World Applied Sciences Journal 7 (11): 1412-1418, 2009
ISSN 1818-4952

Modelling the Relationships between US and Selected Asian Stock Markets

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Abstract: It is well known that many countries around the world depend on the US as their major trade partner. As a result, if something does happen to US economy it surely will affect the economy of all these countries. In this study, we investigate the relationship between the US and four Asian emerging stock markets namely Hong Kong, India, South Korea and Malaysia using monthly data between 1996 and 2008. In order to model the relationships, two approaches are used. They are linear Vector Autoregressive (VAR) model and nonlinear Markov Switching Vector Autoregressive (MS-VAR) model. In general we found that the two models manage to explore the possibility of relationship between all the stock markets. Nevertheless, MS-VAR model provide more insight on when all this relationship occurred. In addition, the result also indicates that the MS-VAR model fitted the data well than the linear VAR model.

Key words: Markov switching vector autoregressive model . vector autoregressive model . cointegration . stock price

INTRODUCTION

It is well known that US is main trading partner of many Asian developing countries. Therefore, whatever happens to the US economy will also affect the economy of these Asian countries. This interrelationship phenomenon in international market is not only a result of the liberalization of capital markets in developed and developing countries and the increasing variety and complexity of financial instrument but also a result of the increasing relatively of the developing and developed economies as developing countries become more integrated in international flow of trade and payment. As a result, this has triggered the interest of economists and policy makers to find the linkages between the stock market of developed countries mainly the US and the stock market of developing countries.

Numerous related studies on the relationship between stock market of US and developing countries have been done by researchers. For instance, Ghosh *et al*. [1] examined whether the stock markets of nine Asian-Pacific countries are driven by US or Japan stock market during the financial turmoil in 1997 using the theory of cointegration. They had identified nine stock markets which can be divided into three groups; those that move with the US stock market, those that move with Japan stock market and those that are not affected by the two stock markets. Then Arshanapalli and Kulkarni [2] studied the interdependence between Indian stock market and the US stock market and the results showed that the Indian stock market was not interrelated with the US stock market.

Later, Yang *et al* [3], investigated the long run relationship and short-run dynamic causal linkages among the US, Japanese and ten Asian emerging stock markets. They discovered that both long-run cointegration relationships and short-run causal linkages among these markets were strengthened during the financial crisis in 1997 and that these markets have generally been more integrated after the 1997 crisis than before the crisis. Wang *et al*. [4] studied the relationship among the five largest emerging African stock markets and US market and uncovered that both long-run relationships and short-run causal linkages show that regional integration between most of African stock markets was weakened after the 1997-1998 crisis. Finally, Serrano and Rivero [5], revealed the mixed results on the existence of long run relationship due to structural breaks between the US and Latin Americans stock markets.

Most of the literatures mention above used similar methodology to analyze the interaction among the stock market. They begin their studies by finding whether the variables are cointegrated or not using cointegration test and followed by modelling the variables using Vector Autoregressive (VAR) or Vector Error Correction (VEC) to show the existent of short run or long run relationships among the variables. However in this study we apply a different approach to study the

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interaction between the US and the selected Asian stock markets. The main objective of this study is to investigate whether nonlinear interaction because of common regime switching behaviour exists among the stock markets by assuming that all the series are regime dependent. Therefore, a two regime multivariate Markov Switching Vector Autoregressive (MS-VAR) model with regime shifts that happened in both the mean and the variance is used to extract common regime switching behaviour from all the series. Furthermore the results of a linear VAR model and a nonlinear MS-VAR model will be compared.

The remainder of this paper is organized as follows. The specification and estimation of the Vector Autoregressive model and the Markov Switching Vector Autoregressive model are given in Section II. Section III presents the empirical results and discussion on the results. Section IV contains the summary and the conclusion.

THE DYNAMIC MODEL

In this section we will give a brief introduction about the Vector Autoregressive (VAR) model and the Markov Switching Vector Autoregressive (MS-VAR) model

Vector Autoregressive (VAR) model: The VAR model is commonly used in forecasting system of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. In essence, VAR model is a multiple time series generalization of the autoregressive model. The VAR model for *k* variables can be written in matrix notation as follows:

$$Y_t = \alpha + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \varepsilon_t \qquad (1)$$

where $Y_t = (Y_{1t}, Y_{2t},\ldots,Y_{kt})$ and $A_1, A_2,\ldots,A_p$ are $(k\times k)$ matrix and ε_t is a *k*-dimensional vector of error with $E(\varepsilon) = 0$. *p* is the optimal number of lag length. The lag length of *p* can be chosen using Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) or Final prediction Errors (FPE).

Even if the variables in level form where Y_t are nonstationary, there may be linear combinations of these series that are stationary and in other words these variables are said to be cointegrated. Before the VAR model is employed, cointegration between variables should be identified as to avoid spurious regression or mis-specification problem. VAR model approach is conducted using series at level if cointegration exists among the variables. Conversely, variables that are not cointegrated suggest the use of VAR model in first differences. The term autoregressive in VAR model is due to the appearance of the lagged value of the dependent variable and the term vector is due to the fact that the analysis is dealing with a vector of variables. Moreover, the VAR model is a system of simultaneous equations and all the variables are considered to be endogenous variables.

Markov Switching Vector Autoregressive (MS-VAR) model: The Markov Switching Autoregressive model (MS-AR) was originally developed by Hamilton [6] to define changes between fast and slow growth regimes in the US economy. It was assumed that in the MS-AR model, the time series, y_t is normally distributed with μ_i in each of k possible regime where i = 1, 2,…,k. A MS-AR model of two states with an AR process of order p, MS–AR(p) is given as follows:

$$\begin{aligned} & y_t = \mu(s_t) + \left[\sum_{i=1}^{p} \alpha_i\left(y_{t-i} - \mu(s_{t-i})\right)\right] + u_t \\ & u_t \,|\, s_t \sim NID\left(0,\sigma^2\right) \quad \text{and} \quad s_t = 1,2 \end{aligned} \qquad (2)$$

where α_i are the autoregressive parameters with i = 1, 2,…,p.

The MS-AR framework of Equation (2) can be readily extended to MS-VAR model with two regimes that allows the mean and the variance to shifts simultaneously across the regime. The model is given below:

$$\begin{aligned} & Y_t - \psi(s_t) = A_1(s_t)\left(Y_{t-1} - \psi(s_{t-1})\right) + \ldots \\ & + A_p(s_t)\left(Y_{t-p} - \psi(s_{t-p})\right) + \varepsilon_t \end{aligned} \qquad (3)$$

where $Y_t = (Y_{1t},\ldots,Y_{nt})$ is the n dimensional time series vector, ψ is the vector of means, $A_1,\ldots,A_p$ are the matrices containing the autoregressive parameters and ε_t is the white noise vector process such that $\varepsilon t|St$ NID $(0,\Sigma(s_t))$ Other specifications of MS-VAR model are being discussed by Krolzig [7].

From Equation (2) and (3), s_t is a random variable that triggers the behaviour of Y_t to change from one regime to another. Therefore the simplest time series model that can describe a discrete value random variable such as the unobserved regime variable s_t is the Markov chain. Generally, s_t follow a first order Markov process where it implies that the current regime s_t depends on the regime one period ago, s_{t-1} and denoted as:

$$P\left[s_t = j \,|\, s_{t-1} = i, s_{t-2} = k, \ldots\right] = P\left[s_t = j \,|\, s_{t-1} = i\right] = p_{ij} \qquad (4)$$

where p_{ij} is the transition probability from one regime to another. From m regimes, these transition probabilities can be collected in a (m×m) transition matrix denoted as P.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{5}$$

with

$$\sum_{j=1}^{m} p_{ij} = 1, \quad i = 1,2,\ldots,m \quad \text{and} \quad 0 \le p_{ij} \le 1$$

The transition probabilities also provide the expected duration that is the expected length the system is going to be stay in a certain regime. Let D define the duration of regime j. Then, the expected duration of the regime j is given by

$$E(D) = \frac{1}{1-p_{jj}} \quad j = 1,2,\ldots \tag{6}$$

The conventional procedure for estimating the model parameters is to maximize the log-likelihood function and then use these parameters to obtain the filtered and smoothed inferences for the unobserved regime variable s_t. However, this method becomes disadvantageous as the number of parameters to be estimated increases. Generally, in such cases, the Expectation Maximization (EM) algorithm is used. This technique starts with the initial estimates of the unobserved regime variable, s_t and iteratively produces a new joint distribution that increases the probability of observed data. These two steps are referred to Kim and Nelson [8].

MODELLING DYNAMIC RELATIONSHIP

This section presents the results of the econometric specifications used for modelling the relationship between US and four Asian emerging stock markets. It begins with a description of the data and testing for stationary using two unit root tests. Then if the data is stationary at the same order, Johansen test is used to examine the existent of cointegration. Later, we show the dynamic relationships using the VAR model and the MS-VAR model. In addition, it follows by the comparison between these two model.

DATA

We used monthly data of US Standard and Poor 500 (SP500) and four Asian stock markets namely Kuala Lumpur Composite Index (KLCI), Bombay Stock Exchange Sensitive Index (BSE), Hang Seng Index (HSI) and Korea Composite Stock Price Index (KOSPI) from January 1996 to September 2008. Simple average monthly data for all stock indices are calculated from daily closing prices obtained from DataStream. The five series are analysed in returns, which is the first difference of natural logarithms multiplied by 100 to express them in percentage terms.

Figure 1 shows the behaviour of the return series of the SP500 Index, the KLCI Index, the BSE index, the HSI index and the KOSPI Index over the study period. It appears that large negative return happened during financial crisis in 1997 for KLCI, BSE, HIS and KOSPI. Meanwhile, large negative return recorded from 2000 to 2002 for SP500 where world recession happened during these two years.

STATIONARITY AND COINTEGRATION TESTS

Many of the econometric models such as Vector Autoregression (VAR) and Vector Error Correction (VECM) require knowledge of stationarity and order of integration for the variables. To determined the order of integration and to test stationarity for each data series, unit root test is employed. Two tests are carried out in this research, namely Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. ADF test has been employed to test the stationarity of the series at level and first difference of each variable. Besides that, the tests have been implemented with and without time trend. On the other hand, an alternative way to examine the stationarity of the series is PP test. Same as ADF test, this test has been carried out at level and first difference on each series with or without time trend.

From Table 1, most of the statistics for series at level are not significant. This suggests that the null hypothesis of unit root test cannot be rejected and the indices are not stationary at level. After first differencing has been employed for the series, the null hypothesis of unit root test can be rejected at 1% level of significance for series with or without trend, Thus, the series are stationary at first difference and integrated of order 1, I(1). Thus, the cointegration test can be carried out after all the series are integrated at the same order.

The Johansen and Juselius, [9] cointegration test is carried out to examine the existence of the long-run relationship among the indices. This test identifies the number of the cointegration vector by using the maximum likelihood method. Two test statistics are used to test the presence of *r* cointegrating vectors, namely trace statistic and maximum eigen statistic. The existence of cointegration among the variables indicates

Table 1: Unit root test

	Level		1st differentiation	
Variables	No trend	Trend	No trend	Trend
ADF test for sector indices				
KLCI	-0.164313	-2.536774	-5.247440**	-5.293921**
BSE	1.312106	-1.721236	-5.012370**	-5.297199**
KOSPI	0.240633	-3.052333	-4.561405**	-4.577696**
HSI	0.738874	-1.746844	-5.528400**	-5.537322**
SNP	1.054308	-2.036893	-4.176579**	-4.495458**
PP test for sector indices				
KLCI	-0.087631	-2.248149	-9.544721**	-9.508495**
BSE	1.583666	-1.513903	-10.08707**	-10.21111**
KOSPI	0.322166	-2.602952	-8.217208**	-8.191878**
HSI	0.628535	-2.021883	-9.241594**	-9.186566**
SNP	1.270871	-2.060797	-10.35602**	-10.57164**

Note: ** Indicates significance at 5%

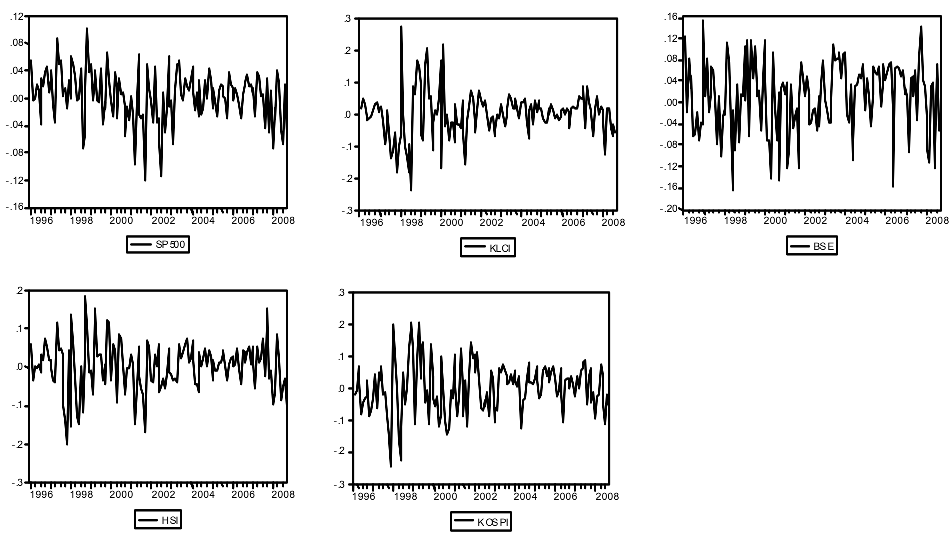

Fig. 1: The return series

the rejection of the non-causality among the variables. The result of the cointegration test is shown in Table 2 and r represents the number of the cointegration relationships of the hypothesis test.

According to Table 2, both trace statistic and maximal eigen statistic suggests that there is no cointegrating vector at 1% level of significance. Thus, each indices does not sustain a stable equilibrium relationship with each other's therefore, this suggests that there is no long-run cointegration among the indices. Next we modeled the relationship using VAR and MS-VAR models.

ESTIMATING VAR AND MS-VAR MODEL

Using the principle of parsimony we found that two regimes Markov Switching Vector Autoregressive model of order one with switching in the mean and the variance or MS-VAR(1) manage to capture the interaction among the five series very well. As a result we manage to estimate VAR(1) model to represent the linear dynamic relationship between the five series. The results of VAR (1) model are given in Table 3.

The results show some strong lead-lag interactions between the series. The Hong Kong (HSI) and Indian (BSE) markets return are significantly affected by the previous 1 month return in the Korean (KOSPI) market. While, Malaysia market return is significantly affected by the previous 1 month return in Hong Kong (HSI) and Korean (KOSPI) markets.

Estimation results for MS-VAR(1) model are presented in Table 4. Estimations are carried out using MSVAR module for Ox [10]. Before discussing further the estimation model, we need to determine whether

Table 2: JJ Cointegration tests for indices

		Trace		Max-eigen	
Null hypothesis	Eigen value	Statistic	1% critical value	Statistic	1% critical value
r = 0	0.1870	73.59	76.07	31.26	38.77
r≤1	0.1365	42.33	54.46	22.16	32.24
r≤2	0.0739	20.17	35.65	11.59	25.52
r≤3	0.0546	8.57	20.04	8.47	18.63

Table 3: VAR estimates for indices

Indices	HSI_t	$SNP500_t$	BSE_t	$KOSPI_t$	$KLCI_t$
HSI_{t-1}	0.335841	0.190180	0.282786	0.085511	0.425539**
$SNP500_{t-1}$	-0.444818	0.014484	-0.317243	0.128192	-0.446586
BSE_{t-1}	-0.111386	-0.009494	-0.102203	-0.114700	-0.171088
$KOSPI_{t-1}$	0.305361**	0.159508	0.346984**	0.060965	0.392006**
$KLCI_{t-1}$	-0.166371	0.059528	-0.028191	-0.069711	-0.030413**

Note: **Indicates significance at 5%

Table 4: Model comparison

	MS-VAR (1)	Linear VAR (1)
Log-likelihood	-2183.4409	-2267.3219
AIC	29.8072	30.6268
HQC	30.3511	30.9921
SBC	31.1460	31.5260

Log-likelihood Ratio (LR) Test167.7620 [.000]

regime shifts happened in the five return series. For this purpose, we use the likelihood ratio (LR) test suggested by Garcia and Perron [11]. As denoted in Table 4, the likelihood ratio test for testing the null hypothesis of linear model against an alternative of regime switching model, it is found that the null hypothesis can be rejected because the Davies [12] p-value (value in the [] bracket) show significance results. Therefore, a nonlinear MS-VAR(1) model is better than linear VAR(1) model in describing the data. Moreover, the minimum value of AIC (Akaike), HQC (Hannan-Quinn) and SBC (Schwartz Bayesian) criteria indicate that the performance of the MS-VAR(1) models are better than the nested linear VAR(1) model.

Table 5 reports the parameters estimated of the two regimes MS-VAR (1). The coefficients of VAR(1) component from the MS-VAR(1) model reveal more information about the lead-lag interactions between the five series. It appears that there exist some dependencies between one stock market with other stock markets. Thus, it shows quite strong interactions between the five stock market indices. Furthermore, the MS-VAR(1) model also gives us information regarding the behavior of the data in more details. It can be seen from Table 5 that the estimated means of the MS-VAR(1) model for each of the two regimes has a clear economic interpretation. The first regime ($S_t = 1$) indicates that all the stock market indices are in the Bear market or contraction phase with negative sign of the monthly expected return, $\mu(S_t = 1)$ and higher volatility, $\sigma^2(S_t = 1)$. Conversely, the second regime captures the Bull market or expansion phase of the stock market indices with positive sign of the monthly expected return, $\mu(S_t = 2)$ and lower volatility $\sigma^2(S_t = 2)$. In addition, the probability of staying in regime 1, $P(S_t = 1 \mid S_{t-1} = 1) = 0.7983$ is higher than the probability of staying in regime 2, $P(S_t = 2 \mid S_{t-1} = 2) = 0.6884$ in which suggesting that regime 1 ($S_t = 1$) is more persistent than regime 2 ($S_t = 2$). Thus, an average all the series staying longer in regime 1 which is about 5 months compare to staying in regime 2 which is only 3 months.

In addition, MS-VAR(1) model also provides us with smoothed regime probability plots of regime 1 and regime 2 which is the probability of staying in either regime 1 or regime 2 at time t. As seen in Fig. 2, the smoothed probabilities of regime 1 are near one just after the smoothed probabilities of regime 2 are near zero. This means the smoothed regime probability plot tell us at which point in time all the series follow the same behavior which is either all the indices are increasing (regime 2) or decreasing (regime 1).

CONCLUSION

In this paper we have discussed two difference approaches in modelling the interactions of US stock markets (SNP500) and selected Asian emerging stock markets the KLCI (Malaysia), BSE (India), KOSPI

Table 5: MS-VAR (1) estimates for indices

	$SNP500_t$	HSI_t	BSE_t	$KOSPI_t$	$KLCI_t$
Regime-dependent means					
$\mu(s_t = 1)$	-0.516693	-0.743525	-1.749450**	-2.211923**	-0.907229
$\mu(s_t = 2)$	1.702575**	2.168063**	5.069093**	4.212444**	1.353152**
Coefficients					
$SNP500_{t-1}$	0.169003**	-0.323890**	0.128155	-0.085681	-0.239831
HSI_{t-1}	0.064532	0.435988**	0.176803**	0.179005	0.336874**
BSE_{t-1}	-0.077203**	-0.130913**	-0.039571	-0.105886	-0.063379
$KOSPI_{t-1}$	0.029238	0.107619	0.084369	0.314830**	0.353883**
$KLCI_{t-1}$	-0.069292	-0.229498**	0.123536**	-0.069421	0.059547
Regime-dependent variances					
$\sigma^2 (s_t = 1)$	3.867555**	7.264876**	6.358074**	8.163605**	7.264583**
$\sigma^2 (s_t = 2)$	2.350401**	2.692375**	2.557107**	3.766973**	2.500573**
p_{ij}	$S_{t-1} = 1$		$S_{t-1} = 2$		E(D)
$S_t = 1$	0.7983		0.2017		4.96
$S_t = 2$	0.3116		0.6884		3.21

Note: **Indicates significance at 5%

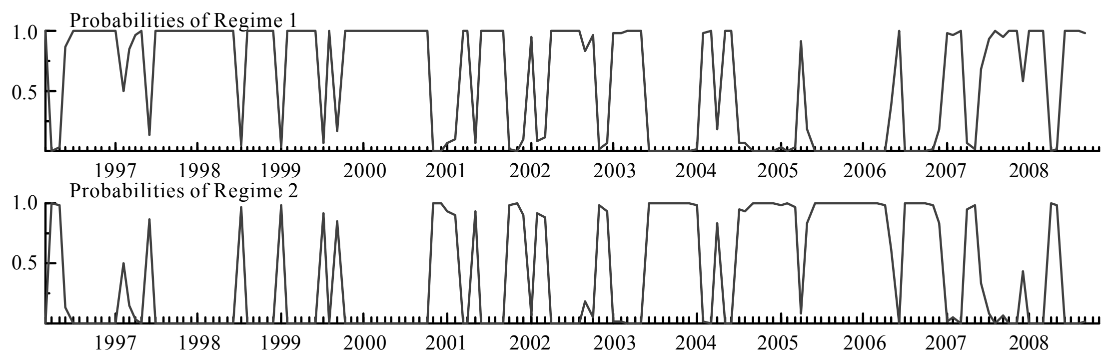

Fig. 2: Smoothed probability plots of the MS-VAR(1) model

(Korea) and HSI (Hong Kong). We modelled the relationship using linear VAR(1) and nonlinear MS-VAR(1) models. All the results point out that MS-VAR model gives more information about the nature of the data as compare to VAR model. In addition, the MS-VAR(1) model uncovers that when the US stock market increasing (decreasing) it will follow by the increasing (decreasing) of the other four stock markets.

ACKNOWLEDGEMENTS

The authors would like to thank USM for financial aid during the research.

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