

Modelling The Relationships Between US and Selected Asian Stock Markets

¹Mohd Tahir Ismail*, ²Rosmanjawati Abdul Rahman

^{1,2} School of Mathematical Sciences, Universiti Sains Malaysia, 11800 USM, Penang

*¹mtahir@cs.usm.my, ²rosmanjawati@usm.my

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 paper, 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. We are going to use two approaches to model the relationship. The first method is by using linear vector autoregressive (VAR) model and the other method is via 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.

Keywords: Markov switching vector autoregressive model, vector autoregressive model, cointegration, stock price.

1. Introduction

It is well known that US is main trading partner of many Asian developing countries. Therefore, whatever happens to the US economy it 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 US stock market and stock market of developing countries have been done by researchers. For instance, Ghosh et al. (1999) 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 found that the nine stock markets can be divide into three groups which those that move with the US stock market, those with move with Japan stock market and those with not affected by the two stock markets. Then Arshanapalli and Kulkarni (2001) 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 (2003), Wang et al. (2003) and Serrano and Rivero (2003) investigated the long run relationship and short-run dynamic causal linkages among the US, Japanese, and ten Asian emerging stock markets, among the five largest emerging African stock markets and US market and between US and Latin American stock markets. Yang et al (2003) 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. Meanwhile, Wang et al (2003) 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. As for Serrano and Rivero (2003), they revealed mix results about the existence of long run relationship because of 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 later modelling the variables using vector autoregressive (VAR) model or vector error correction (VEC) model to show the existent of short run relationship or long run relationship among the variables. However in this paper we use different methodology to study the interaction between the US and selected Asian stock markets. The focus of our study is to investigate whether nonlinear interaction because of common regime switching behaviour exists among the stock markets. Thus, we assume all the series are regime dependent.

Therefore, a two regime multivariate Markov switching vector autoregressive (MS-VAR) model with regime shifts happen in both the mean and the variance is going to be used to extract common regime switching behaviour from all the series. Furthermore we are going to compare the results from linear VAR model and nonlinear MS-VAR model.

The remainder of this paper is organized as follow. 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.

2. 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

2.1 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 follow

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

where $Y_t = (Y_{1t}, Y_{2t}, \dots, Y_{kt})$ and A_1, A_2, \dots, 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 misspecification 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.

2.1 Markov Switching Vector Autoregressive (MS-VAR) Model

The Markov switching autoregressive model (MS-AR) was originally developed by Hamilton to define changes between fast and slow growth regimes in the US economy. Hamilton 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 $i = 1, 2, \dots, k$. A MS-AR model of two states with an AR process of order p , $MS-AR(p)$ is given as follow:

$$y_t = \mu(s_t) + \left[\sum_{i=1}^p \alpha_i (y_{t-i} - \mu(s_{t-i})) \right] + u_t \quad (2)$$

$$u_t | s_t \sim NID(0, \sigma^2) \quad \text{and} \quad s_t = 1, 2$$

where α_i are the autoregressive parameters with $i = 1, 2, \dots, p$.

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:

$$Y_t - \psi(s_t) = A_1(s_t)(Y_{t-1} - \psi(s_{t-1})) + \dots + A_p(s_t)(Y_{t-p} - \psi(s_{t-p})) + \varepsilon_t \quad (3)$$

where $Y_t = (Y_{t1}, \dots, Y_{tm})$ is the n dimensional time series vector, ψ is the vector of means, A_1, \dots, A_p are the matrices containing the autoregressive parameters, and ε_t is the white noise vector process such that $\varepsilon_t | s_t \sim NID(0, \Sigma(s_t))$. Other specifications of MS-VAR model are being discussed by Krolzig (1997).

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:

$$P[s_t = j | s_{t-1} = i, s_{t-2} = k, \dots] = P[s_t = j | s_{t-1} = i] = p_{ij} \quad (3)$$

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

$$P = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1m} \\ p_{21} & p_{22} & \dots & p_{2m} \\ \dots & \dots & \dots & \dots \\ p_{m1} & p_{m2} & \dots & p_{mm} \end{bmatrix} \quad (4)$$

with $\sum_{j=1}^m p_{ij} = 1$, $i = 1, 2, \dots, m$ and $0 \leq p_{ij} \leq 1$. 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

$$E(D) = \frac{1}{1 - p_{jj}} \quad j = 1, 2, \dots \quad (5)$$

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 Hamilton (1994) and Kim and Nelson (1999).

3. Modelling Dynamic Relationship

In this section we will present the results of the econometric specifications used for modelling the relationship between US and four Asian emerging stock markets. This section begins by giving a description of the data and testing for stationary using two unit root tests. Then if the data is stationary at the same order, we use Johansen test to examine the existent of cointegration. Later, we show the dynamic relationship using the VAR model and the MS-VAR model. In addition, we will also compare the results from the two approaches.

3.1 Data

The data used are monthly data of US Standard and Poor 500 (SP500) and four Asian stock markets namely Malaysia, Kuala Lumpur Composite Index (KLCI), India, Bombay Stock Exchange Sensitive Index (BSE), Hong Kong, Hang Seng Index (HSI) and Korea, Korea Composite Stock Price Index (KOSPI) from January 1996 to September 2008. Simple average monthly data that are used 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 things 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. Figures 1 denote 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.

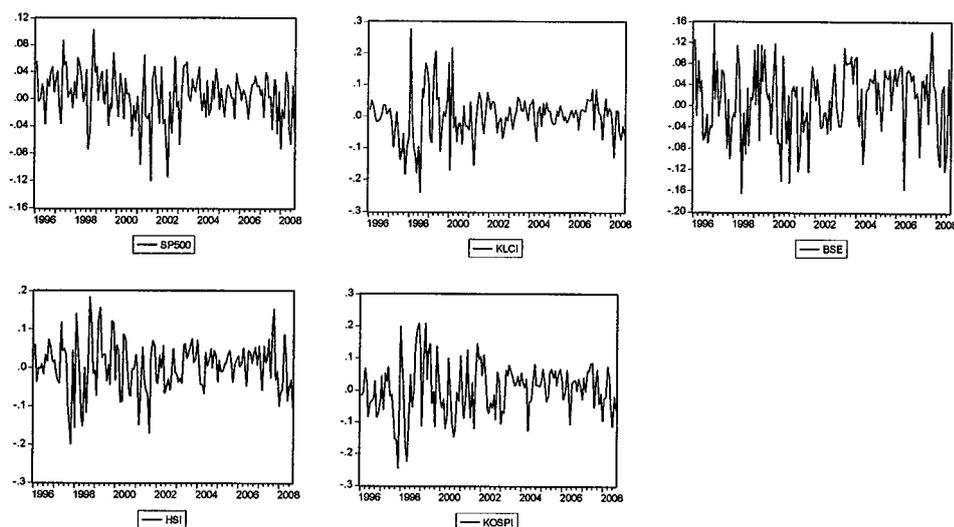


Figure 1 The Return Series

3.2 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 determine 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, 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 of each of the series with or without time trend.

Table 1 Unit Root Test

ADF test for sector indices				
Variables	Level		1 st Differentiation	
	No Trend	Trend	No trend	Trend
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				
Variables	Level		1 st Differentiation	
	No Trend	Trend	No trend	Trend
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%

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 data are integrated at same order.

The Johansen and Juselius (JJ, 1990) cointegration test is carried out to examine the existence of the log-run relationship among the indices. The cointegration 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 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.

Table 2 JJ Cointegration tests for indices

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

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.

3.3 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 also going to estimate VAR(1) model with represent the linear dynamic relationship between the five series. The results of VAR(1) model are given in Table 3.

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%

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 (Krolzig, 1998). Before we further discuss the estimation model, using the likelihood ratio test or LR test suggested by Garcia and Perron (1996), we are going to determine whether regime shifts happen in the five returns series. As denoted in Table 4, likelihood ratio test with test 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 (1987) p -value (value in the [] bracket) show significance results. Therefore, a nonlinear MS-VAR(1) model is better describing the data than linear VAR(1) model. 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 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) Test	167.7620 [.000]	

Table 5 report 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 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, $P(s_t = 1 | s_{t-1} = 1) = 0.7983$ is higher than the probability of staying in regime 2, $P(s_t = 2 | s_{t-1} = 2) = 0.6884$ with suggest 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.

Table 5 MS-VAR (1) estimates for indices

	SNP500 _t	HSI _t	BSE _t	KOSPI _t	KLCI _t
<i>Regime-dependent means</i>					
$\mu(s_t = 1)$	-0.516693	-0.743525	-1.749450**	-2.211923**	-0.907229
$\mu(s_t = 2)$	1.702575**	2.168063**	5.069093**	4.212444**	1.353152**
<i>Coefficients</i>					
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
<i>Regime-dependent variances</i>					
$\sigma^2(s_t = 1)$	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%

In addition, MS-VAR(1) model also provide 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 Figure 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).

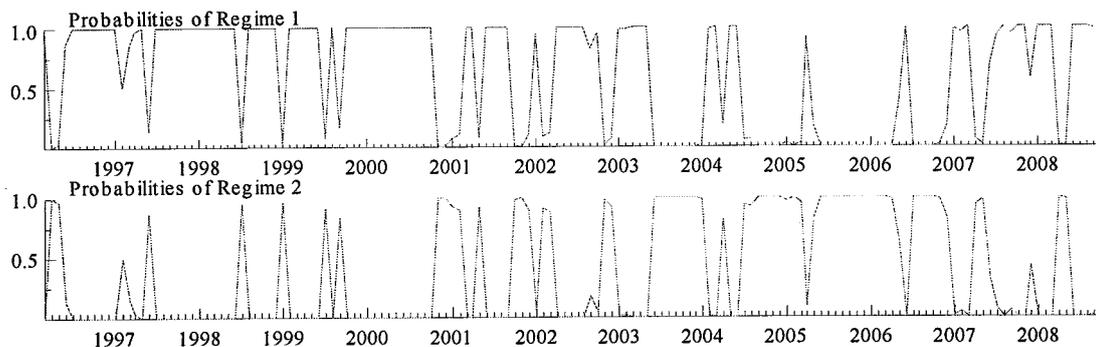


Figure 2 Smoothed Probability Plots of the MS-VAR(1) model

Conclusion

In this paper we have discussed two differences approach in modelling the interactions of US stock markets (SNP500) and selected Asian emerging stock markets (KLCI(Malaysia), BSE(India), KOSPI (Korea), HSI (Hong Kong)) (KLCI). We modelled the relationship using linear VAR(1) model and nonlinear MS-VAR(1) model. All the results point out that MS-VAR model give more information about the nature of the data as compare to VAR model. In addition, the MS-VAR(1) model uncover 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 supporting attendance at this conference.

References

- [1] B. Arshanapalli and M. S. Kulkarni, *Interrelationship between Indian and US Stock Markets*, Journal of Management Research, 1 (2001), 141-148.
- [2] R. B. Davies, R. B. *Hypothesis testing when a nuisance parameter is present only under the alternative*, Biometrika, 74 (1987), 33-43.
- [3] R. Garcia, and P. Perron, *An analysis of the real interest rate under regime shifts*, Review of Economics and Statistics, 78 (1996), 111-125.
- [4] A. Ghosh, R. Saidi and K. H. Johnson, *Who moves the Asia-Pacific stock markets-US or Japan? Empirical evidence based on the theory of cointegration*, The Financial Review, 34 (1999), 159-170.
- [5] J. D. Hamilton, *Time Series Analysis*, Princeton University Press, Princeton, 1994.
- [6] S. Johansen and K. Juselius, *Maximum likelihood estimation and inference on cointegration with applications to the demand for money*, Oxford Bulletin of Economics and Statistics, 52 (1990), 169-210.
- [7] C. J. Kim and C. R. Nelson, *State-Space Models with Regime-Switching: Classical and Gibbs Sampling Approaches with Applications*, MIT Press, MIT, 1999.
- [8] H-M. Krolzig, *Markov Switching Vector Autoregressions: Modelling, Statistical Inference and Application to Business Cycle Analysis: Lecture Notes in Economics and Mathematical Systems*, Vol. 454, Springer-Verlag, Berlin, 1997.
- [9] Krolzig, H.-M. (1998). *Econometric modelling of Markov-switching vector autoregressions using MSVAR for Ox*, <http://www.economics.ox.ac.uk/hendry/krolzig>
- [10] J. L. F.Serrano and S.S. Rivero, *Modelling the linkages between US and Latin American stock markets*, Applied Economics, 35 (2003), 1423-1434.
- [11] Z. Wang, J. Yang and D. A. Bessler, *Financial crisis and African stock market integration*, Applied Economics Letters, 10 (2003), 527-533
- [12] J. Yang, J. W. Kolari and I. Min, *Stock market integration and financial crises: the case of Asia*, Applied Financial Economics, 13 (2003), 477-486