	0.0042	45.18	0.000

Significance test: S&P500 - KSE 100

	Coef.	Std. Dev.	t-stat	P-value
dot com	-0.0412	0.0059	-6.9	0.000
bullmarket	0.0156	0.0062	2.49	0.013
fincrisis	0.0374	0.0081	4.59	0.000
constant	0.0383	0.0032	11.79	0.000

Significance test: S&P500 - BSE 30

	Coef.	Std. Dev.	t-stat	P-value
dot com	-0.0312	0.0075	-4.11	0.000
bullmarket	0.1198	0.0079	15.03	0.000
fincrisis	0.1863	0.0103	18.03	0.000
constant	0.1274	0.0041	30.92	0.000

Significance test: Nikkei 225 - BSE 30

	Coef.	Std. Dev.	t-stat	P-value
dot com	0.0972	0.007	13.84	0.000
bullmarket	0.1795	0.0073	24.34	0.000
fincrisis	0.3255	0.0095	34.03	0.000
constant	0.1212	0.0038	31.77	0.000

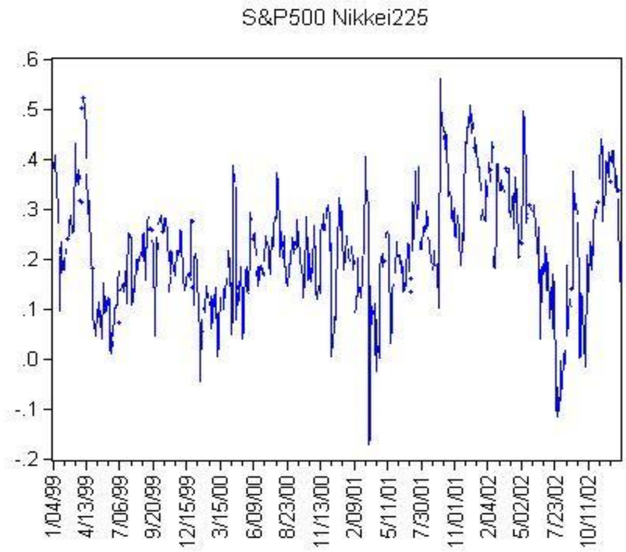
Significance test: Nikkei 225 - Hang Seng

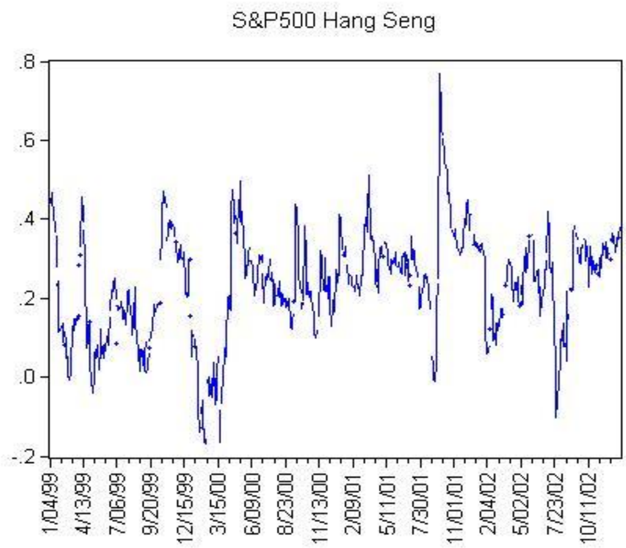
	Coef.	Std. Dev.	t-stat	P-value
dot com	0.1765	0.0071242	24.79	0.000
bullmarket	0.1709	0.0071	4.58	0.000
fincrisis	0.3509	0.0092	8.04	0.000
constant	0.3353	0.0037	9.11	0.000

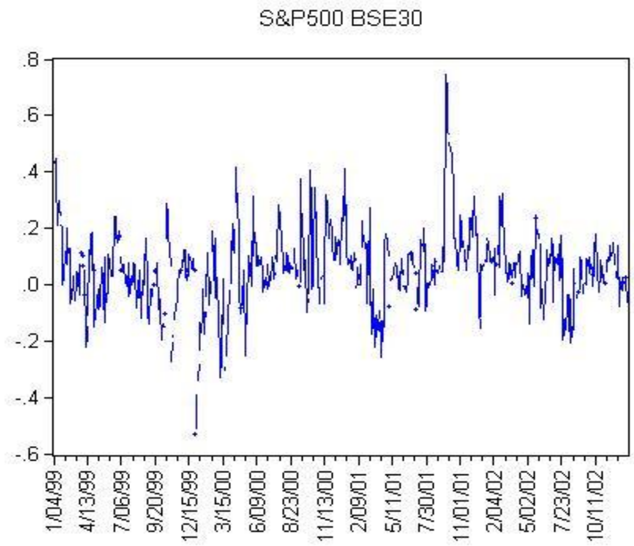
Significance test: Nikkei 225 - KSE 100

	Coef.	Std. Dev.	t-stat	P-value
dot com	0.1765	0.0071	24.79	0.000
Bullmarket	0.1708	0.0074	22.84	0.000
Fincrisis	0.3508	0.0096	36.18	0.000
Constant	0.3352	0.0038	86.66	0.000

Appendix 5 displays the time varying correlation results in the Dot Com Bubble period



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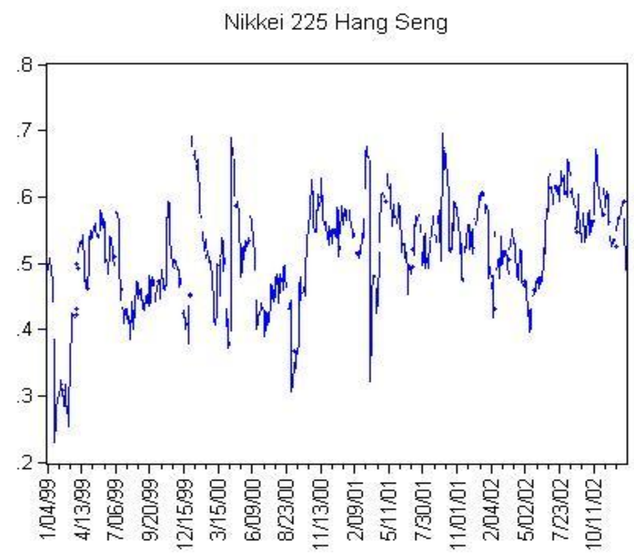
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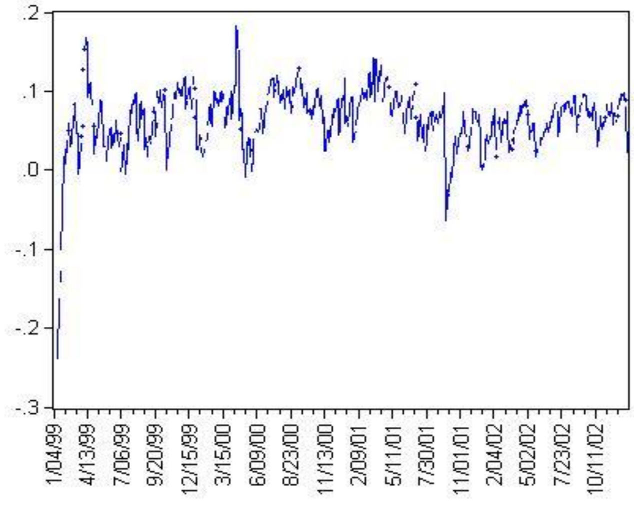
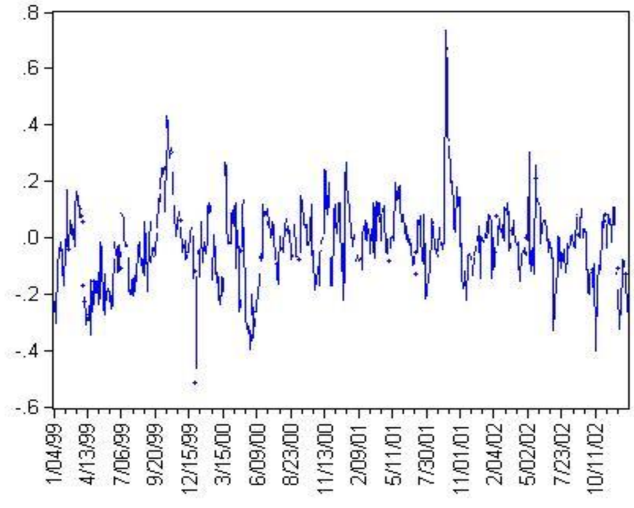
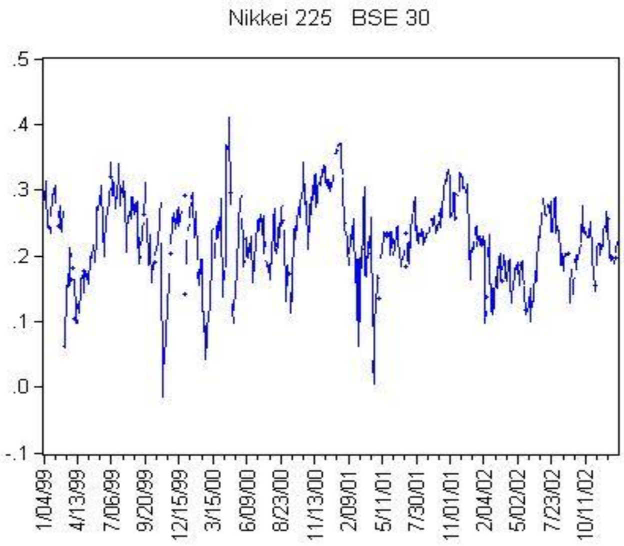
2/04/02
5/02/02
7/23/02
10/11/02

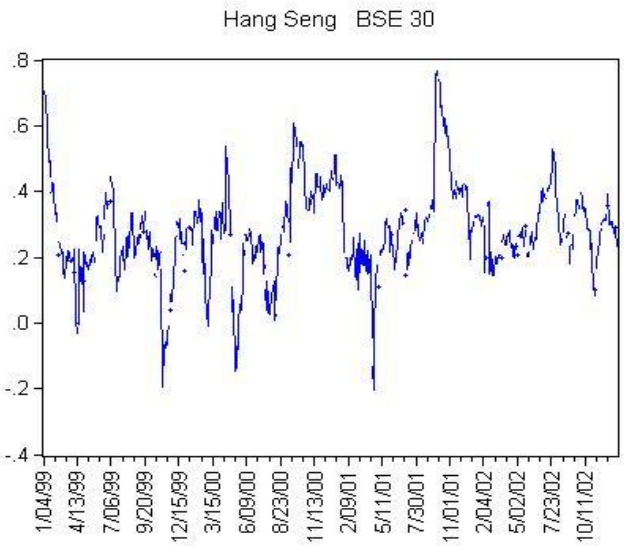
Nikkei 225   KSE 100

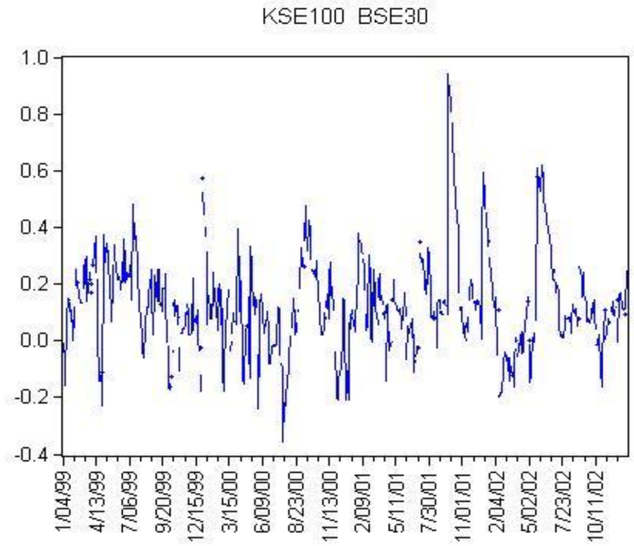


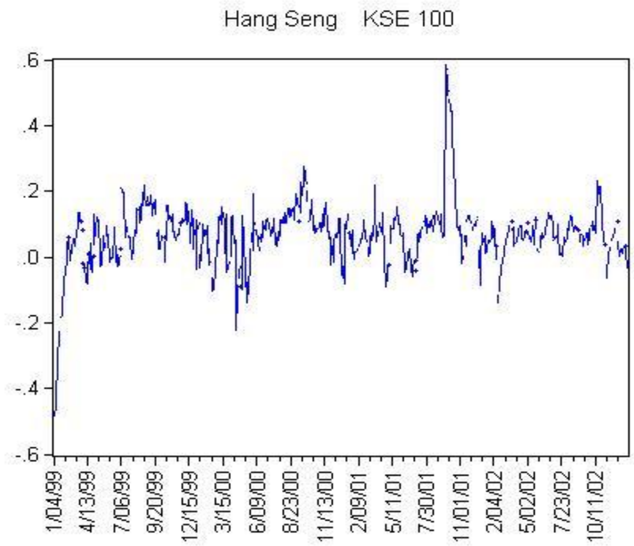
S&P500 KSE100



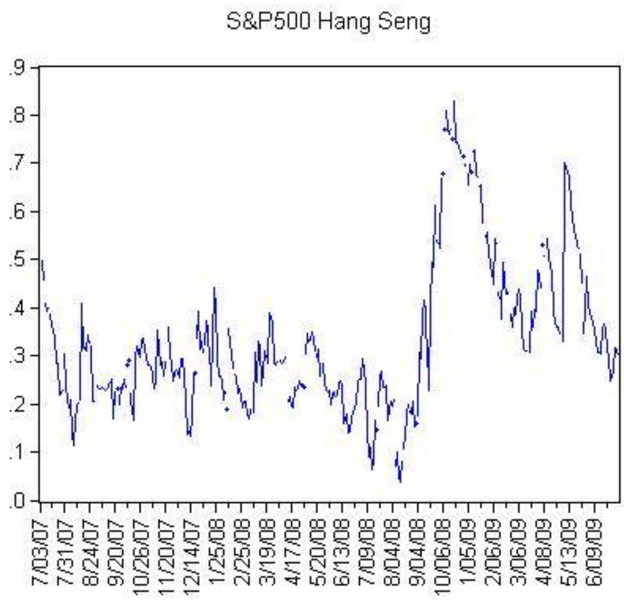

Nikkei 225 BSE 30
.5
.4
.3
.2
.1
.0
-.1
1/04/99
4/13/99
7/06/99
9/20/99
12/15/99
3/15/00
6/09/00
8/23/00
11/13/00
2/09/01
5/11/01
7/30/01
11/01/01
2/04/02
5/02/02
7/23/02
10/11/02

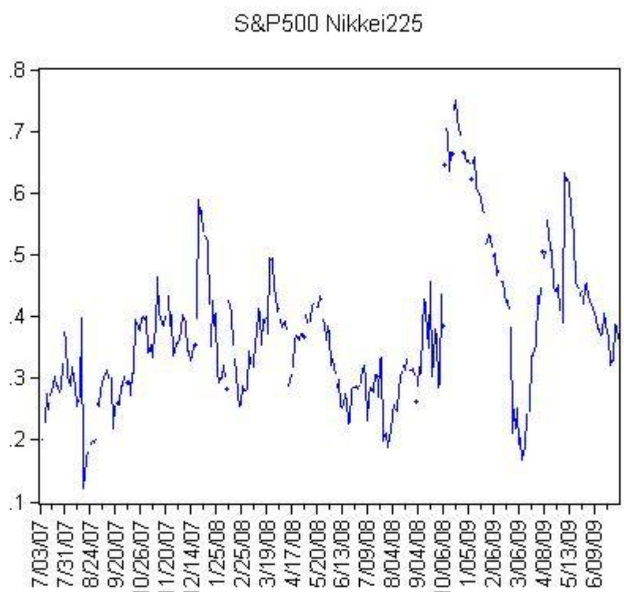

Hang Seng BSE 30
.8
.6
.4
.2
.0
-.2
-.4
1/04/99
4/13/99
7/06/99
9/20/99
12/15/99
3/15/00
6/09/00
8/23/00
11/13/00
2/09/01
5/11/01
7/30/01
11/01/01
2/04/02
5/02/02
7/23/02
10/11/02


KSE100 BSE30
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
1/04/99
4/13/99
7/06/99
9/20/99
12/15/99
3/15/00
6/09/00
8/23/00
11/13/00
2/09/01
5/11/01
7/30/01
11/01/01
2/04/02
5/02/02
7/23/02
10/11/02

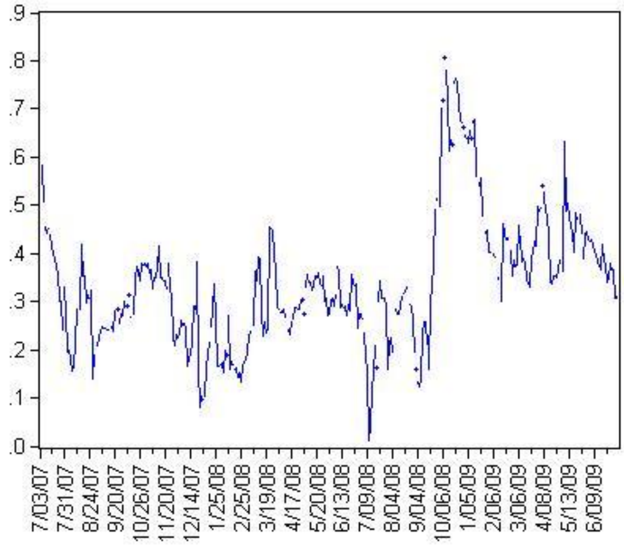

Hang Seng KSE 100
.6
.4
.2
.0
-.2
-.4
-.6
1/04/99
4/13/99
7/06/99
9/20/99
12/15/99
3/15/00
6/09/00
8/23/00
11/13/00
2/09/01
5/11/01
7/30/01
11/01/01
2/04/02
5/02/02
7/23/02
10/11/02

Appendix 6 displays the time varying correlation results in the Financial Crisis Period

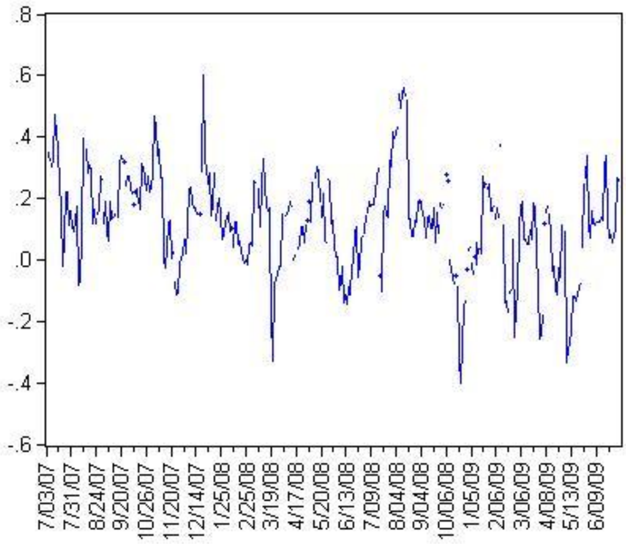




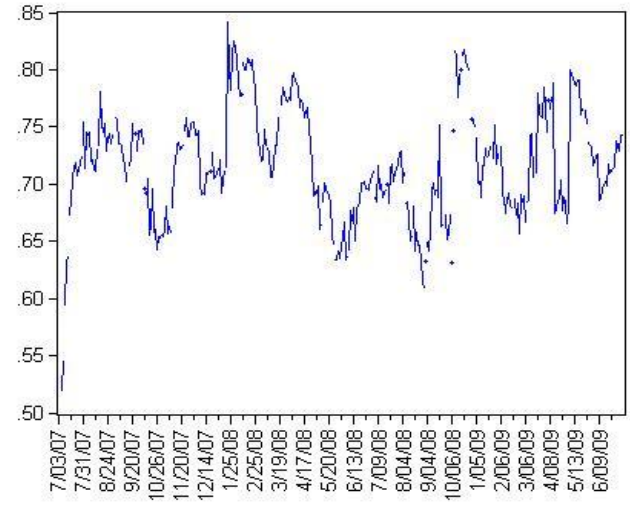
S&P500 BSE30



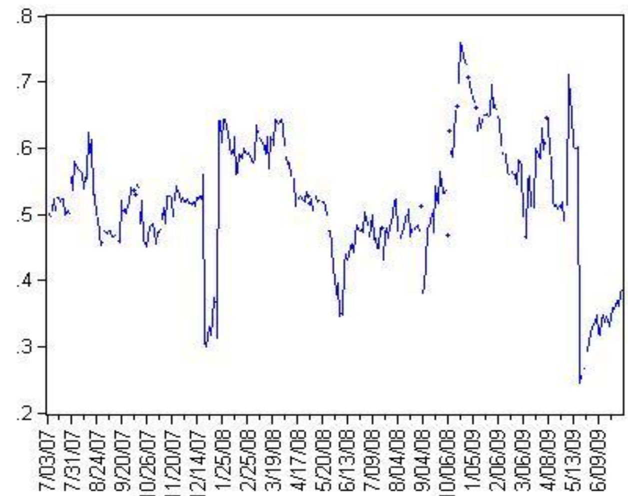
S&P500 KSE100

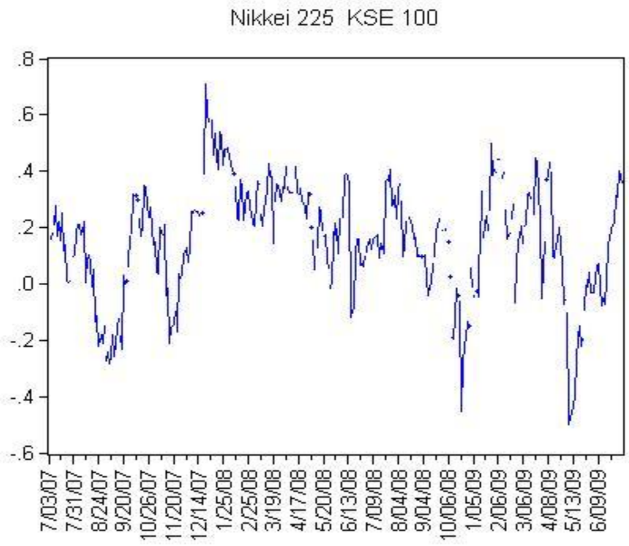


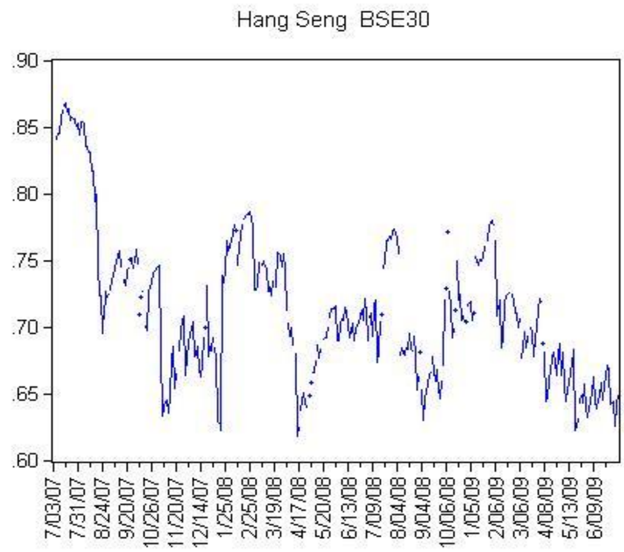
Nikkei 225 Hang Seng

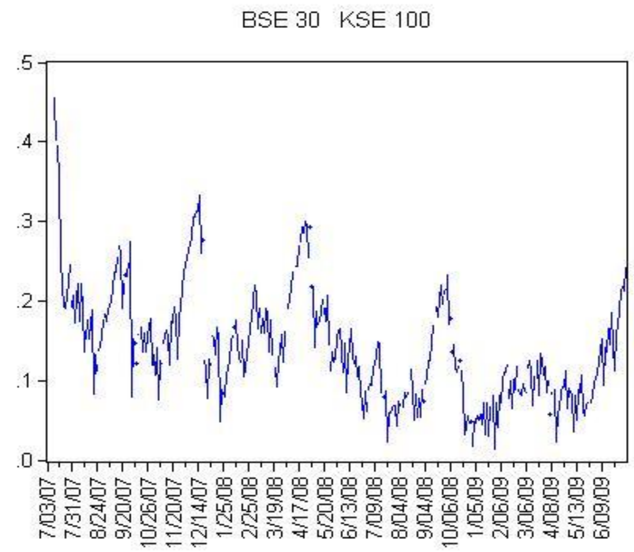


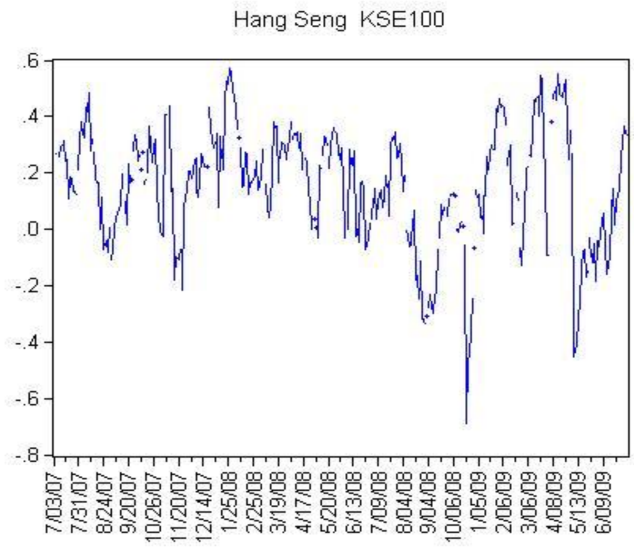
Nikkei 225 BSE 30



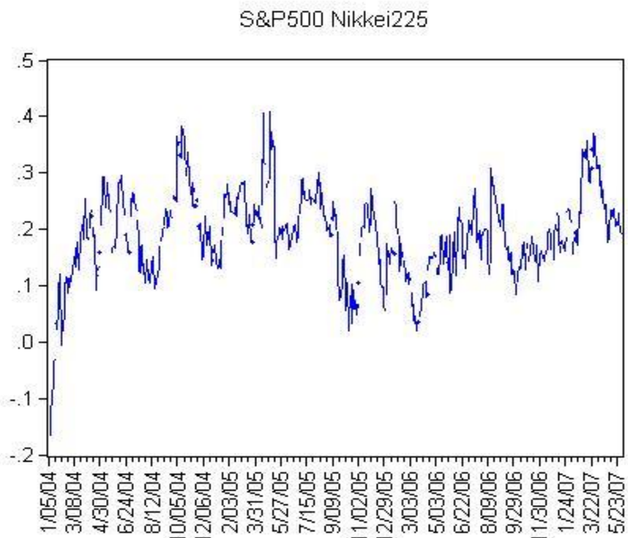

Nikkei 225 KSE 100
.8
.6
.4
.2
.0
-.2
-.4
-.6
7/03/07
7/31/07
8/24/07
9/20/07
10/26/07
11/20/07
12/14/07
1/25/08
2/25/08
3/19/08
4/17/08
5/20/08
6/13/08
7/09/08
8/04/08
9/04/08
10/06/08
1/05/09
2/06/09
3/06/09
4/08/09
5/13/09
6/09/09

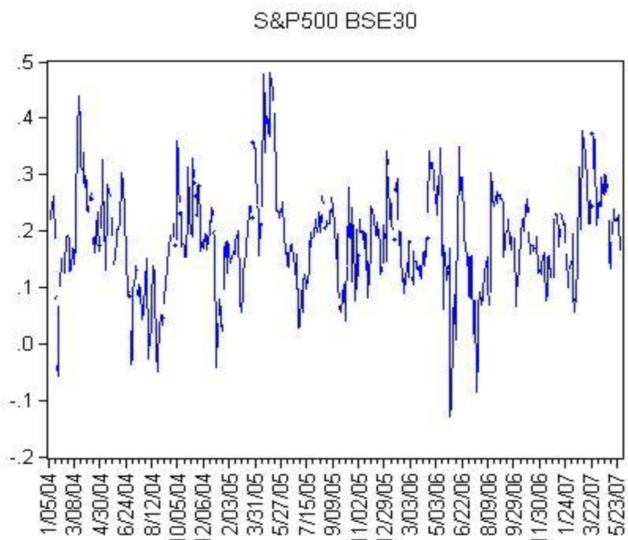

Hang Seng BSE30
.90
.85
.80
.75
.70
.65
.60
7/03/07
7/31/07
8/24/07
9/20/07
10/26/07
11/20/07
12/14/07
1/25/08
2/25/08
3/19/08
4/17/08
5/20/08
6/13/08
7/09/08
8/04/08
9/04/08
10/06/08
1/05/09
2/06/09
3/06/09
4/08/09
5/13/09
6/09/09


BSE 30 KSE 100
.5
.4
.3
.2
.1
.0
7/03/07
7/31/07
8/24/07
9/20/07
10/26/07
11/20/07
12/14/07
1/25/08
2/25/08
3/19/08
4/17/08
5/20/08
6/13/08
7/09/08
8/04/08
9/04/08
10/06/08
1/05/09
2/06/09
3/06/09
4/08/09
5/13/09
6/09/09

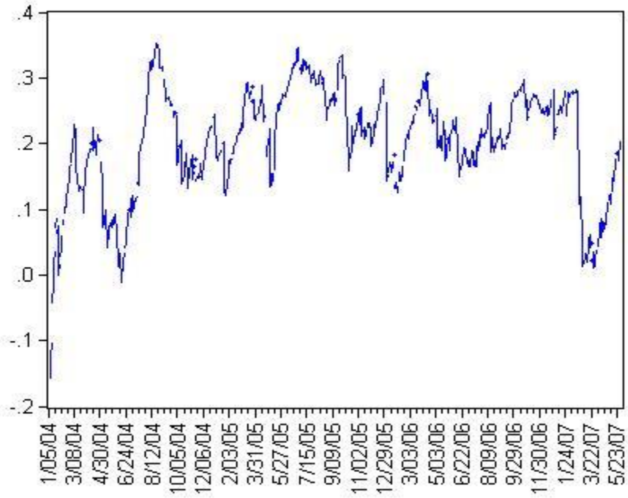

Hang Seng KSE100
.6
.4
.2
.0
-.2
-.4
-.6
-.8
7/03/07
7/31/07
8/24/07
9/20/07
10/26/07
11/20/07
12/14/07
1/25/08
2/25/08
3/19/08
4/17/08
5/20/08
6/13/08
7/09/08
8/04/08
9/04/08
10/06/08
1/05/09
2/06/09
3/06/09
4/08/09
5/13/09
6/09/09

Appendix 7 displays the time varying correlation results in the Bull period

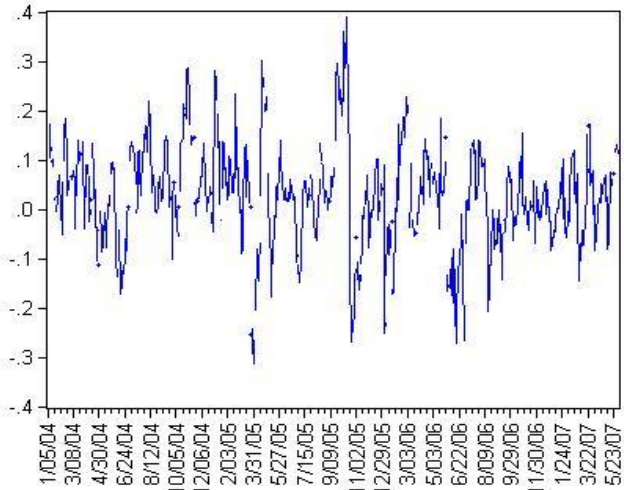




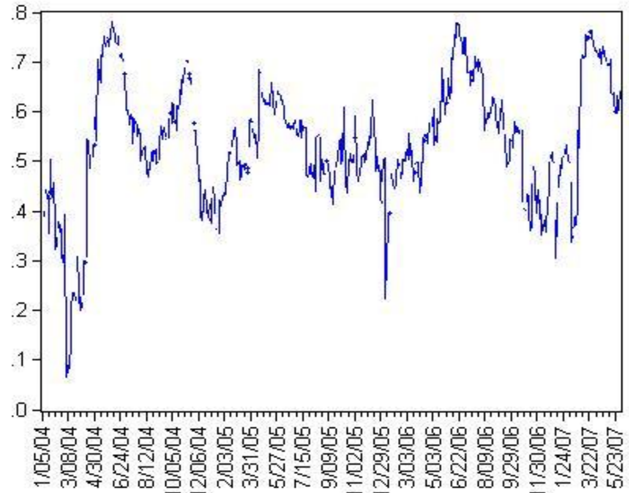
S&P500 Hang Seng



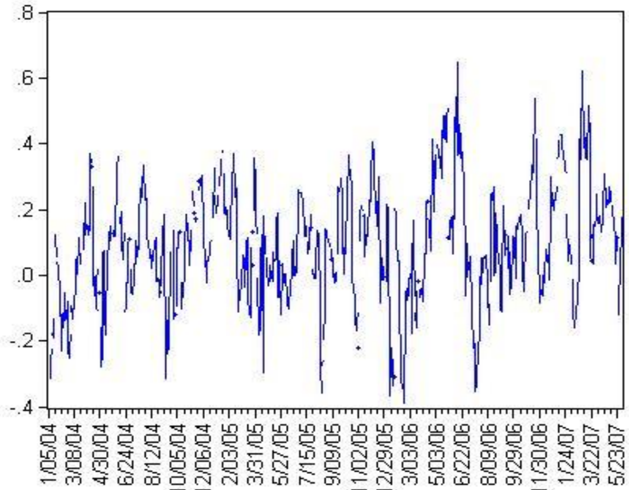
S&P500 KSE100



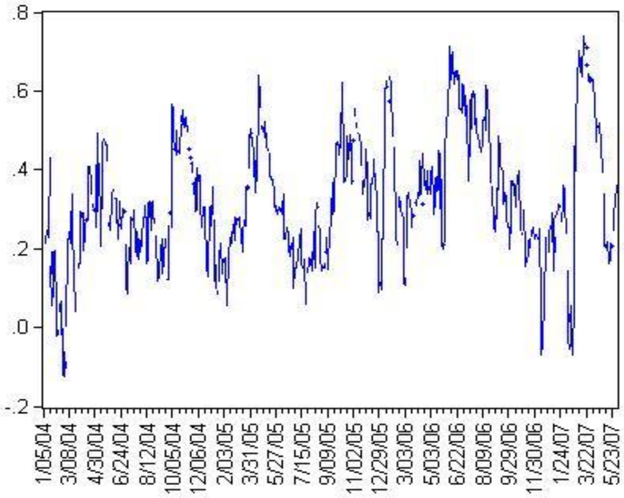
Nikkei 225 Hang Seng



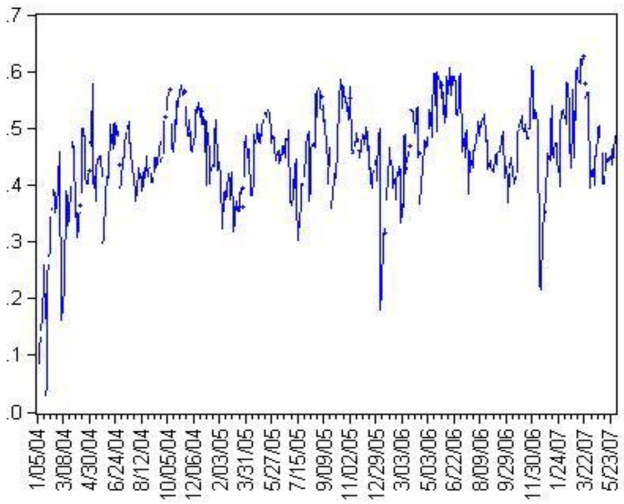
Nikkei 225 KSE100

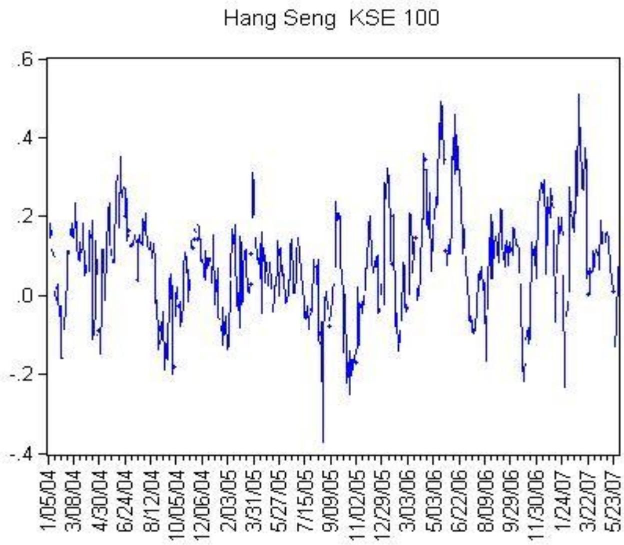


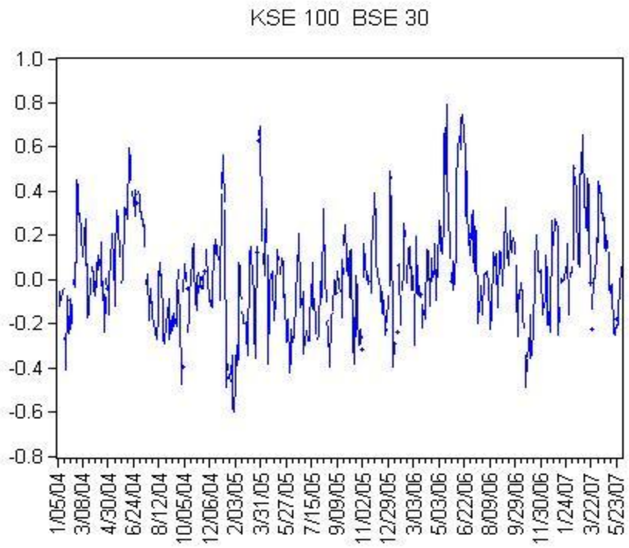
Nikkei 225 BSE 30



Hang Seng BSE 30




Hang Seng KSE 100
.6
.4
.2
.0
-.2
-.4
1/05/04
3/08/04
4/30/04
6/24/04
8/12/04
10/05/04
12/06/04
2/03/05
3/31/05
5/27/05
7/15/05
9/09/05
11/02/05
12/29/05
3/03/06
5/03/06
6/22/06
8/09/06
9/29/06
11/30/06
1/24/07
3/22/07
5/23/07


KSE 100 BSE 30
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
1/05/04
3/08/04
4/30/04
6/24/04
8/12/04
10/05/04
12/06/04
2/03/05
3/31/05
5/27/05
7/15/05
9/09/05
11/02/05
12/29/05
3/03/06
5/03/06
6/22/06
8/09/06
9/29/06
11/30/06
1/24/07
3/22/07
5/23/07

Appendix 8 displays the Granger Causality results for the sample period 1988 to 2009 with 12 lags

Null Hypothesis:	F-Statistic	P Value.
HANG_SENG does not Granger Cause BSE_30	2.41221	0.0041
BSE_30 does not Granger Cause HANG_SENG	0.68892	0.7638
S_P500 does not Granger Cause BSE_30	6.89665	2.00E-12
BSE_30 does not Granger Cause S_P500	1.77041	0.0473
NIKKEI_225 does not Granger Cause BSE_30	1.69847	0.0607
BSE_30 does not Granger Cause NIKKEI_225	3.52666	3.00E-05
S_P500 does not Granger Cause HANG_SENG	21.7855	3.00E-47
HANG_SENG does not Granger Cause S_P500	0.91331	0.5325
S_P500 does not Granger Cause KSE_100	3.28715	9.00E-05
KSE_100 does not Granger Cause S_P500	0.77472	0.6773
NIKKEI_225 does not Granger Cause KSE_100	1.79774	0.043
KSE_100 does not Granger Cause NIKKEI_225	1.66426	0.0681
BSE_30 does not Granger Cause KSE_100	2.7671	0.0009
KSE_100 does not Granger Cause BSE_30	1.01655	0.4301
HANG_SENG does not Granger Cause KSE_100	2.16503	0.011
KSE_100 does not Granger Cause HANG_SENG	2.65083	0.0015
NIKKEI_225 does not Granger Cause HANG_SENG	2.54376	0.0024
HANG_SENG does not Granger Cause NIKKEI_225	1.52352	0.108
NIKKEI_225 does not Granger Cause S_P500	0.62046	0.8266
S_P500 does not Granger Cause NIKKEI_225	29.2091	1.00E-64

Appendix 9 shows the unit root tests for each index with the critical values atttached.

Augmented Dicke-Fuller Unit Root Test

	t-stat	Prob
S&P 500	-24,768	0,000
Nikkei 225	-20,788	0,000
Hang Seng	-20,898	0,000
BSE 30	-26,797	0,000
KSE 100	-24,350	0,000

Test Critical Values:

1%	-3,431	
5%	-2,862	
10%	-2,567	