Are the stock indices of FTSE Malaysia, China and USA causally linked together ?

Nasir, Nur Alissa and Masih, Mansur

INCEIF, Kuala Lumpur, Malaysia, UniKL Business School, Kuala Lumpur, Malaysia

30 May 2018

Are the stock indices of FTSE Malaysia, China and USA causally linked together ?

Nur Alissa Nasir[1] and Mansur Masih[2]

Abstract

In this paper, we test the causal linkages among the FTSE Malaysia, FTSE China and FTSE USA stock market indices. The investigation is conducted using the standard time series econometric techniques using monthly data. The issue is approached from two perspectives: (i) whether these markets move together (ii) and the dynamic linkages of the lead-lag relationships. Our analysis finds one significant cointegrating relationship among the selected markets, with the FTSE Malaysia being the follower and the FTSE China being being the most leading one. These findings tend to suggest that the FTSE Stock Indices of these three markets have a strong long-run equilibrium relationship mostly driven by fundamental elements of the economy. In addition, the strong leading role of the FTSE China Index implies that the China market may have a strong influence over the other regional markets. These findings have strong policy implications.

Keywords: FTSE stock indices, causal linkages, VECM, VDC

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[1] INCEIF, Lorong Universiti A, 59100 Kuala Lumpur, Malaysia.

2 **Corresponding author**, Senior Professor, UniKL Business School, 50300, Kuala Lumpur, Malaysia.

Email: mansurmasih@unikl.edu.my

1.0 INTRODUCTION

Several recent studies have examined whether or not two or more indices of stock prices are cointegrated (see Epps 1979; Cerchi and Havenner 1988; Takala and Perre 1991; Bachman et al. 1996; Choudhry 1997; Crowder and Wohar 1998; Chan and Lai 1993; Ahlgren and Antell 2002). Evidence of cointegration (or co-movement) among several indices of stock prices suggests that these series have a tendency to move together in the long-run even if experiencing short-term deviations from their common equilibrium path. Should the indices of stock prices be cointegrated, their relationship can be represented by an Error Correction Model (ECM) on the basis of which movements in any one of them can be used to predict movements in the other. Accordingly, the ECM associated with cointegrated stock price indices provides investors and policy makers with valuable information regarding their investment decisions and for economic policy. Furthermore, as pointed out by Granger (1986, 1988) and Engle and Granger (1987), knowledge of cointegration is also important in view of the fact that if two economic time series are cointegrated, there must be a causal relationship in at least one direction.

Most of the aforementioned studies have examined the cointegration among international stock prices in a bivariate or multivariate framework. Bachman et al. (1996) have summarized several plausible explanations in favour of cointegration of international prices. Such explanations include the liberalization of international trade and the opening of domestic capital markets to foreigners, the transfer of technology, and the relaxation of restrictions on the domestic ownership of capital stock by foreigners. They have also provided a theoretically plausible framework in favour of cointegration among international stock prices.

There are three practical reasons why testing for cointegration among international equity markets is important. First, it provides an alternative means to assess the extent to which the markets under consideration are integrated. Specifically, if world equity markets are integrated then stock prices in different countries will be cointegrated or have long-run equilibrium relationships (i.e., they operate as one market if highly integrated). Second, the results of cointegration tests enable us to gauge the relative benefits of diversifying investment portfolios internationally, with greater diversification benefits derived from less interdependent markets. Third, the existence of cointegration can be exploited to predict the variables in a cointegrated system by specifying an ECM via which both short-run and long-run relationships can be studied. Clearly, similar arguments can be made in favour of testing for cointegration among domestic equity markets. So far as we are aware, very few studies (other than Arbeláez et al. 2001 who did the case of Colombian stock price indices) have examined cointegration among domestic equity markets even though arguments similar to those provided in Bachman et al. can be advanced in favour of cointegration among domestic equity markets.

The authors are focusing on Malaysia's FTSE Index and have an interest to investigate whether the index is cointegrated with her major trading partners; China and USA or otherwise.

2.0 THE OBJECTIVE & MOTIVATION

In this paper, the authors examine endogenuity and exogenuity of three FTSE indices from three countries; Malaysia, China and USA. FTSE is selected to enable a very focused and specific analysis of a well-recognized market profile. A good understanding of these markets is important because their stock price indices can produce useful predictive information among them for the investors and portfolio managers to plan their participation in these markets strategically and prudently within their risk and return framework. It would be interesting to conduct a detailed investigation of the relationship among these three stock price indices.

One of the great lessons of the portfolio theory of finance is that the investors can gain from portfolio diversification. However if the markets are fully integrated, the gains from diversification would be very limited indeed. A major objective of this study, therefore, is to investigate whether these three FTSE indices are integrated or not? The answer to this question would have certain implications for portfolio diversification. The answer might be the market is cointegrated, disintegrated or even isolated. And the answer should also provide indication on each market endogeneity or exogeneity and the leaders and followers barometer.

3.0 THEORETICAL FRAMEWORK

Stock market stability is given special attention by many countries. This is because a stable stock indices portrays a positive image and good economic positioning. Strong stock stability also becomes an attraction for market players to invest and also act as a guarantee on investments made. Cointegration of stock indices with relevant benchmark stock provides a good information to investors, funds and portfolio managers.

According to Click and Plummer (2005), a cointegrated market is viewed to be more information-efficient and able to provide certain advantages to market enthusiasts. Portfolio investment is easier to manage in this type of market environment. This is also auger very well with the efficient market hypothesis that sees symmetric price-information relatioship. However, Ali et al (2011) noted that such market tend to lose its competitiveness in the long-run as it could led to a reduced benefit for portfolio diversification.

4.0 LITERATURE REVIEW

Early studies of stock market interdependences date back to the early seventies. Authors such as Granger and Morgenstern (1970), Ripley (1973) or Panto et al. (1976) investigated short-run linkages using correlation analysis. With the emergence of the cointegration framework first suggested by Granger (1981) and consequently developed by Granger and Weiss (1983) and Engle and Granger (1987), the methodology of stock market linkages improved. Along with the Autoregressive Conditional Heteroskedasticity (ARCH) approach developed by Engle (1982) and extended by Bollerslev (1986), cointegration has now become the main tool in analysing the relationship between stock markets. Further methodological improvements by Johansen (1988, 1991) eased the treatment of multivariate cointegration and provided a unified approach to estimation and testing.

Kasa (1992) first used Johansen's cointegration test to study the linkages of stock markets. Using a long VAR specification, the author finds strong evidence for a single common trend in the markets of the US, Japan, Germany, Britain and Canada for the period 1974-1990.

Corhay et al. (1993) investigate European stock markets from 1975 to 1991 and also provide empirical evidence for long-run equilibria. In a broader study of 16 markets, Blackman et al. (1994) find cointegration relationships for the 1980s. However, the study by Koop (1994) using Bayesian methods rejects a common stochastic trend between the stock markets of the five aforementioned countries. Fu and Pagani (2010) revisit Kasa's (1992) result and use more accurate small sample corrections on the same data. Though the evidence for cointegration is weaker than in the original paper, the authors still find a cointegration relationship.

The focus of stock market cointegration studies subsequentially shifted from more established to the emerging markets especially those of Asia. The rise of East and Southeast Asian stock markets due to financial deregulation in the early 1990s gave way to numerous studies of Asia's newly industrialized countries (NIC).

Maysami and Koh (2000) observe a cointegration relationship between the markets of Singapore, Japan and the US. The results of Sheng and Tu (2000) in contrast do not suggest a statistically significant cointegration vector for Asian stock markets. Other studies on emerging markets include Chen et al. (2000) find evidence for cointegration among a system of six Latin American markets.

Yang, Kolari and Min (2002) investigated the Asian Financial crisis and find evidence for changing degrees of cointegration. Estimating the vector error correction for different periods, they find that the markets move closer together in the post-crisis period. Wong et al. (2004) also conclude that market linkages in Asia intensified with the crisis of 1997. Lim (2007) approves this results for the ASEAN1 countries.

5.0 METHODOLOGY & DATA

This study uses Time Series Techniques to test the cointegration of Malaysia's Stock Index and her two major trading partner stock indices using microfit 5.0 to run the analysis. Using time series technique, this study will try to analyse factors that are cointegrated with the stock indices movement. The cointegration test may select other controlling variable as proxies to world economic event in the long term equilibrium. The VECM will identify the causal relationship between cointegrated variables. While the VDCs and IRF try to find the most leading variable, the persistence profile may inform us about the duration required for cointegrated variables to return back to their equilibrium when the external shock occurs.

The theory is derived from past studies carried out on growth indicator. The variable included FTSE Malaysia Index (FMY), FTSE China Index (FCN) and FTSE USA Index (FUS) from January 2000 to March 2014 as the focal variables. In order to absorb changes in the world financial and capital market, the author added two controlling variable as proxies to the variation in that market. They are London Gold Bullion (GLD) and Brent Crude Oil (OIL) for the same time period. The variables to construct the model will include:

Table 1: List of variables and their forms

No	Variable	Symbol	Level Form	Differenced Form
1	FTSE Malaysia	FMY	LFMY	DFMY
2	FTSE China	FCN	LFCN	DFCN
3	FTSE United States	FUS	LFUS	DFUS
4	London Gold Bullion	GLD	LGLD	DGLD
5	Brent Crude Oil	OIL	LOIL	DOIL
6	Dummy for Economic Crisis	DEC	-	-

To facilitate the study, the authors employed monthly data spanning the period from 30 January 2000 to 30 March 2014, obtained from the Datastream historical time series database compiled by Thomson Financial. Given previous evidence of the sensitivity of unit root and cointegration tests to be employed, the author conducted investigations using two widely used unit root tests, namely, the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979, 1981), and the Phillips-Perron (PP) test (Phillips and Perron 1998). An additional objective of the study is to test for causality among the three FTSE stock indices. The author incorporated other two controlling variables namely Brent Crude Oil Price (OIL), Gold Bullion Price (GLD) and a Dummy Variable for Economic Crises (DEC). The first two are the proxies for market variation and volatility while the latter is to capture market noises during the study period such as Dot Com Bubble, Turkish Financial Crisis, Argentine Loan Default, Eurozone Financial Crisis and finally the Global Financial Crisis. In addition, both OIL and GLD might also provide some market information for traders, managers and investors.

The above time series data will be subjected to the following tests in a serial order: unit root test, VAR selection, Cointegration Test, Long-Run Structural Modelling Test, Vector Error Composition Model Test, Variance Decomposition Test, Impulse Response Function Test and Persistent Profile Test. This is the so-called 8-Step Time Series Technique.

6.0 RESULTS AND INTERPRETATION

In this section, the 8-Step of the time series technique will be performed. All variable will be derived to the theories relating to index movement explained in the literature review.

6.1 Testing Stationarity of Variables

This step is to identify the stationarity of the variables. A variable is stationary if its mean, variance and covariance is constant over time. To test for non- stationary test is carried out using Augmented Dickey- Fuller or ADF and Phillips Perron or PP test. Testing the null p=0 given by the t-ratio of the coefficient of xt-1. If the t-ratio of the coefficient is not statistically significant then null is accepted this means that variable is non-stationary and is a random walk which has a long term memory. The advantage of ADF tests solves autocorrelation problem in the data. Whereas the advantage of PP test is that it not only takes care of autocorrelation but heteroscedasticity problem in the data as well. Table 2 shows summary of both ADF and PP tests. The differenced form for each variable used is created by taking the difference of their log forms. For example, DFMY = LFMY – LFMY(-1). the author then conducted the Augmented Dickey-Fuller (ADF) test on each variable (in both level and differenced form). PP test requires second difference for example D2DFMY= DFMY-DFMY(-1), variable are in both test in there level and second difference form.

Table 2: Summary of ADF and PP Test Output

Variable	Level Form t-statistic		Differenced Form t-statistic		Test Results
	ADF Test	PP Test	ADF Test	PP Test	
FMY	-3.2442*	-2.8747*	-9.3831**	-12.5547**	I(1)
FCN	-1.9618*	-1.6653*	-8.0801**	-11.3728**	I(1)
FUS	-1.8562*	-1.2976*	-10.4920**	-13.2576**	I(1)
GLD	-1.2965*	-2.2138*	-10.4062**	-14.6467**	I(1)
OIL	-3.2499*	-2.7917*	-6.7272**	-14.0839**	I(1)
Critical Value	-3.4377	-3.4370	-2.8791	-2.8786	

** Variable is Non-Stationary at Level Form*
*** Variable is Stationary at Differenced Form*

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According to the table the variables are non-stationary in their level form (critical value > test statistic) and stationary in their difference (critical value < test statistic). From the above result, it is concluded that all variables involved are I(1) and therefore the test for cointegration can be done. But before that, the next step will help determine the lag order of the VAR model. Appendix 1 to Appendix 4 shows ADF and PP test outputs.

6.2 Determination of order of the VAR model

Before proceeding with test of cointegration, order of vector auto regression (VAR) model needs to be determined that is, the number of lags to be used. Appendix 5 provides the computational analysis. To choose the appropriate lag, the highest value of AIC, which is 1145.3 at order 0 is selected and the highest value of SBC which is 1129.9 also at order 0 is picked. Due to the agreement between AIC and SBC, therefore the best lag is at order 0. However, if zero or even 1 lag is taken from VAR, it would result in the Microfit software to not give full results for the vector error correction model whereby Microfit will only give the error correction term (Masih 2013). Hence, the author purposely ignored lag 0 and 1.

To proceed, the out of the Order of VAR suggested the order of 2 where AIC and SBC are again in agreement. Since both are not conflicting, the possibility of the serial correlation is negated.

Table 3: Order of VAR

	Model Selection Criteria	
	AIC	SBC
Optimal order of lags	2	2

6.3 Testing for Cointegration

Two test are carried out to see cointegration in the study. One is the Engle-Granger method which identifies at most, one cointegration and the Johansen method which could actually identify more than one. The Engle-Granger method is in fact the residuals method, therefore it is just testing the stationary of the residuals once saved in the Microfit, in this case as RESID. This is similar to the first step that uses the ADF on RESID. The interpretation would be that if it is stationary, it means that there is a cointegration among the variables. Results are shown below:

Table 4: Engle-Granger

Test Statistic	Critical Value	Interpretation
-3.8801	-2.8790	Stationary

Table 5: Johansen Cointegration

Cointegration LR Test based on Maximal Eigenvalue

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
R = 0	R = 1	46.3716	37.8600	35.0400
R = 1	R = 2	25.6532	31.7900	29.1300

Cointegration LR Test based on Trace of Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
R = 0	R = 1	101.7919	87.1700	82.8800
R = 1	R = 2	55.4203	63.0000	59.1600

From the summarized version of the Engle-Granger Method (Table 4) above, the author concludes that there is one cointegration (since Engle-Granger is able to suggest the existence of a cointegration). In order to determine the number of cointegration, Johansen cointegration test is applied. This brings us to Eigenvalue and Trace criteria under Johansen Method (Table 5). Both criteria suggested only one cointegration.

6.4 Long Run Structural Modelling

This step estimates theoretically meaningful cointegrating relations. Long-run relations are imposed and then tested by over-identifying restrictions according to theories and information of the stock indices under review. In other words, this step will test the coefficients of our variables in the cointegration equations against the theoretical expectation. This LRSM step also tests the coefficients of our variables whether they are statistically significant. The cointegration equation is derived from the coefficients. Since there is one cointegration, the exact identification will impose one restriction only. Normalization is imposed by putting long-run coefficient of LFMY equal to one where long-run coefficients of all remaining level-form variables are obtained. As in this case the level-form variables, the t-ratio is greater than two. It may imply all variables in the long-run equation are statistically significant. Therefore, 0 was not imposed to each variable. To show what this means Table 6 summarizes the exact and over identification restriction for one vector.

Table 6: Exact and over Identifying Restrictions on the Cointegrating Vectors

Variable	Panel A	Panel B
FMY	1.0000 (*NONE*)	1.0000 (*NONE*)
FCN	-0.41451 (0.18930)	-0.41295 (0.18184)
FUS	-0.73011 (0.11839)	-0.72950 (0.11662)
GLD	-0.55470 (0.16414)	-0.55173 (0.13277)
OIL	0.49825 (0.14583)	0.49818 (0.14580)
Trend	0.00005594 (0.0019563)	-0.0000 (*NONE*)
CHSQ (1)	-	0.0009398[0.976]

According to the Table 6, we accept the null as the value of chi-square more than 10%. This mean that the coefficient of trend is not equal to 0.The cointegration equation is in line with the theory of stock indices indicators therefore all variables should be in this equation. The magnitude of the long run coefficients is unknown therefore the coefficients are estimated by the equation

Cointegration equation:

1 FMY	- 0.41451FCN	– 0.73011FUS	– 0.55470GLD	+ 0.49825OIL	+ 0.00
	(0.18930)	(0.11839)	(0.16414)	(0.14583)	

The equations above do not give the information about which variable is exogenous and which variable is endogenous. There is no “equal sign” and the equations do not tell the causal relationship. Therefore, the next step which is VECM addresses this issue

6.5 Vector Error Correction Model (VECM)

Error-correction term (ECT) is the stationary error term, in which this error term comes from a linear combination of the non-stationary variables that makes this error term to become stationary if they are cointegrated. It means that the ECT contains long term information since it is the differences or deviations of those variables in their original level form. VECM uses the concept of Granger causality that the variable at present will be affected by another variable at past. Therefore, if the coefficient of the lagged ECT in any equation is insignificant, it means that the corresponding dependent variable of that equation is exogenous. This variable does not depend on the deviations of other variables. It also means that this variable is a leading variable and initially receives the exogenous shocks which results in deviations from equilibrium and transmits the shocks to other variables. On the other hand, if the coefficient of the lagged ECT is significant, it implies that the corresponding dependent variable of that equation is endogenous. It depends on the deviations of other variables. This dependent variable also bears the brunt of short-run adjustment to bring about the long term equilibrium among the cointegrating variables.

At previous step, the author define the initial normalization a1=1 that is the FMY as the dependant variable. The result shown here confirm that FMY is indeed endogenous and it happen, it is only endogenous variable while the arrest are exogenous. The drawback of this method however, it cannot determine which of the variables are most exogenous and endogenous when there more than one of the same type. For example in this case, there are four exogenous variables but we do not know which one is the ultimate exogenous. The table below shows the result of each variable.

Table 7: Vector Error-Correction Estimates

Variable	ECM(-1) t-ratio[prob]	Interpretation
FMY	-5.11130 [0.000]	Variable is endogenous
FCN	-0.36156 [0.718]	Variable is exogenous
FUS	1.15080 [0.252]	Variable is exogenous
GLD	-0.72000 [0.473]	Variable is exogenous
OIL	-1.39970 [0.164]	Variable is exogenous

The diagnosis of all equations of the error-correction model (testing for the presence of autocorrelation, functional form, normality and hetroscedasticity) tend to indicate that the equation is well specified. From Appendix 9, we see that the each equation is well specified with the acception of Normality for FMY, FUS and FOIL. Stability test of coefficient using CUSUM and CUSUM SQUARE test shown below in Table 8 below:

Table 8: Cusum and Cusum Square

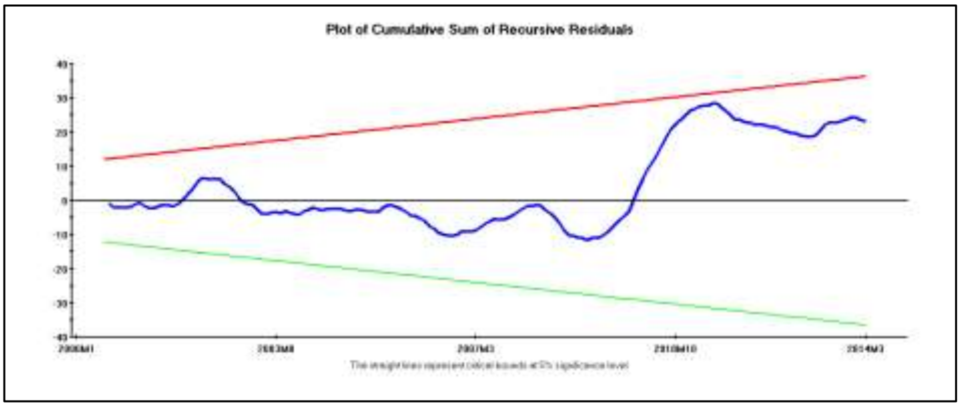

Figure 1 - CUSUM

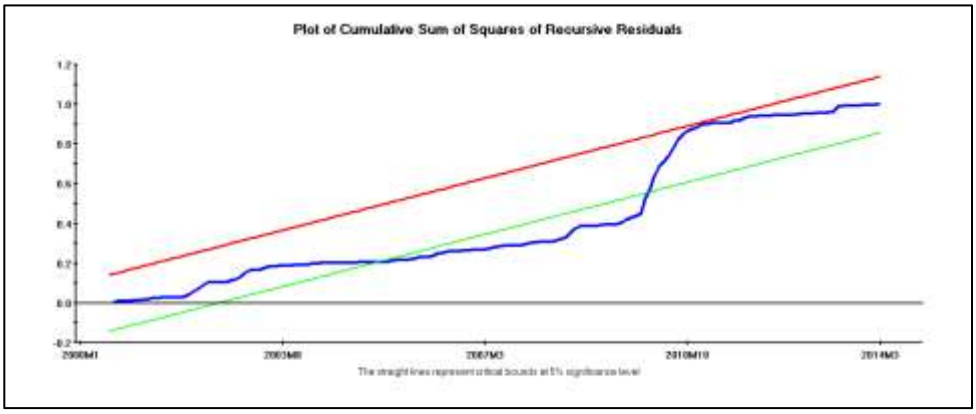

Figure 2 – CUSUM Square

Table 8 above, show minor structural break between 2005 and 2010 as the sum of recursive residual goes outside the critical bounds. This could be due to the economic crisis that may have had impact on stock indices but in the long run they remain within the critical bounds.

6.6 Variance Decomposition (VDC)

The forecast error variance decomposition presents decomposition of the variance of the forecast error of a particular variable in the VAR at different horizons. It will break down the variance of the forecast error of each variable into proportions attributable to shocks in each variable in the system including its own. The variable which is mostly explained by its own past shocks is considered to be the most leading variable of all. In this study, the author will use Orthogonalized Variance Decomposition Analysis and Generalized VDC. The Orthogonalized VDCs are not unique and depend on the particular ordering in the VAR. It also assumes that when a particular variable is shocked, all other variables in the system are switched off. On the other hand, Generalized does not depend on the order while it also does not impose the restriction of switching off. The result in Table 9, show that only FCN and GLD switched their leading position in the Orthogonalized and generalized category. Otherwise, the ranking is consistent throughout all period, long term and short term. FCN tend to show its strong exogeneity followed by GLD and OIL. FMY consistently remain the most endogenous.

Table 9: Orthogonalized & Generalized VDC

ORTHOGONALIZED VDC

Self-Dependency

	Horizon	FMY	FCN	FUS	GLD	OIL
MONTH	12	50%	95%	54%	87%	71%
	24	35%	95%	51%	85%	67%
	36	30%	95%	50%	84%	66%
	48	28%	95%	50%	84%	65%
	60	26%	95%	49%	84%	65%

Exogeneity Ranking

	Horizon	FMY	FCN	FUS	GLD	OIL
MONTH	12	5	1	4	2	3
	24	5	1	4	2	3
	36	5	1	4	2	3
	48	5	1	4	2	3
	60	5	1	4	2	3

GENERALIZED VDC

Self-Dependency

	Horizon	FMY	FCN	FUS	GLD	OIL
MONTH	12	39%	87%	60%	89%	70%
	24	29%	87%	59%	89%	67%
	36	26%	87%	58%	89%	66%
	48	24%	87%	58%	89%	66%
	60	23%	87%	58%	89%	65%

Exogeneity Ranking

	Horizon	FMY	FCN	FUS	GLD	OIL
MONTH	12	5	2	4	1	3
	24	5	2	4	1	3
	36	5	2	4	1	3
	48	5	2	4	1	3
	60	5	2	4	1	3

6.7 Impulse Response Functions (IRFs)

The information which is presented in the VDCs also can be equivalently represented by Impulse Response Functions (IRFs). IRFs will present the graphical expositions of the shocks of a variable on all other variables. In other words, IRFs map the dynamic response path of all variables owing to a shock to a particular variable. The IRFs trace out the effects of a variable-specific shock on the long-run relations. The IRFs are normalized in which the zero will represent the steady-state value of the response variable. We shock each variable and see the response of other variables in the graph. The author will also present IRF both in Orthogonalized and generalized. However, the author will rely on generalized IRF with the advantage of no-order and no-switching off restrictions.

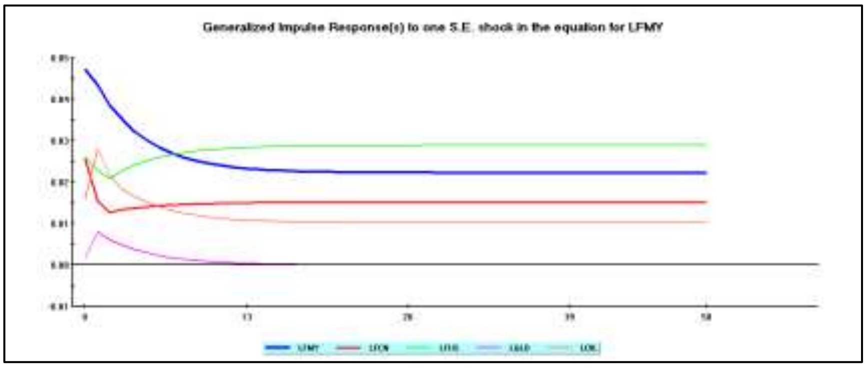

Figure 3 – IRF FMY

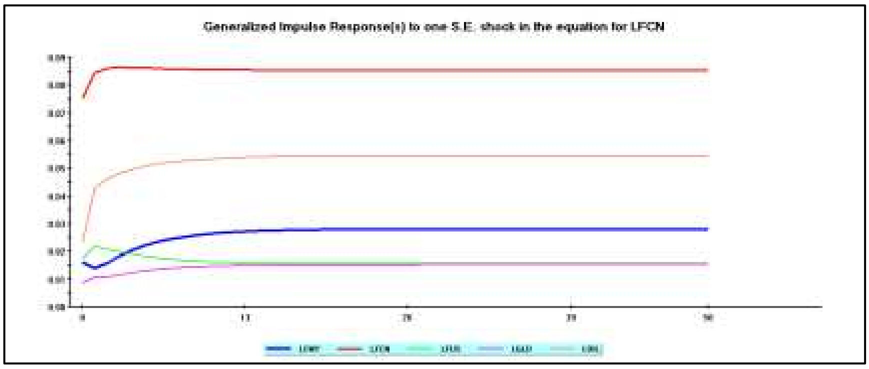

Figure 4 – IRF FCN

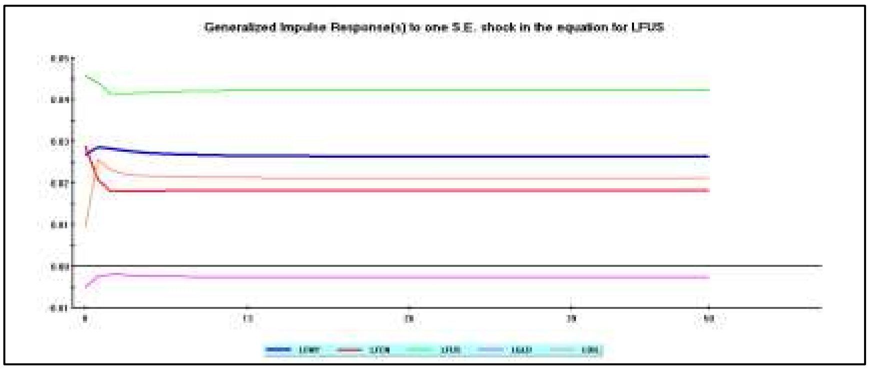

Figure 5 – IRF FUS

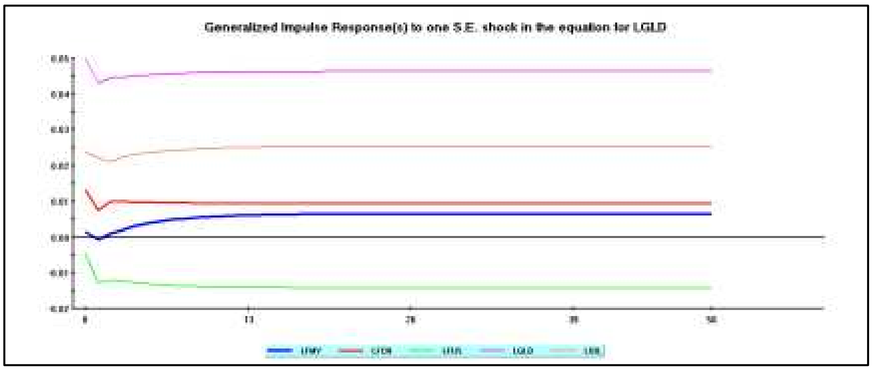

Figure 6 – IRF GLD

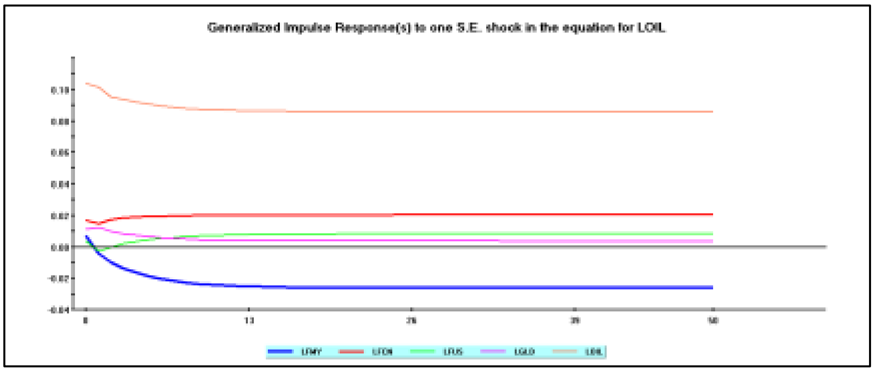

Figure 7 – IRF OIL

The above Generalized Impulse Response function are generated when we impose a one standard error shock in the equation for all the variable exclusively. Figure 3, this IRF output implies that if FCN, the most leading variable, is shocked, it will relatively gave a mild impact to FMY and FUS respectively. This disturbance will last almost a year, while the two other markets adjusted and stabilized.

8.8 Persistence Profile

The persistence profile will indicate the time horizon required for all variables to get back to equilibrium when a system-wide shock occurs. The main difference between the persistence profiles and IRFs is that the persistence profiles trace out the effects of a system-wide shock on the long-run relations. On the other hand, the IRFs trace out the effects of a variable-specific shock on the long run relations. In the persistence profiles, we shock our whole equation whereby this shock comes from external factor outside our equation or our system. Then, we see how many periods it takes for all variables to get back to the equilibrium. When we give the external shock to our equation, the result shows that all variables will deviate from the equilibrium, meaning that each of variables will move differently in the short run. They are temporarily not cointegrated. However, according to Figure 8 all variables in the cointegrating equation will require approximately 47 months for them to cointegrate again and return to the long-run equilibrium.

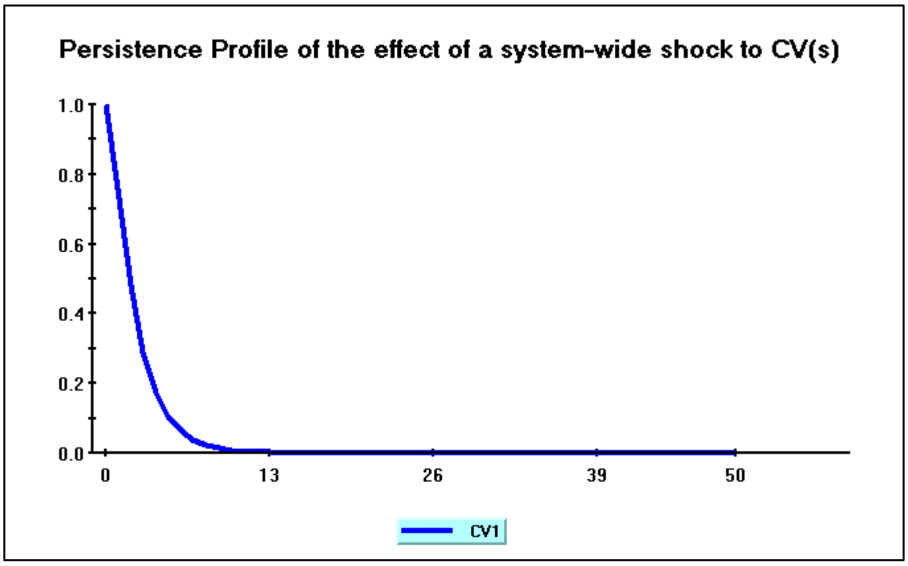

Figure 8 – Persistent Profile

7.0 CONCLUSION

This study examines the stock indices linkage among FTSE Malaysia, FTSE China and FTSE USA starting the new millennium. Monthly data spanning from Jan 2000 to March 2014 was used together with employing the Johansen and Engle Granger test for cointegration. The study found evidence that there exists a long-run equilibrium relationship among the said indices despite experiencing national, zonal, regional and global crises. Other than that, the variance decomposition analysis applied in this study tend to indicate that the FTSE Malaysia is the only endogenous variable and the FTSE China to be the most exogenous among all. The results of this study also supports the previous empirical studies that stock indices remain cointegrated after the crisis period. Among others, the impact of changes due to the control variables GOLD and OIL were relatively low to all the three FTSE indices.

8.0 LIMITATIONS AND RECOMMENDATIONS

The author acknowledge that this paper is having some limitation due to very limited time frame put for the preparation of this report. The data lacks diagnostic test at group and model level. Additionally, this study covers only two major trading partners of Malaysia. It shall include many other FTSE indices and the FTSE UK itself should have been included. Apart from that, the dummy variable is not adequately constructed to capture economic crisis during the study period such as Dot Com Bubble, Turkey Financial Crisis, EU Financial Crisis, Argentine Loan Default etc. A separate dummy for each of the crisis is recommended in order to statistically gauge its significant throughout the study period. The author also omitted macroeconomic variable which might have greater impact on the indices at national level.

9.0 REFERENCES

Ahlgren, N. and J. Antell (2002), Testing for Cointegration Between International Stock Prices, *Applied Financial Economics,* 12, 851-861.

Bachman, D., J.J. Choi, B.N. Jeon and K.J. Kopecky (1996), Common Factors in International Stock Prices: Evidence From a Cointegration Study, *International Review of Financial Analysis*, 5, 39-53.

Chan K. C. and P. Lai, (1993), 'Unit Root and Cointegration Tests of World Stock Prices' in "International Financial Market Integration" by Stansell S. R. (Ed.), *Blackwell Publishers, Cambridge*, USA, 278–287.

Crowder, W.J. and M.E. Wohar (1998), Cointegration, Forecasting and International Stock Prices, *Global Finance Journal*, 9, 181-204.

Fu, R. and M. Pagani (2010): On the Cointegration of International Stock Indices, Journal of Economics and Finance 30, 1-18.

Kasa, K. (1992): Common Stochastic Trends in International Stock Markets, Journal of Monetary Economics 29, 95-124.

Maysami, R.C. and T.S. Koh (2000): A Vector Error Correction Model of the Singapore Stock Market, International Review of Economics and Finance 9, 79-96.

Yang, J., J. Kolari, and I. Min (2003): Stock Market Integration and Financial Crises. The Case of Asia, Applied Financial Economics 13, 477-486.