Discerning the effect of international stock markets before and after the subprime crisis

Rahmali, Atiqah and Masih, Mansur

INCEIF, Malaysia, Business School, Universiti Kuala Lumpur, Kuala Lumpur, Malaysia

31 May 2017

Discerning the effect of international stock markets before and after the subprime crisis

Atiqah Rahmali[1] and Mansur Masih[2]

Abstract

The recent financial crisis spread to markets worldwide. Therefore, the purpose of this paper is to test the interdependencies of capital markets selected which are DJIA, NIKKEI, FTSE, SSE and IBEX, before and after the Global Financial Crisis. Furthermore, it also identifies which index influences or affects FTSE, if any. The study is important because it attempts to test whether the rise in FTSE index is due to the other indices or speculative reasons. Using data from Jan 2000 to June 2007as the first period (before the crisis) and the period from July 2007 onward as the second period (after the crisis), we examine if the FTSE index is affected by the past behaviour of the DJIA, NIKKEI (JAP), Shanghai (CHSA) and IBEX indices. The method of estimation is the standard Time series Techniques. This study found that during the first period (before the crisis) Shanghai Stock Index and IBEX impacted FTSE performance, however, during the second period (after the crisis) Shanghai Stock index and NIKKEI impacted FTSE performance. Contrary to the popular belief, the results did not indicate that the American DJIA was influential in affecting the other stock markets. Thus, we suggest that investors should focus on emerging market performance when it comes to the investment selection.

Keywords: Effects of international stock markets, subprime crisis, VECM, VDC

---

[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

Objective and Motivation of Research

The purpose of this study is to test the interdependencies of capital markets selected which are DJIA, NIKKEI, FTSE, SSE and IBEX, before and after the Global subprime Financial Crisis. In addition, this study also examines the effect of the indices of DOW, NIKKEI, Shanghai and IBEX on the FTSE index. Finally, this study analyses, of the main capital markets (stock indexes) selected (which are DJIA, NIKKEI, FTSE, SSE and IBEX), which is the most influential in line with the theoretical assumption?

Research questions:

1. Assuming the five selected markets only, which stock is the most influential in affecting other stocks? Is it the same before and after the crisis event?
2. Assuming the five selected markets only, is DOW a good predictor of global indices? is it the same before and after the crisis event?
3. Assuming the five selected markets only, which stock will influence FTSE index? Is it the same before and after the crisis event?

Findings of this research would be of particular interest to an investor limited to international stock index only namely DJIA, NIKKEI, FTSE, SSE and IBEX. Therefore it would help the investor to determine which stock market is the more appropriate reference point as a benchmark in anticipating an investment returns whether before or after the crisis.

Literature Review and Theoretical framework

Crises expand rapidly from one market to another and stock markets are impacted in a very brief period of time. History has proven, as a general rule, financial markets tend to go through crises all together. According to the many literature available, financial crises tend to strengthen correlations between markets instead of weakening them and this statement is supported by Bennett and Kelleher (1988) which stated in his paper that The 1987 crisis, which affected developed countries and countries in Latin America, was caused by the crash of the American stock exchange spread to several markets. Therefore, it shows that stocks markets have a possibility to influence one another in their performance, but will the influence be the same both before and after the crisis? This is the research gap that this study seeks to address.

In addressing the first research question, theory would argue that US Stock Market would have more influence on the other stock markets as it consistent with the views by Morana and Beltratti, (2008) that DOW is a good predictor of global indices but other global indices are not good predictors of the DOW. In Addition, according to the Baur and Jung (2006) after the crisis 1987, the FTSE market is influenced by the movement of US stock market. Therefore, our study examines if global indices have an effect on FTSE based on analyzing past performance of four global indices selected as we mention that market shocks are likely to have a larger global effect than previously. In this study, we examine the effect of the indices of DOW, NIKKEI, Shanghai and IBEX on the FTSE index. Thus, we would let the empirical data decide as to whether this intuition is correct. Following that, we will now proceed with the quantitative analysis of this study.

Research Methodology

The weaknesses of Regression is basically the dilemma in testing non-stationary variables which is in other way means that regression will fail in testing the level form non-stationary variables since it will invalidate conventional stationary test. But however, if the variable we differenced form by making it stationary, we will lose the long term information. Therefore, in other way to overcome this issue is by implementing the time series technique as it able to manage the shortcoming inherent in traditional regression.

According to the Masih, Al-Elg and Madani (2009), the standard time series techniques required 8 steps to perform. The first step is to test the stationarity of the data in differenced and level form. The second step is to determine the optimum order (or lags) of the vector autoregressive model. The order given will be used in the third step subject to certain conditions. The third step is testing cointegration which implies that the relationship among the variables is not spurious i.e. there is a theoretical relationship among the variables and that they are in equilibrium in the long run (Masih, 2009). The fourth step is Long Run Structural Modeling (LRSM). This test confirms whether a variable is statistically significant and tests the long run coefficients of the variables against theoretically expected values.

However, step1 to step 4 is able to test the theory but is not able to test causality, therefore we need step 4 onwards to test the causality. Vector Error Correction Model (VECM) is the fifth step, and it is used to test Granger causality. The VECM shows the leading and lagging variables but it is unable to show relative exogeneity and endogeneity. The sixth step (Variance Decompositions or VDCs) ranked the variables by determining the proportion of the variance explained by its own past shocks whereby the variable that is explained mostly by its own shocks (and not by others) is deemed to be the most exogenous of all (Masih, 2009). Step seven, the Impulse Response Function (IRF) and step eight, Persistence Profiles (PP) is in graph form. According to Masih (2009), IRF exposes relative exogeneity and endogeneity (similar to VDC) while PP estimates the speed with which the variables get back to equilibrium when there is a system-wide shock (unlike the IRF which traces out the effects of a variable-specific shock on the long-run relationship).

Data Description

To test interdependencies of capital markets, we have considered to use the data consisting of monthly values for the representative indexes of stock markets in the world's main financial centres, namely that of the New York Stock Exchange (DJIA), Tokyo Stock Exchange Nikkei (JAP), London Stock Exchange (FTSE), Shanghai Stock Exchange SSE (CHSA), and Spain Stock Exchange (IBEX). In this study only SSE stock index under the emerging market group while the rest are developed markets.

Henceforth, the analysis requires of 5 stock market indexes between January 2000 and October 2013 before and after the global financial crisis, the data are divided into two groups:

1. Jan, 2000– June, 2007: period before the crisis, when the global economy was in the growth stage of the economic cycle
2. July, 2007–October, 2013: period when the global financial system and the world economy went through difficult times marked by the beginning of the financial crisis in the United States and it is expand through worldwide, the global recession and the time of economic recovery.

All monthly index prices are taken a natural logarithm (LDJIA, LJAP, LFTSE, LCHSA and LIBEX) for the period before the crisis and for the period during the crisis. This conversion is necessary to achieve stationarity in variance (Masih et. al., 2009). Therefore, all the variables are used as 'level' form variables.

Unit Root Test

Following the discussion by Augmented Dickey and Fuller (1979, 1981) and the Phillips-Perron Test (PP) which is an alternative test for a unit root (Masih, 2009)
First, we need to check whether the variables chosen were stationary or not.

- **ADF Test**

To confirm the stationarity, the variables on before and after the crisis are tested at the 'level' form (Table 1a & 1b) and 'differenced' form (Table 2a & 2b). Therefore, the figures are obtain from Akaike Information Criterion (AIC) and Schwarz

Bayesian Criterion (SBC), the ADF regression order are selected based on the highest computed value for AIC and SBC. By ignoring the minus sign, if the test statistic is lower than the critical value in all variables in level form, therefore we cannot reject the null making the variable to be non-stationary in its level form.

Level Form	**First Period: Before the Crisis**			
Variable	Test Statistic		Critical Value	Results
	AIC	SBC		
LDJIA	-2.4237	-2.4237	-3.4704	Non-Stationary
LJAP	-3.075	-2.9743	-3.4704	Non-Stationary
LFTSE	-2.3193	-2.3193	-3.4704	Non-Stationary
LCHSA	0.68318	0.68318	-3.4704	Non-Stationary
LIBEX	-2.6933	-2.6933	-3.4704	Non-Stationary

Table 1(a): Augmented Dickey Fuller Test for Level Form (Before the crisis)

Level Form	**Second Period: After the Crisis**			
Variable	Test Statistic		Critical Value	Results
	AIC	SBC		
LDJIA	-2.9433	-2.6941	-3.4739	Non-Stationary
LJAP	-2.1023	-1.8337	-3.4739	Non-Stationary
LFTSE	-3.4452	-2.9205	-3.4739	Non-Stationary
LCHSA	-4.3219	-3.4277	-3.4739	Non-Stationary
LIBEX	-2.204	-2.204	-3.4739	Non-Stationary

Table 1(b)): Augmented Dickey Fuller Test for Level Form (After the crisis)

Based on the table 2(a) and 2(b) below, the entire variable tested is in “differenced” form. The observation for test statistic is required based on the highest AIC and SBC. Therefore according to the result, all the variables before and after the crisis have a higher test statistic than the critical value and thus the null hypothesis can be rejected, which means the variables are stationary.

Thus, from the ADF Test we can conclude that all of the variables are known as I(1) which means the variable is non-stationary in level form but after we change it to difference form it becomes to stationary.

Difference form	First Period: Before the Crisis			
Variable	Test Statistic		Critical Value	Results
	AIC	SBC		
DDJIA	-8.0587	-8.0587	-2.9012	Non-Stationary
DJAP	-6.684	-6.684	-2.9012	Non-Stationary
DFTSE	-7.8333	-7.8333	-2.9012	Non-Stationary
DCHSA	-6.4212	-6.4212	-2.9012	Non-Stationary
DIBEX	-8.4035	-8.4035	-2.9012	Non-Stationary

Table 2(a): Augmented Dickey Fuller Test for Difference Form (Before the crisis)

Difference form	Second Period: After the Crisis			
Variable	Test Statistic		Critical Value	Results
	AIC	SBC		
DDJIA	-3.561	-7.0887	-3.4749	Non-Stationary
DJAP	-6.9262	-6.9262	-2.9035	Non-Stationary
DFTSE	-2.9298	-7.8861	-2.9035	Non-Stationary
DCHSA	-3.5227	-8.8123	-2.9035	Non-Stationary
DIBEX	-7.6133	-7.6133	-2.9035	Non-Stationary

Table 2(b): Augmented Dickey Fuller Test for Difference Form (After the crisis)

- **Phillips-Perron Test (PP)**

The other ways to confirm stationarity is by using PP test. Similar with the ADF, the variables on before and after the crisis are tested at the 'level' form (Table 3) and 'differenced' form (Table 4). The results are concluded based on the p-value where its informs the error we are making when rejecting the null (i.e. variable is non-stationary). If the p-value is higher than 0.05, the null hypothesis cannot be rejected. On the other hand, if the p-value is lower than 0.05, the null hypothesis can be rejected which means the variable is stationary.

Based on the table 3 below, all the level form variables on the first period (before the crisis) are stationary which is I(1) and its consistent with the previous result on the ADF test. However, all the level form variables on the second period (after the crisis) in contrast to ADF test above, which is the PP test for 'level' form variables shown that JAP and IBEX is stationary . Furthermore, based on the table 4, the result on the PP test is consistent with ADF test, which is shows that all the 'differenced' form variables either before and after the crisis are stationary.

Through PP test, it can be concluded that all the variables are I(1) except for JAP and IBEX which is I(0). However we still have to retain these variables because it was I(1) in the ADF test previously. Through this, all the variable are confirm to have a 3 elements which is short term info, long term info and random info that are very beneficial in step 3.

	First Period: Before the Crisis		Second Period: After the Crisis	
Variable	Test Statistic (p-value)	Results	Test Statistic (p-value)	Results
LDJIA	0.523	Non-Stationary	0.506	Non-Stationary
LJAP	0.852	Non-Stationary	0.004	Stationary
LFTSE	0.433	Non-Stationary	0.126	Non-Stationary
LCHSA	0.472	Non-Stationary	0.053	Non-Stationary
LIBEX	0.806	Non-Stationary	0.01	Stationary

Table 3: PP result for Level Form (Differenced Once)

	First Period: Before the Crisis		Second Period: After the Crisis	
Variable	Test Statistic (p-value)	Results	Test Statistic (p-value)	Results
DDJIA	0.000	Stationary	0.000	Stationary
DJAP	0.000	Stationary	0.000	Stationary
DFTSE	0.000	Stationary	0.000	Stationary
DCHSA	0.000	Stationary	0.000	Stationary
DIBEX	0.000	Stationary	0.000	Stationary

Table 4: PP result for Differenced Form (Differenced Twice)

<u>Determination of the order (or lags) of the Vector Autoregressive (VAR) model</u>

Before proceeding to the cointegration test, it is compulsory to determine the optimum order (or lags) of the vector autoregressive model which is to determine the number of lags to be used. Based on the full result in appendix, we can see that all of the p-value for all the orders of the lags on the first period and second period is greater than 0.05 which means all of the number of the lags is significant at 95% confidence level. However, which orders of the lags are more preferable or optimum are based on the highest value of AIC and SBC. As expected, SBC gives lower order as compared to AIC. This difference is due to the AIC tries to solve for autocorrelation while SBC tries to avoid over-parameterization. In other words, the different lag values may be attributable to the different nature or concern of the test.

Referring to Table 5, on the first period, it is found that there is a contradicting optimum order given by the highest value of AIC and SBC. As expected, SBC gives lower order as compared to AIC, but the order of the lags given in AIC which is favour of 1 lag may give a conflicting result in VECM test as it fail to provide the short term information of delta variables. However, during the second period, it is found that there is a consistent result between AIC and SBC which is both favour zero lag. Given this obvious conflict between recommendation of AIC and SBC, we could address this by checking for serial correlation for each variable as the following results.

	First Period		Second Period	
	AIC	SBC	AIC	SBC
Optimum lag	1	0	0	0

Table 5: AIC and SBC results for order (or lags) of the VAR model

Because of that, by following the results in table 6, on the first period we have examined that there is no evidence of residual serial correlation in the case of all variables output equations. But if we are using AIC result that favour 1 lag may give a conflicting result in VECM test as it fail to provide the short term information of delta variables. Aware on this issue, the order of the lag used 3 are selected because it has a cointegration and can provide short term information through delta variable in VECM test.

On the second period there is a statistically significant evidence of residual serial correlation in the case of JAP and CHSA equation. It make sense since during the crisis period, study by Ioana Moldovanl and Claudia Medrega (2011) explained that after the financial crisis, the correlation of evolutions registered by international capital markets is one of the effects of globalization because investors was panic at times of crisis is more intense than enthusiasm expressed during growth periods. Hence, panic determines massive sell-offs that cause stocks to fall, and the negative sentiment fuels itself as most investors rush to sell and avoid bigger losses. Therefore, since both AIC and SBC suggest an unfavourable lag, the order of the lag used 4 is selected because it has a cointegration and can provide short term information through delta variable in VECM test.

	First Period		Second Period	
Variable	Chi- Sq p-value	Implication (at 5%)	Chi- Sq p-value	Implication (at 5%)
DJIA	0.15	There is no serial correlation	0.361	There is no serial correlation
JAP	0.102	There is no serial correlation	0.009	There is serial correlation
FTSE	0.203	There is no serial correlation	0.985	There is no serial correlation
CHSA	0.84	There is no serial correlation	0.049	There is serial correlation
IBEX	0.936	There is no serial correlation	0.643	There is no serial correlation

Table 6: Serial correlation test results

Testing Cointegration

- **Johansen Method**

Cointegration is defined as a situation where linear combinations of non-stationary time series are stationary. This implies the existence of a long-run equilibrium between the variables. Therefore, before we proceed with the testing cointegration, it is important to ensure that the series were non-stationary and hence integrated of order 1 based on the steps 1 that I did before.

To test the hypothesis that all these variables have at least cointegration, we have used 2 tests namely Johansen method and Engle-Granger method to identify cointegration between the variables. The Johansen method uses maximum likelihood (i.e. eigenvalue and trace) and may identify more than one cointegrating vectors while the Engle-Granger method can only identify one cointegrating vector. The determinant of the number cointegration vectors selected are based on the ADF test result for all variables, This test considers the available number of cointegrating vectors or r. In the case when the null hypothesis r = 0 is rejected, there is cointegration vectors. Refer the summarize according to the Johansen method, Table 7(a) and 7(b):

First Period: Before the Crisis					
H0	*H1*	Statistic	Critical Value		Results
			95%	90%	
Maximal eigenvalue					
r=0	r=1	38.7278	37.86	35.04	Cointegration
r<=1	r<=2	26.0169	31.79	29.13	
Trace Statistic					
r=0	r>=1	91.4204	87.17	82.88	Cointegration
r<=1	r>=2	52.6926	63.00	59.16	

Table 7(a): Johansen ML results for multiple cointegrating vectors – DJIA. JAP, FTSE, CHSA and IBEX,(Jan 2001-June 2007), 80 0bservations

Second Period: After the Crisis					
H0	*H1*	Statistic	Critical Value		Results
			95%	90%	
Maximal eigenvalue					
r=0	r=1	37.836	37.86	35.04	Cointegration
r<=1	r<=2	27.6063	31.79	29.13	
Trace Statistic					
r=0	r>=1	97.9087	87.17	82.88	Cointegration
r<=1	r>=2	60.0727	63.00	59.16	

Table 7(b): Johansen ML results for multiple cointegrating vectors – DJIA. JAP, FTSE, CHSA and IBEX (July 2007-Oct 2013). 76 Observations

Notes: The statistics refer to Johansen's log-likelihood maximal eigen value and trace test statistics based on cointegration with unrestricted intercepts and restricted trends in the VAR. The above results show at least one cointegrating vectors at 95% level. The order (or lags) used is 3 in table 7(a) and 4 in table 7(b).

According to the Johansen method Table 7a and 7b (Before and after the crisis), refer to Johansen's log likelihood maximal eigenvalue and trace test statistics based on cointegration with unrestricted intercepts and restricted trends in the VAR. Therefore, we could see both tables shows the eigenvalue value statistic and trace statistics give a result at one cointegration vector (r=1). However, based on the observation on Akaike information criterion (AIC) and Schwarz Bayesian (SBC), we could see before the crisis both AIC and SBC favour r=5, whereas on the observation after the crisis shows that SBC select r=0 and the AIC favour r = 3. Henceforth, we have found that there is at least one cointegrating vectors between the variables which confirm cointegration but for the purpose of this study we shall assume that there is one cointegrating vector r=1. Through this, my result indicates that there is cointegration among the stock index of DJIA, JAP, FTSE, CHSA and IBEX that would mean that there is no diversification opportunity for investors looking to invest pairwise into the stock market indices of these countries. However, it could not be denied that there is still diversifiction opportunities in the short-run.

- **Engle-Granger method**

The other ways to test the cointegration is by using Engle-Granger Method rather than Johansen Test. However, by referring the summary result in Table 8, we could see that all the variables either on the first period or the second period are non stationary which means there is no cointegration between the variables. This result is very much contradicts with the earlier Johansen method test of cointegration and the reasons of this contradiction might be due to the inefficiencies of this residual-based cointegration tests. However, it is not surprising to see such contradiction as mentioned in Pesaran and Pesaran (2009) where if there is more than two I(1) variables it could possibly give a contradicting result as compared to Johansen method. But as for our study, we will relied on Johansen method which is shows that there is a cointegration between the variable.

	First Period: Before the Crisis				Second Period: After the Crisis			
Variable	Test Statistic AIC	SBC	Critical Value	Results	Test Statistic AIC	SBC	Critical Value	Results
LDJIA	-3.0932	-3.0932	-4.6041	Non-Stationary	-3.9197	-3.9197	-4.6148	Non-Stationary
LJAP	-3.1617	-3.1617	-4.6041	Non-Stationary	-2.5109	-2.3766	-4.6148	Non-Stationary
LFTSE	-1.5497	-1.931	-4.6041	Non-Stationary	-2.8912	-3.9375	-4.6148	Non-Stationary
LCHSA	-0.7184	-0.7184	-4.6041	Non-Stationary	-2.9622	-2.9622	-4.6148	Non-Stationary
LIBEX	-2.6547	-2.6547	-4.6041	Non-Stationary	-4.4288	-3.4059	-4.6148	Non-Stationary

Table 8: Engle-Granger results for single cointegrating vector for (Jan 2001-June 2007) and (July 2007-Oct 2013).

Long Run Structural Modeling (LRSM)

Earlier, we have mentioned that we want to identify the direction of causality between FTSE and International index variables. In other words, our focus variable in this paper is FTSE. Thus, we first normalized LFTSE (i.e. normalizing restriction of unity) at the 'exactly identifying' stage (Panel A of Table 9a and 9b). Refer table 9(a) for the first period, When we normalized FTSE, we found that the coefficients of the cointegrating vector for LCHSA and LIBEX are significant except for LDJIA and LJAP. However, when we imposed restriction of one on JAP (refer Panel B of Table 9(A), we found that the overidentifying restriction is rejected (with a p-value of 0.021 error while rejecting the null).

However, even the panel A shows that LDJIA and LJAP are insignificant, we still insist to continue to include LDJIA and LJAP as our variable in the following tests based on the several reasons. For the LJAP, the reasons to include is because Japanese stock market has a lead-lag relationship to other stock markets means that according to the Chong et al (2008) found that the NIKKEI index is well predicted to the movement of the FTSE Index and also evidence also suggests that the NIKKEI have a significant affects returns in some markets. While the reasons of including LDJIA is because DJIA is a good predictor of global indices but other global indices are not good predictors of the DOW according to the Morana and Beltratti (2008), and also US stock markets have a significant impact on Japanese equities based on the several studies and that is the reason we insist to include LDJIA AND LJAP as our variable in the following test.

	First Period: Before the Crisis			
	Panel A		Panel B	
LDJIA	0.1355	(0.15145)	-0.62598	(0.69130)
LJAP	-0.018124	(0.11538)	1.0000	(*NONE*)
LFTSE	1.0000	(*NONE*)	1.0000	(*NONE*)
LCHSA	0.089375*	(0.03377)	0.34434*	(0.14164)
LIBEX	-0.90969*	(0 .10200)	-1.5297*	(0.30500)
Trend	0.0031385	(0.00040)	0.00073	(0.00191)
Log-likelihood	780.7976		778.1186	
Chi Square	None		[.021]	

Table 9(a): Exact and over identifying restrictions on the cointegrating vector (First Period)
Notes: The output above shows the maximum likelihood estimates subject to exactly-identifying (Panel A) and over-identifying (Panel B) restrictions. The 'Panel A' estimates show that variables of LCHSA and LIBEX are significant while LDJIA and LJAP insignificant (FTSE are in parenthesis). In addition, the overidentifying restriction on JAP=1 gives result of P-value that rejecting the null. Thus, we rely with 'Panel A' instead.
*Indicates significance

Refer table 9(b) for the second period, When we normalized FTSE, we found that the coefficients of the cointegrating vector for all the variable are insignificant. However, when we imposed restriction of one on JAP (refer Panel B of Table 9(b), we found that the over identifying restriction is accepted (with a p-value of 0.678 error while accepting the null).Thus, we continue to include all of our variable in the following tests by relying on Panel B.

	Second Period: After the Crisis			
	Panel A		Panel B	
LDJIA	-1.7638	(1.64470)	-3.2959*	(1.19350)
LJAP	0.4739	(0.57275)	1.0000	(*NONE*)
LFTSE	1.0000	(*NONE*)	1.0000	(*NONE*)
LCHSA	0.57691	(0.86181)	1.3602*	(0.75939)
LIBEX	-0.93876	(0.83958)	-1.7036*	(0.56655)
Trend	0.0060833	(0.01217)	0.017171*	(0.01137)
Log-likelihood	667.0728		666.9869	
Chi Square	None		[.678]	

Table 9(b): Exact and over identifying restrictions on the cointegrating vector (Second Period)
Notes: The output above shows the maximum likelihood estimates subject to exactly-identifying (Panel A) and over-identifying (Panel B) restrictions. The 'Panel A' estimates show that all variables are insignificant (FTSE are in parenthesis). In addition, the overidentifying restriction on JAP=1 gives result of P-value that accepting the null. Thus, we rely with 'Panel B' instead.
*Indicates significance

<u>Vector Error Correction Model (VECM)</u>

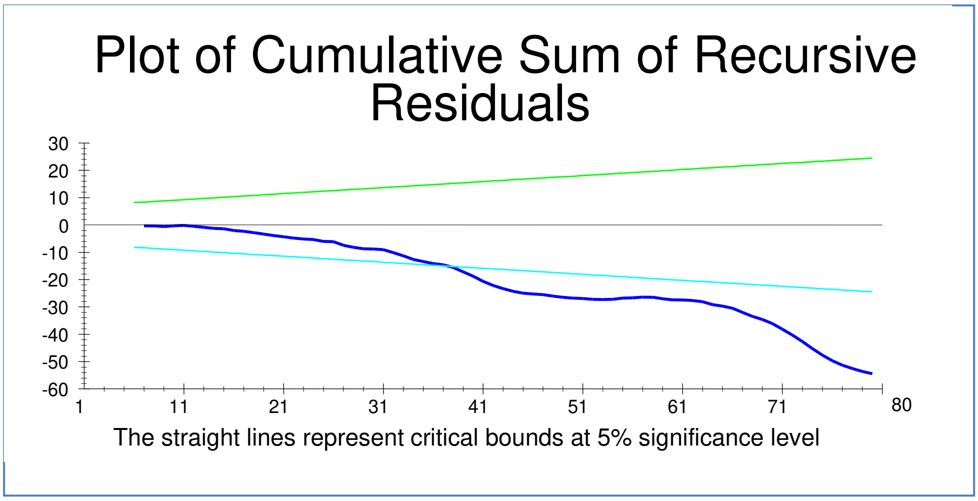
This steps and onwards is an important step to test the causality while the previous four steps before only tested theories and confirm that there is cointegration between the variables but it did not help us to show which variable exogenous and which endogenous variables.

Henceforth, this steps onwards are the most favourable steps especially for the practitioners like policy maker and even CEO since its able to provide such result that can show which variable is the leader to focus their policies on those variables to make the biggest impact. Thus, we have performed VECM and the results are summarized in Table 10(a) and (b).

The statistical results showed that on the first period, LDJIA, LCHSA and LIBEX are exogenous while LJAP and LFTSE are endogenous. Therefore, US market still 'causes' some index market countries during the period of crisis, reflecting the US market's persisting dominant role same goes to LIBEX and CHSA as well. However, after the crisis only LJAP is exogenous while the rest of the variables which are LDJIA, LFTSE, LCHSA and LIBEX are endogenous. Therefore, we could see that the degree of exogeneity for all indices has been reduced implying that only JAP that once endogenous before the crisis becomes exogenous to the financial crisis. Based on this, the result is against Becker, Finnerty and Gupta (1990) because they found that US market greatly influence Nikkei but this statement only valid before the crisis only but not applicable after the crisis, since the result becomes reverse and the reasons behind this might be due to the changing global capital markets, information is being processed and past along faster than ever. This could cause even smaller indices to have an effect on larger global indices. Henceforth, Masih et. al. (2009) explained about the significance of the error correction term in the equation. One of the functions of error correction term is to show long term relationship of the variable. In addition, the VECM produces a statistic that may be of interest to investors. The coefficient of et-1 tells us how long it will take to get back to long term equilibrium if that variable is shocked. The coefficient represents proportion of imbalance corrected in each period. For instance, in the case of the FTSE, the coefficient before and after the crisis is both around 0.09. This implies that, when there is a shock applied to this index, it would take, on average, 11 weeks for the index to get back into equilibrium with the other indices in the event of before or after the crisis

The diagnostics test allows us to check for specification problem in terms of autocorrelation, functional form, normality and heteroskedasticity. Unfortunately, there seems to be some problems in the equation. In addition, we have used the CUSUM and CUSUM SQUARE (Figure 1) to check the stability of the coefficients. The CUSUM and CUSUMSQ tests employ the cumulative sum of recursive residuals based on the first set of observations and is updated recursively and plotted against the break points. If the plots of the CUSUM and CUSUMSQ statistics are found to be within the critical bounds of 5 percent level, the H that all coefficients in the model are stable cannot be rejected. On the other hand, if the lines are found to be crossed, the H of coefficient constancy can therefore be rejected at 5 percent significance level.

Hence, figure 1(a) in the event on the first period, it is found that the parameters are structurally unstable which indicates structural breaks. Structural breaks before the crisis happen around year of 2003 onwards might be caused by major political event, or economic event or even policy damages, but selecting the most important economic events is a daunting task, and it is very subjective because there is so much event happen in 2003 onwards such as, The Dow Jones index of stock prices closes at 10,008.16, an 18-month high, and further event take place in US market where President Bush sends Congress fiscal 2004 budget, proposing to bring federal outlays up to $2.23 trillion and incur record deficits in coming years. However, this structural break can be corrected by using dummy variables but unfortunately, we are unable to correct the structural break because of the limitation time. However, in figure 1(b) in the event of the second period, it is found that the parameters are structurally stable which indicates no structural breaks which means there is some recoveries from the global financial crisis that broke out in 2007. Therefore, the recovery might be due to the large number of macro and financial factors that are responsible for the deeper crisis and the recovery.



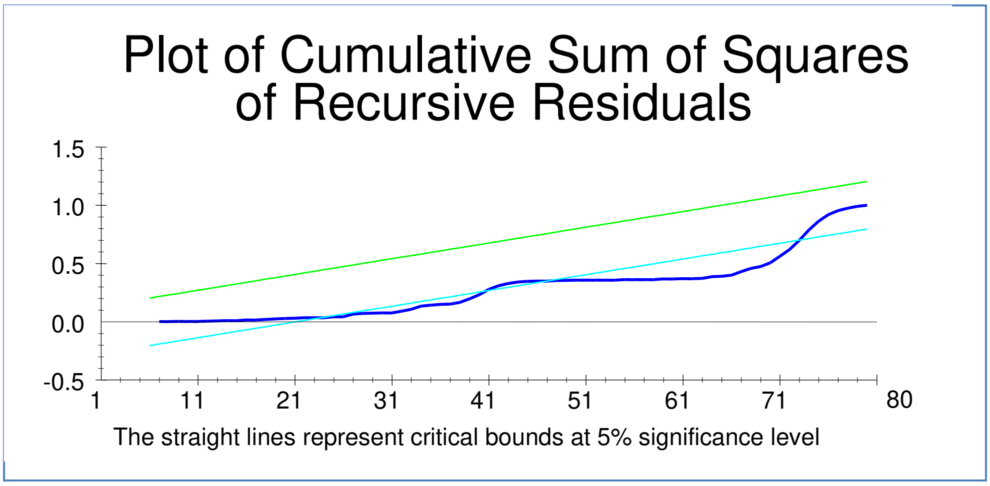
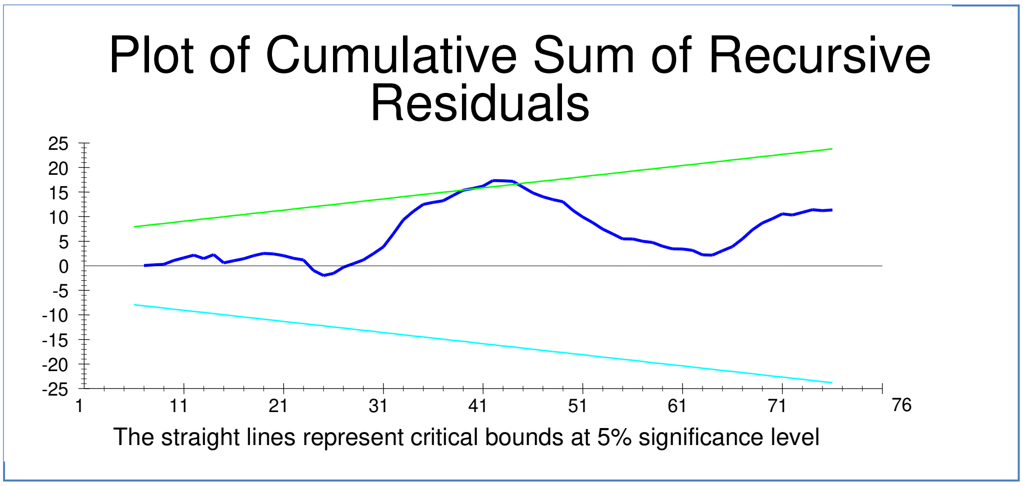


Figure 1(a): (a) Plot of cumulative sum of recursive residuals and (b) plot of cumulative sum of squares of recursive residuals (First period)



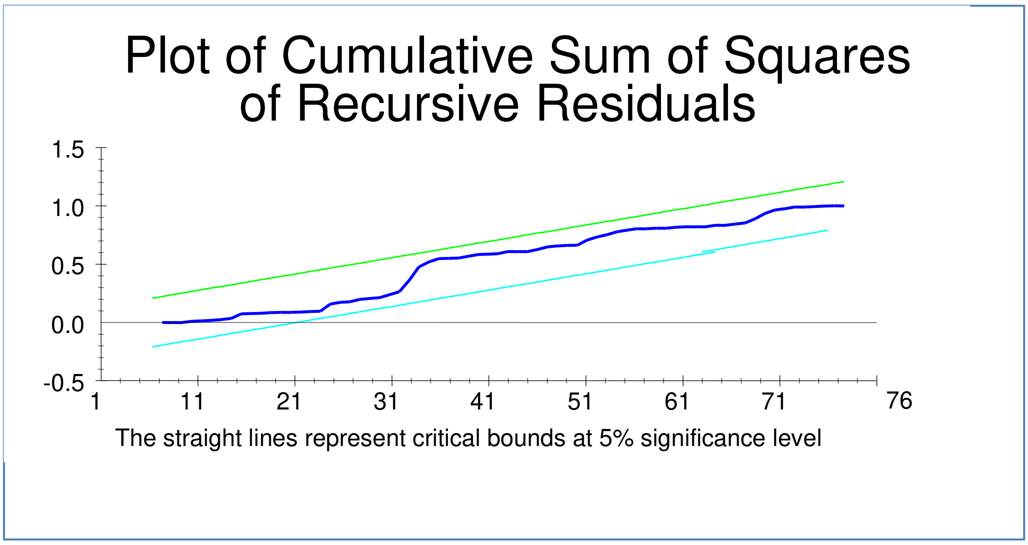


Figure 1(b): (a) Plot of cumulative sum of recursive residuals and (b) plot of cumulative sum of squares of recursive residuals

Variance Decompositions (VDCs)

- **Orthogonalized VDC**

Variance Decompositions (VDCs) can be used to explain information about relative exogeneity/endogeneity, for example, identify which variable is most exogenous, which one is the most endogenous. Hence, VDC are made up of orthogonalized VDC and generalized VDC. Orthogonalized VDC result are shown in Table 11(a) and 11(b). Hence, it showed the variance of forecast error once we shocked 1 variable. Basically, we are interested on the variance of forecast error of the shocked variable on itself. The orthogonalized VDCs are not unique and in general depend on the particular ordering of the variables in the VAR. Furthermore, The orthogonalized VDCs assumes that when a particular variable is shocked, all other variables in the model are switched off and this will impact the result to be bias therefore we will not discuss the orthogonalized result because of the issue of bias.

First Period: Before the Crisis					
Quarter	ΔLDJIA	ΔLJAP	ΔLFTSE	ΔLCHSA	ΔLIBEX
Relative variance in ΔLDJIA					
1	0.98	0.00	0.00	0.01	0.00
12	0.90	0.02	0.04	0.01	0.03
48	0.78	0.08	0.06	0.01	0.06
Relative variance in ΔLJAP					
1	0.28	0.70	0.00	0.01	0.01
12	0.44	0.21	0.03	0.09	0.23
48	0.42	0.06	0.07	0.18	0.27
Relative variance in ΔLFTSE					
1	0.76	0.01	0.23	0.00	0.00
12	0.56	0.10	0.26	0.04	0.04
48	0.42	0.21	0.22	0.08	0.07
Relative variance in ΔLCHSA					
1	0.01	0.01	0.02	0.95	0.00
12	0.02	0.06	0.01	0.81	0.10
48	0.05	0.19	0.00	0.57	0.17
Relative variance in ΔLIBEX					
1	0.69	0.01	0.07	0.00	0.23
12	0.46	0.08	0.14	0.01	0.31
48	0.37	0.17	0.14	0.04	0.28

Table 11(a): Percentage of forecast variance explained by innovations in: Orthogonalized variance decompositions (First period)

Second Period: After the Crisis					
Quarter	ΔLDJIA	ΔLJAP	ΔLFTSE	ΔLCHSA	ΔLIBEX
Relative variance in ΔLDJIA					
1	0.97	0.02	0.00	0.00	0.00
12	0.16	0.20	0.10	0.36	0.18
48	0.07	0.14	0.14	0.46	0.19
Relative variance in ΔLJAP					
1	0.35	0.64	0.01	0.00	0.00
12	0.06	0.67	0.06	0.16	0.05
48	0.02	0.59	0.09	0.23	0.07
Relative variance in ΔLFTSE					
1	0.73	0.09	0.18	0.00	0.00
12	0.14	0.21	0.26	0.33	0.07
48	0.12	0.14	0.28	0.39	0.08
Relative variance in ΔLCHSA					
1	0.06	0.14	0.01	0.79	0.00

12	0.21	0.07	0.10	0.61	0.01
48	0.27	0.04	0.11	0.57	0.01
Relative variance in ΔLIBEX					
1	0.27	0.11	0.02	0.01	0.60
12	0.23	0.23	0.06	0.26	0.22
48	0.33	0.17	0.09	0.33	0.08

Table 11(b): Percentage of forecast variance explained by innovations in: Orthogonalized variance decompositions (Second Period)

- **Generalized VDC**

Generalized VDC does not depend on the particular ordering of the variables in the VAR and does not make such an assumption of all other variables switched off. For the Generalized, the variance of forecast error given in each horizon will not be equal to 1. In other words, the results generated have to be recalculated to obtain Table 12 (refer Appendix for details). In VDC test, the variable that is explained mostly by its own shocks (and not by others) is deemed to be the most exogenous of all (Masih et. al., 2009).

In our results Table 12(a) before the crisis, contributions of own shocks to each variable at the end of forecast horizon 48 are as follows: LDJIA (33%), LJAP (4%), LFTSE (35%), LCHSA (68%) and LIBEX (43%). Generalized VDC result confirmed that LCHSA is the most exogenous variable while LJAP is the most endogenous. Therefore, Generalized VDC result confirmed that LCHSA is the most exogenous variable while real LJAP is the most endogenous. However, there is conflicting in result on Generalized VDC pertaining on LDJIA and LFTSE since it is not congruent with the result in VECM, where supposedly LDJIA is exogenous and LFTSE is endogenous but however the reverse result happen in Generalized VDC, where LDJIA have a lower rank than LFTSE.

First Period: Before the Crisis					
Quarter	ΔLDJIA	ΔLJAP	ΔLFTSE	ΔLCHSA	ΔLIBEX
Relative variance in ΔLDJIA					
1	0.36	0.09	0.29	0.01	0.25
12	0.34	0.05	0.30	0.00	0.30
48	0.33	0.02	0.32	0.00	0.33
Relative variance in ΔLJAP					
1	0.15	0.53	0.14	0.01	0.17
12	0.21	0.20	0.21	0.04	0.34
48	0.23	0.04	0.25	0.09	0.39

Relative variance in ΔLFTSE					
1	0.28	0.08	0.37	0.00	0.27
12	0.27	0.02	0.37	0.02	0.32
48	0.26	0.01	0.35	0.05	0.33
Relative variance in ΔLCHSA					
1	0.01	0.00	0.00	0.99	0.00
12	0.02	0.03	0.01	0.90	0.05
48	0.06	0.09	0.04	0.68	0.13
Relative variance in ΔLIBEX					
1	0.26	0.08	0.28	0.00	0.38
12	0.25	0.02	0.30	0.01	0.43
48	0.24	0.01	0.30	0.03	0.43

Table 12. Percentage of forecast variance explained by innovations in: Generalized variance decompositions

While, our results in Table 12(b) after the crisis, contributions of own shocks to each variable at the end of forecast horizon 48 are as follows: LDJIA (10%), LJAP (39%), LFTSE (7%), LCHSA (44%) and LIBEX (6%). Therefore, Generalized VDC result confirmed that LIBEX is the most endogenous variable unfortunately, we found this result somewhat puzzling this is because Generalized VDC result not congruent with VECM which shows that LCHSA is the most exogenous whereas it is supposedly endogenous in VECM. Thus, The Generalized VDCs confirm the results of the VECM in that Shanghai Stock Index is the most exogenous variable for the first and second period of the crisis.

Second Period: After the Crisis					
Quarter	ΔLDJIA	ΔLJAP	ΔLFTSE	ΔLCHSA	ΔLIBEX
Relative variance in ΔLDJIA					
1	0.37	0.19	0.27	0.04	0.12
12	0.15	0.19	0.17	0.41	0.08
48	0.10	0.08	0.06	0.61	0.15
Relative variance in ΔLJAP					
1	0.15	0.42	0.22	0.08	0.12
12	0.05	0.44	0.16	0.30	0.05
48	0.03	0.39	0.11	0.46	0.02
Relative variance in ΔLFTSE					
1	0.26	0.21	0.35	0.03	0.14
12	0.15	0.16	0.21	0.39	0.09
48	0.21	0.05	0.07	0.56	0.12
Relative variance in ΔLCHSA					
1	0.05	0.14	0.07	0.72	0.03
12	0.27	0.04	0.05	0.56	0.09

48	0.34	0.04	0.06	0.44	0.12
Relative variance in ΔLIBEX					
1	0.14	0.17	0.17	0.02	0.51
12	0.32	0.08	0.08	0.28	0.25
48	0.51	0.02	0.09	0.32	0.06

Table 12. Percentage of forecast variance explained by innovations in: Generalized variance decompositions

Therefore, we insist to stick with the result in Generalized VDC since it capable to tell which variable is the strongest leader and which variable is the weakest follower (by ranking the variables based on the degree of dependence on their own past lags) as compared to the VECM that cannot tell which variable is the strongest leader and which variable is the weakest follower and besides the rejection result on VECM is caused by the problem of serial correlation and functional form test based on the result of chi-square.

<u>Impulse Response Functions (IRFs)</u>

We have also performed orthogonalized IRFs in Appendix but again we will not discuss its result. Next, we performed generalized IRFs for the most endogenous (JAP) and exogenous (CHSA) variable in Figure 2(a), 2(b) and 3(a), 3(b) respectively. Consistent to our earlier results, during first period it can be seen that the JAP variable is more responsive to the shock by CHSA as compared to the reverse. Whereas, during the second period IBEX variable is more responsive to the shock by CHSA. We have also performed generalized IRFs on all other variables too. Thus, both result of IRFs and VDC use a variable-specific shock therefore IRFs essentially produce the same information as the VDCs, except that they can be presented in a graphical form. Hence, our further explanation can be rely upon on the VDC as well. For the full result, please refer Appendix.

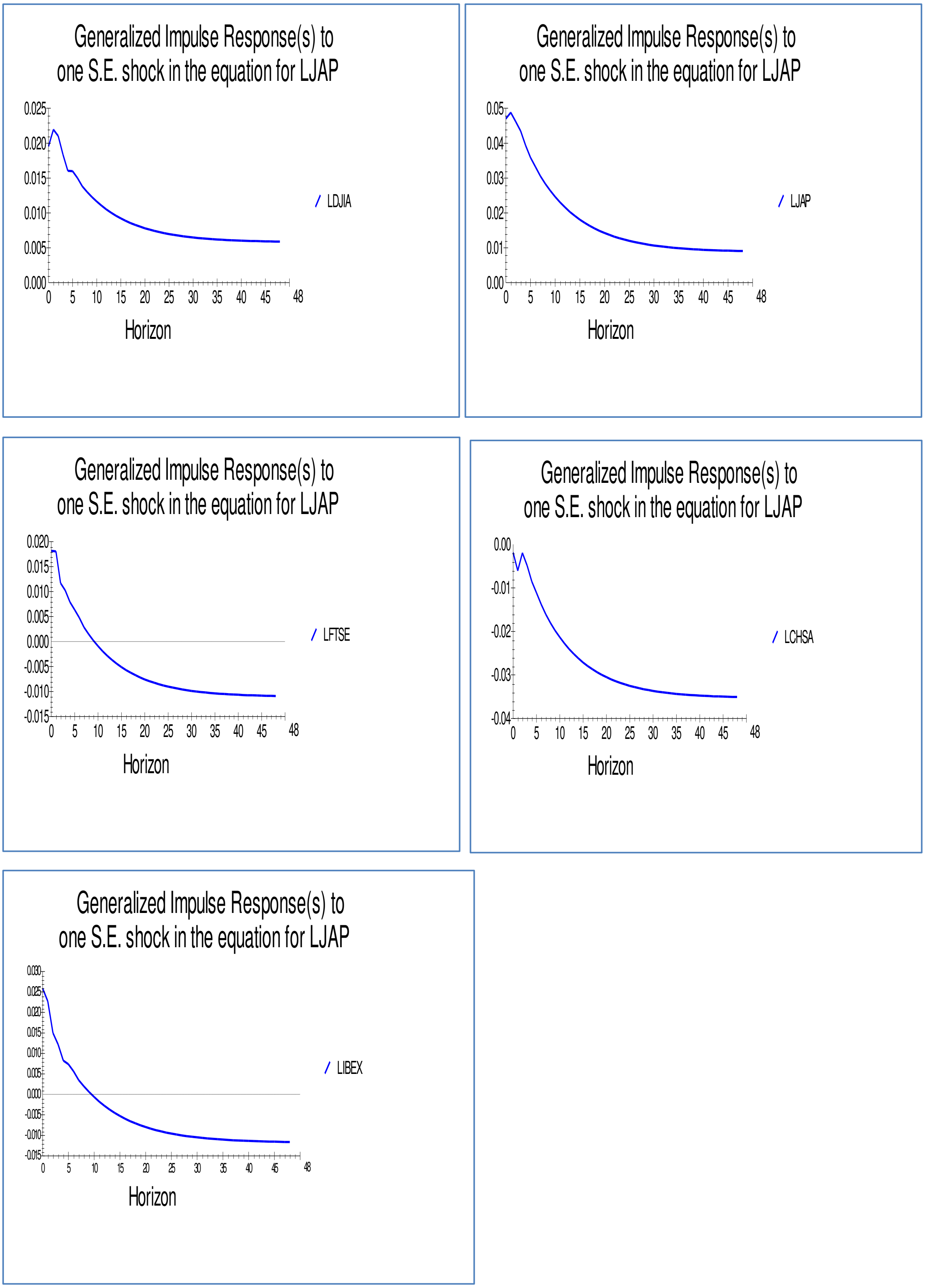
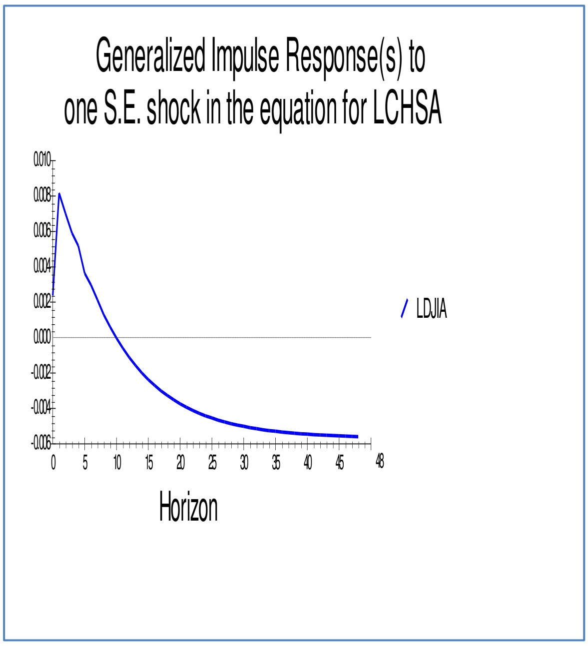
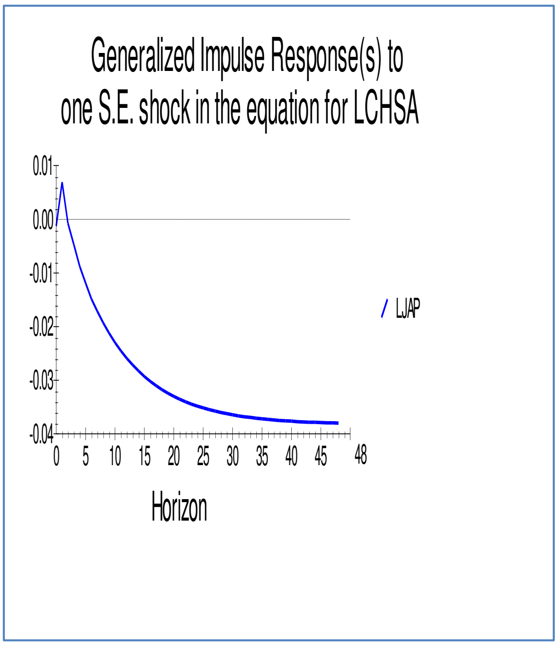
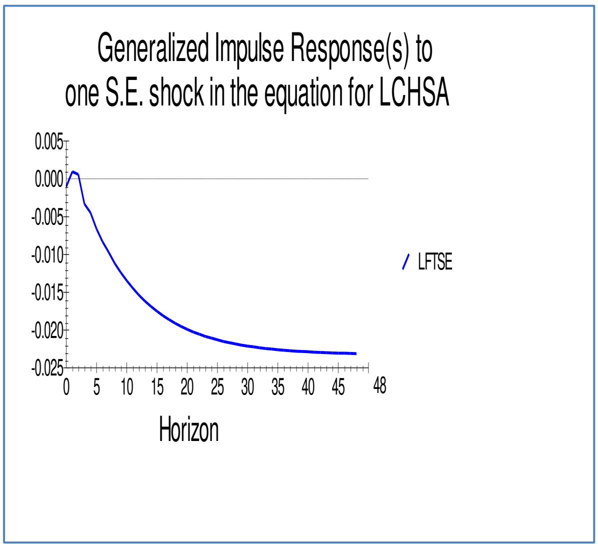
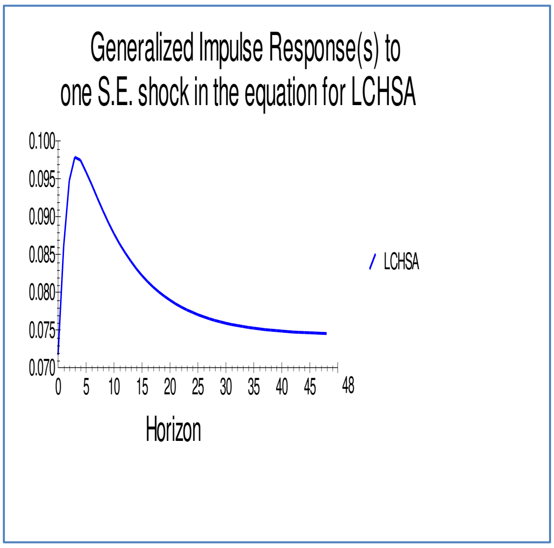


Figure 2(a): Generalized impulse responses to one SE shock in the equation for CPI


Generalized Impulse Response(s) to
one S.E. shock in the equation for LCHSA
LDJIA
Horizon


Generalized Impulse Response(s) to
one S.E. shock in the equation for LCHSA
LJAP
Horizon


Generalized Impulse Response(s) to
one S.E. shock in the equation for LCHSA
LFTSE
Horizon


Generalized Impulse Response(s) to
one S.E. shock in the equation for LCHSA
LCHSA
Horizon

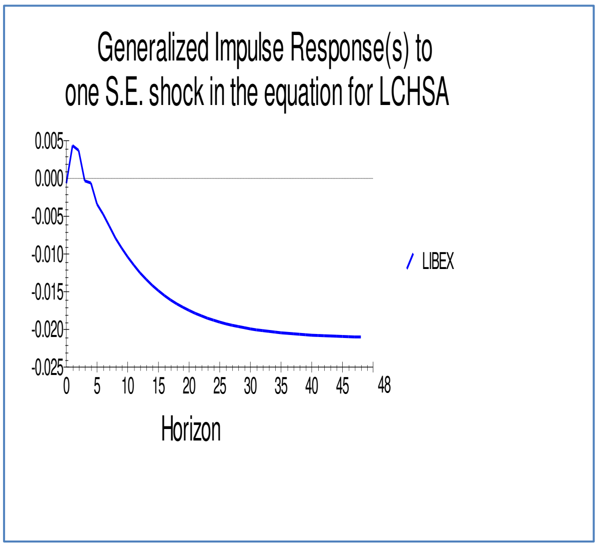

Generalized Impulse Response(s) to
one S.E. shock in the equation for LCHSA
LIBEX
Horizon

Figure 2(b): Generalized impulse responses to one SE shock in the equation for CHSA

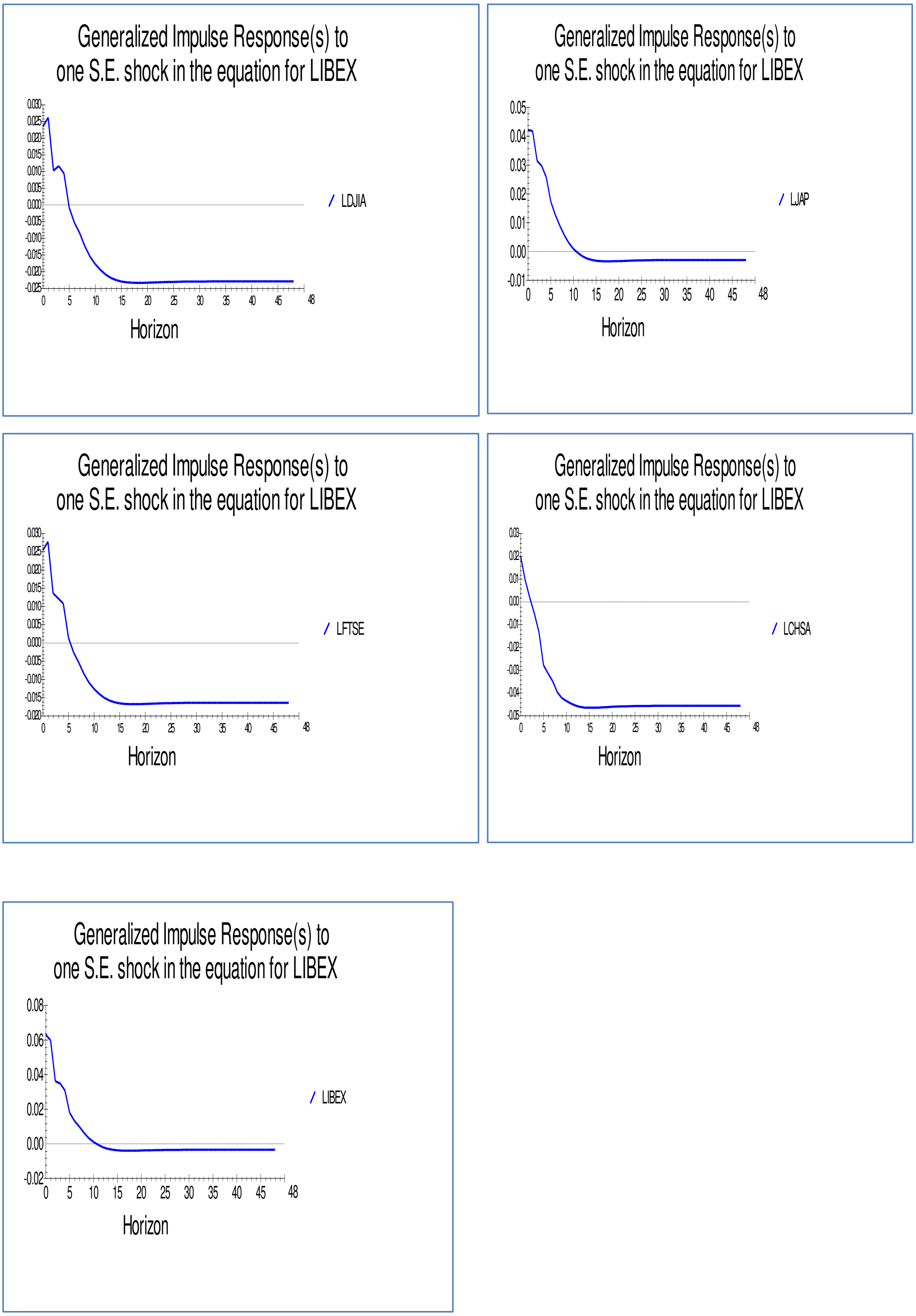
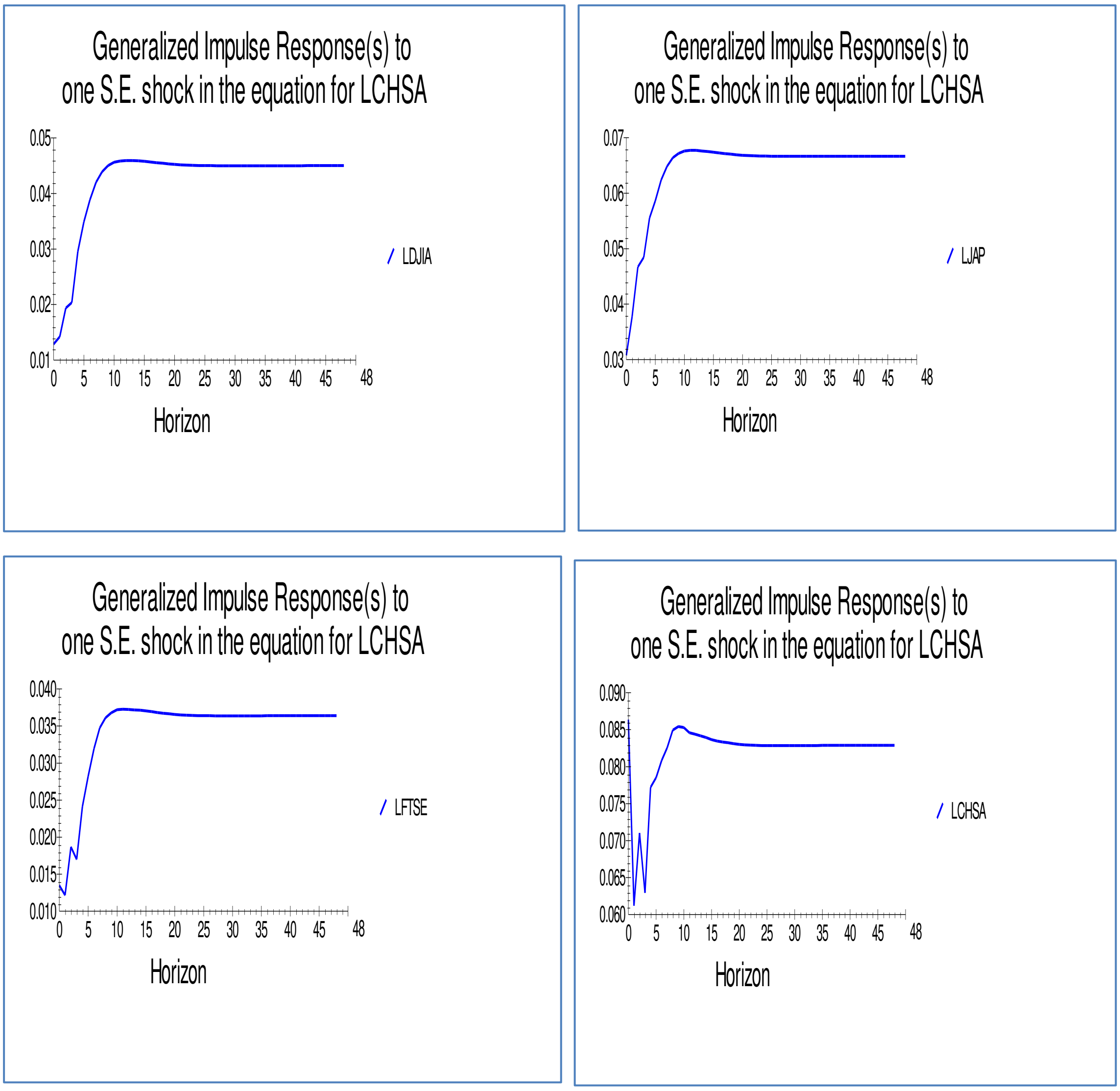


Figure 3(b): Generalized impulse responses to one SE shock in the equation for IBEX



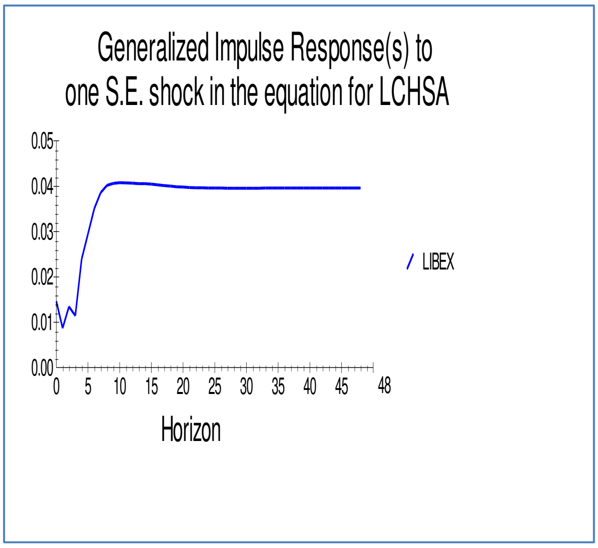


Figure 3(b): Generalized impulse responses to one SE shock in the equation for CHSA

<u>Persistence Profiles (PF)</u>

Finally, persistence profile indicated the system-wide shock to the cointegrating relationship. During the first period, it will take about 2 years to regain equilibrium, whereas during the second period it will take about 1 year to regain equilibrium.

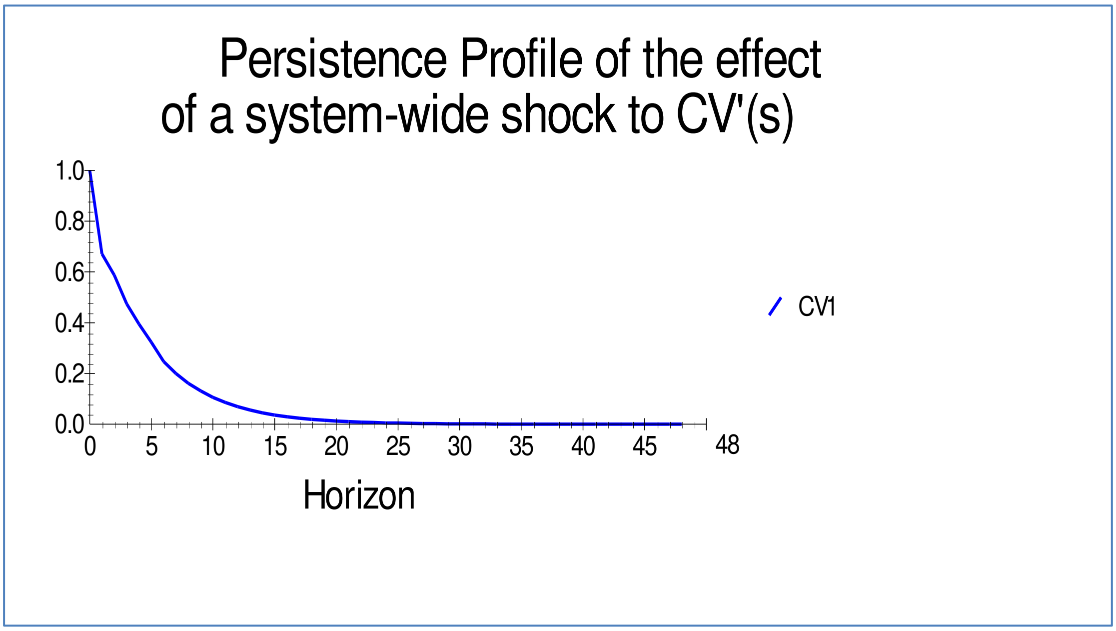


Figure 4(a): Persistence profile of the effect of a system-wide shock (Before the crisis)

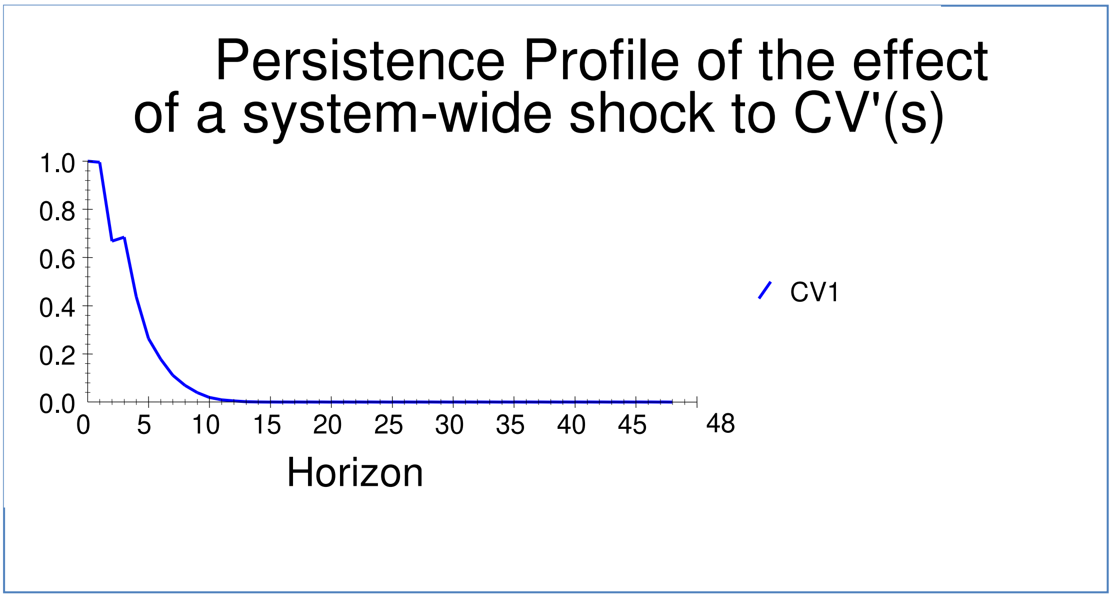


Figure 4(b): Persistence profile of the effect of a system-wide shock (After the crisis)

DISCUSSION OF RESULTS

In conclusion, based on the above quantitative analysis, we found the answers for our research question to be:

1. Based on the five stock selected market in this study, Shanghai Stock Index is the most influential in affecting other stocks either before or after the crisis as compared to another index. Thus, the results contradict the assumption that US Stock Market would be more influencial than the other stock markets as it is consistent with the views by Morana and Beltratti, (2008)

2. Based on the five stock selected market, US Stock Market is not more influencial than the other stock markets as it consistent with the result in VDC that shows DJIA is endogenous even before or after the crisis.

3. During the first period, FTSE index is very much influential by the Shanghai Stock Index and also IBEX. However, on the second period, Shanghai Stock Index remains to be the most influential but IBEX is no longer influential as it is being replaced by NIKKEI to be the second index affecting FTSE performance. Therefore, this result

contradicts the views by Baur and Jung (2006) after the crisis 1987, the FTSE market is influenced by the movement of US stock market

From the results, we can conclude the policy maker or investor who favours to invest in international stock should consider policies that would develop and focus on the stock of developing market specifically Shanghai Stock Index as it has a high influence on the other developed stock markets namely DJIA, NIKKEI, FTSE and IBEX.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

There is a limitation of this study especially with regard to the choice of stock market in this study and hence presents opportunities for future research. The choice of indices is somewhat arbitrary. Many other available indices could have been considered and may have produced additional or even different results. We recommended further study to include group of indices consisting developed, emerging stock or even shariah compliant index in the quantitative analysis just to know which stock has the most exogenous character to influence others.

The theoretical foundation and framework of this study also leave something to be desired especially in term of the time event since in this study the data are divided into 2 time event which is before and after the crisis, so in our opinion it would be recommended to divide the time series into 3 time event which is before the crisis, during the crisis and after the crisis.

References

Baur, D.and Jung, R. (2006). Return and volatility linkages between the US and German stock markets. *Journal of International Money and Finance*, 25, 598 – 613.

Becker, K., Finnerty, J., and Gupta, M. (1990). The intertemporal relation between the U.S. and Japanese stock markets. *The Journal of Finance, 45,* 1297 – 1306.

Chong, T., Wong, Y., and Yan, I. (2008). International linkages of the Japanese stock market. *Japan and the World Economy*, 20, 601 – 621.

Engle, R. F., and Granger, C. W. (1987). Cointegration and error-correction representation, estimation, and testing. Econometrica, 55(2), 251–276.

Hassan, M. K. and Naka, A.(1996), Short-run and long-run dynamic linkages among international stock markets, 594), 387 -405.

Johansen, S. (1991), Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, Econometrica, 59(6), 1551-1580

Masih, M., Al-Elg, A. and Madani, H. (2009). Causality between financial development and economic growth: an application of vector error correction and variance decomposition methods to Saudi Arabia, *Applied Economics,* 41, 1691–1699

Masih, R. and Masih, M. (2001) Long and Short-Term Dynamic Causal Transmission Amongst International Stock Markets, *Journal of International Money and Finance* , **20**(4), 563-587.

Morana, C. and Beltratti, A. (2008). Aggregate hedge funds' flow and returns. *Applied Financial Economics*, 18, 1755 – 1764.

Pesaran, M.H. and Shin, Y. (2002). Long Run Structural Modeling. Econometric Reviews, 21(1), 49-87.