Role of global financial crisis in causing dynamic connectedness of Asian equity markets

Ariff, Azwar and Masih, Mansur

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

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Azwar Ariff[1] and Mansur Masih[2]

Abstract

Dynamic connectedness of equity markets especially when shock happened has been a concern for policymakers and market participants. In this paper, we examine the connectedness of Asian equity markets within the region when the US subprime crisis or better-known as the global financial crisis occurred in 2008.This paper wants to know whether there has been a shift in terms of net shock givers and receivers over the time? Subsequently, how has connectedness in equity markets changed over time? Finally, do markets become more connected during crisis period? We employ daily data of US, Japan, South Korea, China, Singapore, Malaysia, Indonesia and Thailand. We find that Singapore, US, Malaysia and South Korea played significant roles in bringing about dynamic connectedness of Asian equity markets. In terms of the global financial crisis, emerging market economies such as Singapore, Malaysia and South Korea seem to be vulnerable to the shock and may have contributed as spillover effect of shock to other Asian equity markets. Whereas economies such as China and Japan became a net receiver of shock.

Keywords: Dynamic connectedness, Global Financial Crisis, Asian equity markets

[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. Introduction: Objective and Motivation

What is dynamic connectedness?

It is crucial to understand the frequency dynamics of the connectedness as shocks to economic activity impact variables at different frequencies with different strength. Granger and Yoon (2002) mention that economic data are cointegrated because they respond to shocks together.

Understanding how shocks are transmitted across markets is a critical issue for policymakers and market participants in highly connected economies. During times of crisis, the degree of market interdependence comes to the forefront of discussions and market monitoring. For example, during the Latin America debt crises of 1982, shocks from Mexico indebtedness brought ripple effects to neighboring markets. During the Asian financial crisis of 1997-1998, shocks from Thailand also brought ripple effects to neighboring markets, and subsequently to other markets across Asia. During the United States of America (US) global financial crisis of 2008, shocks from the US reached nearly all corners of the global economy at varying degrees, reflecting not only the size and significance of the initial shock, but also the powerful transmission mechanism, particularly trade and financial linkages.

The 2008 global financial crisis that begins with subprime fiasco expectedly turns the US as the epicenter of crisis connectedness. Generally, subprime contagion effect stems from "overconsumption" of house mortgages that adversely affect low savings. Soon, fiscal deficit tend to become uncontrollable that subsequently affects US's sovereign debt to soar. Financially, these housing mortgages make excessive credit expansion through securitization of debt that enormously make banking system highly leveraged. Due to this lack of oversight, the S&P lower the US federal government credit rating from AAA to AA+. Statistics from IMF show that there were up to USD$1.7 trillion to USD$3.6 trillion total loss estimated. This crisis connectedness transmitted to the rest of the world through trade and financial channels. Subsequently, the crisis generally writes off most banks globally by USD$850 billion to USD$900 billion.

Since the Asian financial crisis, policymakers in Asia have tried to work together to close the gap in financial integration. These efforts include regional inclusion through the Association of Southeast Asian Nations (ASEAN) "plus three" of Asia (China, Japan and Korea) that could end up pulling large amounts of capital into ASEAN and more recently, the ASEAN Capital Markets Infrastructure (ACMI) Blueprint was developed in 2013 outlining guidelines that enable issuers and investors to access cross-border ASEAN equity and bond markets through integrated access, clearing, custody, and settlement systems and arrangements (Almekinders et al. 2015) . Despite these efforts, financial integration within the region and with the rest of the world still lags that of trade integration (IMF 2015, Cheng et al. 2015). According to the IMF 2015, the degree of financial integration within Asia has increased but remains relatively low that is only about 30 percent of cross-border portfolio investment.

Moreover, recent events in financial markets also suggest that emerging market economies in Asia can become a major source of financial shocks that may be transmitted widely, including to advanced economies. The ASEAN-5 (Indonesia, Malaysia, Philippines, Singapore and Thailand – the biggest economies in South East Asia) export are more linked to investment than to consumption in China suggesting that rebalancing from investment to consumption in China would adversely affect these countries on top of the growth slowdown (Dizioli et al 2016). Likewise, an adverse financial shock in China reduces equity prices by more in countries with higher trade exposure to China. In fact, financial spillovers from China to Asian countries have increased since the global financial crisis and are higher for economies with stronger trade links with China (Arslanalp et al. 2016). Spillover effects are economic events in one context that occur because of something else in a seemingly unrelated context. Even though the effect may not be so tremendous and it is subject to various contexts, this spillover effect still has its own impact in financial dynamic connectedness.

Financial integration within Asia, while not as strong as trade integration, has been on the rise. With the greater emphasis on regional financial integration initiatives in Asia, it is important to understand how the interdependence of financial markets across Asian economies has evolved not only among them but also extend to the US and European markets.

In this paper, we examine the connectedness of Asian equity markets within the global financial crisis shock by quantifying the contribution of shocks from US to selected countries in Asia other countries' at specific points in time. Against this backdrop, we address the following questions in this paper: (1) how has the connectedness in equity changed over time? Do equity markets become more connected during crises periods? Which country will become net spillover and shock contribution from main sources? (2) Which equity markets are major recipients of shocks? Has there been a shift in terms of the net shock receivers (directional connectedness over time)? Is there is any codependency of Asian equity markets to US markets? Finally, I take the opportunity to investigate has China emerged as an important source (or transmitter) of financial shocks to other economies inside and outside of the region, especially after global financial crisis.

2. Background of the study and theoretical underpinnings

Is there is any dynamic connectedness? This is because Kirman (1997) argue that market are not centralized, but rather consist of a complex structure of bilateral trades and relationship. However, mainstream media reports about the impact of global financial crisis to the world are prevalent. With this in mind, the dynamic connectedness is shows its relevancies.

Dynamic connectedness is a phenomenon, which, though obvious, is assumed to be widely prevalent globally. Unfortunately, dynamic connectedness is not well defined by financial theory, unlike most concepts in economics. To begin with, Sheiner and Willig (2011) manage to capture the idea of connectedness in ecology theory, that dynamics occur in one place (a single local community) are not necessarily independent of those that occur at other places.

So, aside from earlier ecology theory, questions arise; does dynamic connectedness have any impact on financial markets particularly equity market? Or does financial markets promote dynamic connectedness? Is there any theoretical relationship between the two?

Earlier, Jakson (2008) pinning that connection as a collection of nodes and links between nodes where from there, networks of connections can be a useful representation of financial systems. Later, information and communication technology especially Internet has making connection much more prevalent between nodes and making the theory of dynamic connectedness much more relevant. This notion of internet dynamism of connection was captured by Newman (2010) from mathematical perspective that brings dynamism of connection to a sophisticated manner. Newman believe that algorithm can explain epidemic on social network vis-a-vis financial markets.

Babus et al. (2009) mention that the risk of contagion happened when failure of one financial institution leads to the default of other financial institutions through a domino effect. In term of structures, Yilmaz (2013) defines the dynamic connectedness occur in three level of dynamics; that is connectedness across continent, connectedness across country level and also across institution level. However, Demirer (et al. 2015) manages to capture the dynamic connectedness in more focus manner. From Demirer perspectives, network connectedness is central to modern financial risk measurement and management. This measurement covers market risk, credit risk, counter part risk and systemic risk.

Interestingly, Acemoglu (2012) brings the idea of "channels of influence" where social connections may predict the crisis where market participants might favor financial institutions crisis connection based on existing social connections. On the other hand, Babus (2013) manage to capture the idea dynamic connectedness by mentioning that it can only be happen if market participants provide "means to model" that is the specifics of economic interactions network analysis where it can better explain certain economic phenomena.

The above theory explains that dynamic connectedness is real and may exist in domino effect through various interactions and form such as across continents, countries or firm. It may cause by several factors such as internet connectivity, financial risk, over-leverage, market risk and systemic risk. Moreover, the connectedness of financial markets will determine the dynamism of financial markets itself. It is evident from numerous literatures discussed that there is dynamism of financial sector (i.e. debt and equity markets, banking) on connectedness at country level.

3. Literature Review

There are many literature that try to look into relationship of dynamic connectedness.

A study done by Acharya et al. (2010), present a simple model of systemic risk and show that each financial institution's contribution to systemic risk can be measured as its systemic expected shortfall. Subsequently, Allen et al. (2010) able to develop model where institutions form connections in order to diversify their individual risk. They found that in clustered network groups of financial institutions may hold identical portfolios and later will default together. While, in an unclustered network, defaults are more dispersed. On the other hand, Diebold and Yilmaz (2009), concludes that there is striking evidence in interdependence of asset returns and volatilities spillover, where return spillovers display a gently increasing trend but no bursts, whereas volatility spillovers display no trend but clear bursts. Later, Barigozi and Brownlees (2013) proposed novel network estimation techniques for the analysis of multivariate time series. This network estimation technique is a long run partial correlation network for time series because financial data is a serial dependence data and should captures contemporaneous and led-lag effects.

Acharya et al. (2012) tentatively concluded that capital shortfalls could be used to measure systemic risk firms' size, leverage and interconnectedness. Likewise, Adrian and Brunnermeier (2008) find that characteristics such as leverage, size, maturity mismatch, and asset price booms significantly predict systemic risk contribution. On the other hand, Billio et al. (2012) find a significant contributing factor of global financial crisis that is interconnectedness among hedge funds, banks, brokers, and insurance companies, which amplified shocks into systemic events.

Study on US connectedness effect by Ang and Longstaff (2013) find that systemic risk is smaller among the US states compared to European countries although macroeconomic fundamentals are much more similar among the U.S. states. Subsequently, Wang and Moore (2012) claim that the US interest rate is the main driving factor behind the higher correlation.

Generally, in terms of domestic factor, Minoui et al. (2013) found that increases in a country's financial interconnectedness and decreases in its neighbors' connectedness are associated with a higher probability of banking crises after controlling for macroeconomic fundamentals. However, Bostanci and Yilmaz. (2015) found that global factors are more important than domestic factors in the determination of sovereign credit default swaps returns and volatilities. They also found that emerging market countries are the key generators of connectedness of sovereign credit risk shocks while severely problematic countries as well as developed countries play relatively smaller roles. Yilmaz (2009) also found that there is substantial difference between the behavior of the East Asian return and volatility spillover indices over time. While the return spillover index reveals increased integration among the East Asian equity markets, the volatility spillover index experiences significant bursts during major market crises, including the East Asian crisis. Hence, Diebold & Yilmaz (2013) found that global connectedness is sizable and time varying over the business cycle and connectedness corresponding to transmissions to others from the United States and Japan is disproportionately important.

4. Measure of Connectedness

In this paper we use a measure of connectedness across Asian equity markets in different countries as the effect of shock in global financial crisis. This paper will use time series approach in measuring connectedness although there is measure of connectedness that is based on dynamic variance decompositions from vector auto regression developed by Diebold and Yilmaz (2009, 2012, 2014) to assess the degree of connection.

5. Data and Model Theoretical Specification

The main underlying data are daily equity stock market indexes taken from Thomson Reuters Eikon at INCEIF terminal. Total observation are 1264 data. The main reason that data start at end of 2007 because the initial tremors of the subprime mortgage crisis were first felt at the end of 2007. In fact, the most severe impacts of the financial crisis of 2007–2009 arose immediately after the failure of Lehman Brothers on September 15, 2008. So, the data collected from end of 2007 is worth to examine the impact of the connectedness from the global financial crisis.

To measure the stock market indices, daily-end closing values of eight stock market index were used. The stock chosen are as below:

[Table 1: Source of Data and Its Measurement]

Name of variables	Abbreviations	Purpose

New York Stock Exchange Composite Index (NYSE)	US	Sources of shock
Nikkei 225 Stock Average Index (NIKKEI)	JP	Receiver of shock
Korea Composite Stock Price (KOSPI)	SK	
Shanghai Stock Exchange Composite Index (SSE380I)	CH	
Singapore Straits Times Index (STI)	SG	
Thailand Stock Exchange (SETI)	TH	
Indonesia Composite Index (IDC)	ID	
Kuala Lumpur Stock Exchange (KLSE)	MY	

The sample includes 7 Asian economies (China, Indonesia, Japan, South Korea, Malaysia, Singapore and Thailand) and the one and only US. From 7 Asian economies, three countries are advanced countries that are China, South Korea, Japan and Singapore. The remaining three countries in Asia are considered as developing countries that is Indonesia, Thailand and Malaysia. As requirement for time series analysis, it is necessary to examine the property of time series, that is, the stationary properties. This is very critical to avoid spurious regression. In this study, we employ augmented Dickey-Fuller (ADF) unit root test, which was developed by Dickey and Fuller (1979). This requires to test the significance of δ whether the time series is stationary or otherwise. In each form, the hypotheses are as follow ; Null hypothesis: $H0 : \delta = 0$ (i.e. the time series is non-stationary) , Alternative hypothesis: $H1 : \delta < 0$ (i.e. the time series is stationary). The first econometric step that has been used is to test the null hypothesis that the series are random walk or non-stationary by using Augmented Dickey-Fuller test. If the variables were found to be non-stationary, then the variables can be tested for the possibility of one or more co-integrating relationships using the Johansen (1990) methodology in the form of two test statistics namely, the Trace test and the Maximal Eigen value during the above-mentioned time periods.

The interrelationship among indexes has been captured by the both vector autoregressive (VAR) model and co-integrating vector error correction model (VECM). However, VECM cannot tell us which variable is relatively more exogenous and endogenous. The VDC technique is designed to indicate the relative exogeneity and endogeneity of a variables by decomposing (or portioning) the variance of the forecast error of a variable into proportions attributable to shocks (or innovation) in each variable in the system including its own (Masih *et al*, 2008). Then, Impulse Response Function Analysis that traces the response of exchange rate to one standard deviation change in interest rate. The IRF is presenting in a graphical way. Finally, the persistence profiles will be applied. They are designed to give the information about how long it will take for system to get back to equilibrium by using a system-wide shock.

6. Empirical result and interpretation

Step 1: Unit Root Test

Prior to kicking off the process, the stationarity of variable should be checked first. The variable is stationary if it always has a constant mean, variance, covariance throughout the time. In this step, the objective is to check whether the variables chosen were stationary or not. The test can be done by using the Augmented Dickey-Fuller (ADF) test and Phillips-Perron Test (PP).

ADF test

We kicked off our empirical testing by determining the stationarity of the variables chosen. In order to proceed with the testing of cointegration later, ideally, our variables should be I (1), in that in their original level form, they are non-stationary and in their first differenced form, they are stationary. The differenced form for each variable used is created by taking the difference of their log forms.

For example, DJP = LJPt – LJPt-1. We, then conducted the Augmented Dickey-Fuller(ADF) test on each variable in both level and differenced form. The table below summarizes the results.

[Table 2: ADF Test]

Variable	Test Statistic	Critical Value	Implication
Variable in Level form			
LJP	6.0387	3.4158	Non-Stationary
LMY	6.9789		Non-Stationary
LSK	7.0668		Non-Stationary
LUS	.3941		Non-Stationary
LTH	5.5777		Non-Stationary
LID	6.5653		Non-Stationary
LSG	7.8573		Non-Stationary
LCH	6.6188		Non-Stationary
Variable in Difference form			
DJP	20.0255	2.8643	Stationary
DMY	20.6061		Stationary
DSK	20.7264		Stationary
DUS	20.7228		Stationary

Variable	Test Statistic	Critical Value	Implication
DTH	21.4946		Stationary
DID	21.1544		Stationary
DSG	20.9568		Stationary
DCH	21.2890		Stationary

The above table shows that in level form, we couldn't reject the null hypothesis, while with the difference form we were able to reject the null hypothesis. By relying primarily on the AIC and SBC criteria, the conclusion that can be made is all the variables in this analysis are I(1) and therefore can proceed to next step. For ADF test statistics, we have selected the ADF regression order based on the highest computed value for AIC and SBC.

PP-test

The Phillips-Perron (PP) test also gave us the same results. In the PP test, the null hypothesis is that the variable is non-stationary. The null cannot be rejected if the test statistics is lesser than the critical value in absolute terms and can be rejected if the test statistics is larger than the critical value. We tested the variables based on these judgment criteria and accordingly get the results that all variables are I(1).

[Table 3: PP Test]

Variable	Test Statistic	Critical Value	Implication
Variable in Level form			
LJP	18.7947	3.4158	Non-Stationary
LMY	15.5150		Non-Stationary
LSK	16.7478		Non-Stationary
LUS	16.2108		Non-Stationary
LTH	13.7901		Non-Stationary
LID	14.9119		Non-Stationary
LSG	16.4745		Non-Stationary
LCH	15.7908		Non-Stationary
Variable in Difference form			
DJP	96.0548	2.8551	Stationary
DMY	85.4751		Stationary
DSK	79.3280		Stationary
DUS	83.3684		Stationary
DTH	90.0564		Stationary
DID	86.5481		Stationary
DSG	72.6717		Stationary
DCH	86.4091		Stationary

Step 2: Determining the Order of Lags of the VAR

Prior to doing cointegration test, we needed to determine order of the VAR that helps us to select how many lags we are going to use for cointegration test. Vector auto regression (VAR) is the test that needs to be done before moving on to the test for cointegration. In VAR the number lags needs to be used in this study. Table below shows the AIC and SBC.

[Table 4: Order of VAR]

	Choice Criteria	
	AIC	SBC
Optimal order	6	2

From the above table, it showed a contradicting optimum order given by the highest value of AIC and SBC. As expected, SBC gives lower order (order 1) as compared to AIC (order 2). This difference is due to the AIC tries to solve for autocorrelation while SBC tries to avoid over- parameterization. Given this apparent conflict between recommendation of AIC and SBC, we address this in the following manner. First, we checked for serial correlation for each variable and obtained the following result.

[Table 5: Tests for serial correlations of the variables]

Variable	LM (P-value)	Implication at 10% significance level
DJP	0.024	Serial correlation
DMY	0.005	Serial correlation
DSK	0.056	Serial correlation
DUS	0.004	Serial correlation
DTH	0.036	Serial correlation
DID	0.007	Serial correlation
DSG	0.077	Serial correlation
DCH	0.024	Serial correlation

According to the table, serial correlation does exist in the eight variables. Therefore, if we adopted a lower order of lags, the effects of serial correlation may be encountered. On the other hand, if a higher order of the lag is taken, it leads to the disadvantages of risking over-parameterization. However in our case, we have 1254 observations and then the higher VAR order of 6 is chosen.

Johansen method

The Johansen method uses maximum likelihood (i.e. eigenvalue and trace) and may identify more than one cointegration vectors while the Engle-Granger method can only identify one cointegration vector. According to the Johansen method (Table 6), we have not found that there are cointegrating vectors between the variables based on eigenvalue. In the case when the null hypothesis is r = 0, there is no cointegration when we fail to reject the null. If the t-statistics are lower than critical value (CV), we fail to reject the null, that is no cointegration between variables and otherwise there is cointegration if the null is rejected. Meanwhile, if we see the output with the trace statistics, we have found one cointegration vector between the variables.

[Table 6:Johansen Test]

Null	Alternative	Statistics	95% Critical Value	90% Critical Value
Maximal Eigenvalue Statistic				
r=0	r=1	172.8944	55.1400	52.0800
r <=1	r=2	94.8211	49.3200	46.5400
r <=2	r=3	78.0632	43.6100	40.7600
r <=3	r=4	74.9519	37.8600	35.0400
r <=4	r=5	68.1326	31.7900	29.1300
r <=5	r=6	48.3285	25.4200	23.1000
r <=6	r=7	22.0455	19.2200	17.1800
r <=7	r=8	9.8437	12.3900	10.5500
Trace Statistic				
r=0	r=1	569.0809	182.9900	176.9200
r <=1	r=2	396.1865	147.2700	141.8200
r <=2	r=3	301.3655	115.8500	110.6000
r <=3	r=4	223.3023	87.1700	110.6000
r <=4	r=5	148.3504	63.0000	59.1600
r <=5	r=6	80.2178	42.3400	39.3400
r <=6	r=7	31.8892	25.7700	23.0800
r <=7	r=8	9.8437	12.3900	10.5500

From the above results, we select one cointegrating vector based on the Eigen value and trace test Statistics at 95% level. The underlying VAR model is of order 8. If we follow eigenvalue test, there is 7 cointegration. Subsequently, with the trace tests of cointegration, we can also find there is 7 cointegrating vector among the variables, since null hypothesis of having no cointegration is rejected based on t-Stat. > 95% C.V. Here we do not have conflict problem between the eigenvalue and trace test. Generally if eigenvalue and trace conflicting each other, we may rely on the theory. From the result shown above, we know that there is 7 cointegrating vector and there is relationship between equity indexes across continent (between US and Asia) and between Asian countries. So, we will assume that there is 7 cointegrating vector.

Engle Granger Test

We also conducted Engel-Granger test whether the test results consistent with Johansen method. In E-G test, we assumed an OLS regression based on theories and empirical studies: LUS = α + β1 LJP + β2 LMY+ β3 LSK+ β4 LTH+ β5 LID+ β6 LSG+ β5 LCH + et. The result was made by comparing test statistics of the highest value of AIC and SBC with Dickey-Fuller (DF) critical value at 95%. In this result, We couldn't find cointegration among variables based on AIC and SBC value of DF critical value is not available. I try to change the combination of dependent and independent, still the critical value is not available.

[Table 7: Engle-Granger test result]

	Test statistics	DF critical value
AIC	8.2383	None
SBC	8.7042	

Even though no cointegration was found in this test, it is still concluded that there is 7 cointegrating vector as what we found with the Johansen test.

If they are cointegrated, then there is a long-term equilibrium relationship between the variables. These results imply that relationship between 8 indices are not spurious, and that each variable contains information for the prediction of other variable. However, cointegration cannot tell us the direction of Granger- causality as to which variable is exogenous and which variable is endogenous, for which the Vector Error Correction Modeling technique (VECM) will be applied. Now, in order to make the coefficients of the cointegrating vector consistent with theoretical expectations, we applied the long run structural model (Masih and Algahtani,2008).

Step 4 : Long Run Structural Model

This step will estimate theoretically meaningful cointegrating relations as I impose on those long-run relations and then test the over-identifying restrictions according to theories and information of the economies under review. In other words, this step will test the coefficients of variables in the cointegration equations against theoretical expectation. This LRSM step also can test the coefficients of variables whether they are statistically significant or not.

In this study, we want to see the impact of shock of equity indexes in US to selected Asian countries. In other words, our focused variable in this paper is LUS. Thus, we first normalized LUS (i.e. normalizing restriction of unity) at the 'exactly identifying' stage (Panel A). Next, we imposed restriction of zero on the other variable at the 'over identifying' stage (Panel B, Panel C). By calculating the t-ratios manually, we found that only LJP, LID, LSG AND LCH were significant; other variables such as LMY, LSK and LTH were insignificant. To verify the significance of these variables, we applied over-identifying restrictions.

[Table 8: Exact and over identifying restrictions on the cointegrating vector]

	Panel A	Panel B	Panel C
LJP	1.3186	1.3771	1.3838
	(0.39940)	(0.39281)	(0.41790)
LMY	0.30182	0.0000	0.33656
	(0.45118)	(None)	(0.48142)
LSK	-0.12440	-0.0000	-0.13845
	(0.24723)	(None)	(0.26353)
LUS	1.0000	1.0000	1.0000
	(None)	(None)	(None)
LTH	-0.12763	-0.0000	0.00
	0.25843	(None)	(None)
LID	-1.5807	-1.6980	-1.8227
	(0.62249)	(0.34696)	(0.46669)
LSG	-0.64570	-0.59403	-0.65157
	(0.17548)	(0.13733)	(0.18828)
LCH	0.69633	0.73288	0.77623
	0.21846	(0.15172)	(0.17369)
Chi-Square	None	0.81652[0.846]	0.21364[0.644]

When we imposed the over-identifying restrictions on LMY, LSK and LTH the null hypothesis of LMY, LSK and LTH is insignificant - was not rejected. The p-value was higher than 5% . This means that the restriction was correct, in other words, LMY, LSK and LTH is insignificant (Panel B).

Meanwhile, when we made the over-identifying restrictions for LTH indexes simultaneously, it also failed to reject the null hypothesis (Panel C), it means that LTH indexes is still insignificant. However, based on our intuition, we would like to include all variables into our model. The reason is that in dynamic connectedness, these days global equity markets have tendency in moving together and get affected by major countries' markets.

Step5 : Vector Error Correction Model

Error-correction term (ECT) is the stationary error term, in which this error term comes from a linear combination of our 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. The previous four steps tested theories and confirm that there is cointegration between the variables but it did not show which were the leader and the follower variables. Step 5 onwards allows us to answer this shortcoming. The statistical results generated from these steps will be welcomed by policy makers.

Policy makers want to know which variable is the leader to focus their policies on those variables to make the biggest impact. By checking the error correction term 'e t-1' for each variable whether it is significant, we found five exogenous variable that is LJP, LMY, LSK, LTH and LSG and three endogenous variables that is LUS,LID and LSG as follows.

[Table 9: Exogeneity and Endogeneity of variables]

Variable	ECM(-1) t-ratio [p-value]	Implication
LJP	0.0041932[0.804]	Exogenous
LMY	0.0029485[0.851]	Exogenous
LSK	0.014094[0.426]	Exogenous
LUS	-0.057217[0.005]	Endogenous
LTH	0.040302[0.079]	Exogenous
LID	0.10108[0.00]	Endogenous
LSG	-0.0045819[0.842]	Exogenous
LCH	-0.077408[0.011]	Endogenous

This result means that, as the exogenous variable, when LJP, LMY, LSK, LTH and LSG receive market shocks, other factors such as LID and LCH will be affected by the shocks. In case of LUS, if there is other shock outside US that affect exogenous country, then US will be affected by the shock through receiving the shock from exogenous countries. This tends to indicate that the LJP, LMY and LSK indexes lead LUS, LID and LCH. However, in this paper, we wan to examine the effect of global financial crisis from US. So, we can assume that if the shock is coming from US itself, then the effect will be receive first by exogenous countries and other endogenous country will receive the shock. Since VECM does not give information about relative exogeneity and endogeneity, we will have to perform the next step to identify the ranking of the variables.

Step 6: Variance Decomposition Analysis

Although VECM results identified LJP, LMY, LSK, LTH and LSG as the leaders among variables, we could not say the relative endogeneity or exogeneity of variables. VDC test will help us to ascertain the relative degree of endogeneity among those variables. The relative exogeneity or endogeneity of a variable can be determined by the proportion of the variance explained by its own past. If a variable is mostly explained by itself, it is the most exogenous variable. Meanwhile, the most endogenous variable is mostly explained by others. The relative endogeneity and exogeneity of the variables are important for the policy makers.

Generally we can use two kind of method for VDC analysis. But orthogonalised VDCs have some limitations. Firstly, it assumes that when a particular variable is shocked, all other variables are switched off. Secondly, it is dependent on a particular ordering of variables thus, the first variable would report as the highest percentage.

So we herewith, have used generalized VDCs, and compared the exogeneity / endogeneity of variables for 12 weeks, 54 weeks and 132 weeks. Generalised VDCs is more reliable than orthogonalised VDCs, since it does not make such a restrictive assumption and independent on a particular ordering of variables. However, when we interpret the numbers generated by the Generalised VDCs, we need to be careful and perform additional computations to make the numbers add up to 100% for a specified horizon (the numbers add up to 100% in the case of orthogonalised VDCs). Based on generalized VDCs, the forecast error variance of each variable are as table 8.

[Table 10: Generalised Variance Decompositions]
Forecast at Horizon = 12weeks

	LJP	LMY	LSK	LUS	LTH	LID	LSG	LCH
LJP	2%	14%	11%	23%	9%	11%	19%	11%
LMY	6%	15%	11%	14%	14%	14%	14%	12%
LSK	4%	14%	19%	16%	8%	10%	17%	12%
LUS	3%	14%	11%	19%	8%	10%	22%	13%
LTH	6%	19%	12%	14%	10%	13%	15%	12%
LID	4%	14%	12%	14%	9%	13%	16%	19%
LSG	7%	15%	12%	13%	11%	16%	14%	13%
LCH	18%	14%	12%	11%	10%	13%	12%	10%

Forecast at Horizon = 54 weeks

	LJP	LMY	LSK	LUS	LTH	LID	LSG	LCH
LJP	17%	12%	9%	19%	7%	10%	16%	9%
LMY	17%	12%	9%	19%	7%	10%	16%	9%
LSK	4%	14%	19%	16%	8%	11%	17%	12%
LUS	3%	14%	11%	19%	8%	11%	22%	13%
LTH	6%	19%	12%	14%	9%	13%	15%	12%
LID	16%	14%	12%	11%	10%	15%	12%	10%
LSG	7%	15%	12%	14%	10%	15%	14%	13%
LCH	4%	14%	12%	14%	9%	14%	16%	19%

Forecast at Horizon = 132weeks

	LJP	LMY	LSK	LUS	LTH	LID	LSG	LCH

LJP	17%	12%	9%	19%	7%	10%	16%	9%
LMY	6%	15%	12%	14%	13%	14%	14%	12%
LSK	3%	14%	19%	16%	8%	11%	22%	13%
LUS	3%	14%	11%	19%	8%	11%	22%	13%
LTH	6%	19%	12%	14%	9%	13%	15%	12%
LID	16%	14%	12%	11%	10%	15%	12%	10%
LSG	7%	15%	12%	14%	10%	15%	14%	13%
LCH	4%	14%	12%	14%	9%	14%	16%	19%

I depicted the above result tables into the table 10 below where the variable relative exogeneity / endogeneity of our variables are shown below.

[Table 11:Variables' relative exogeneity/endogeneity]

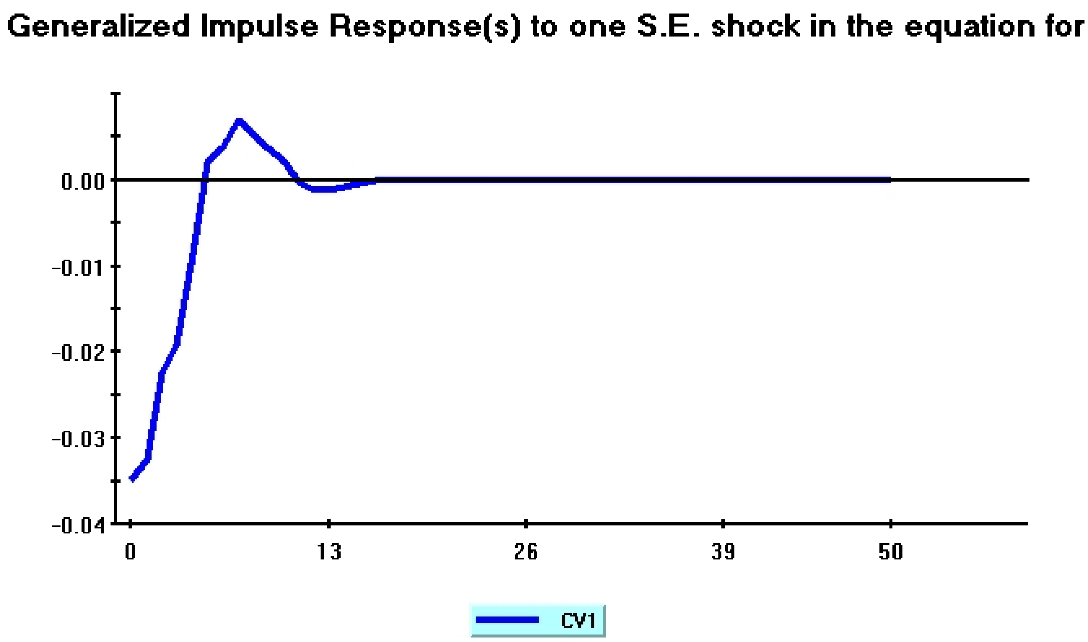
No.	Time horizons		
	12 weeks	54 weeks	132 weeks
1	LUS	LSG	LSG
2	LSG	LUS	LUS
3	LMY	LMY	LMY
4	LCH	LSK	LSK
5	LSK	LCH	LCH
6	LJP	LJP	LJP
7	LID	LID	LTH
8	LTH	LTH	LID

From the above table, LSG index can be said to be the lead variable compared to the others and then followed by LUS, LMY, LSK, LCH, LJP, LID and LTH index. Actually we have found this result is all similar to VECM result. However, because we have found in VECM that the exogenous variables are LJP, LMY, LSK, LTH and LSG and the rankings in VDC are consistent with our previous result. From the above result, we can conclude that, LSG index is most influential factor to the other major indexes.

Step 7: Impulse Response Function

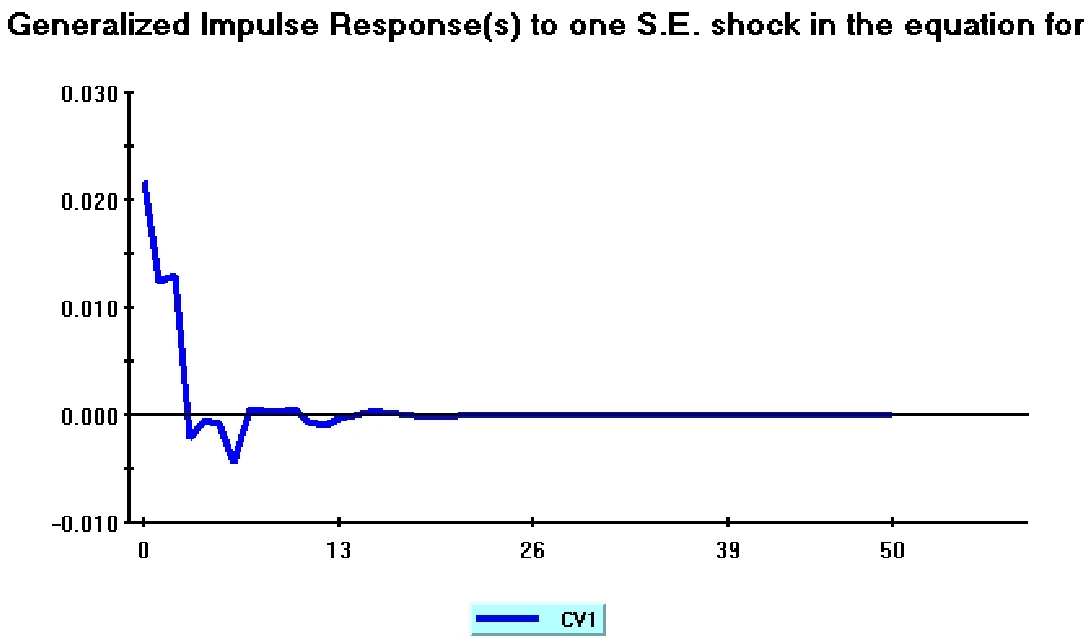
The information, which is presented in the VDCs, also can be equivalently represented by Impulse Response Functions (IRFs). IRFs will present the graphical explanations of the shocks of a variable on all other variables. In other words, IRFs map the dynamic response path of all variables owing to a shock to a particular variable. The IRFs trace out the effects of a variable-specific shock on the long-run relations. Here, IRF shows China and Japan as spillover countries as we compare with other remaining countries, except US as shock contributor.

Graph 1 (Indonesia) : Contribution from others



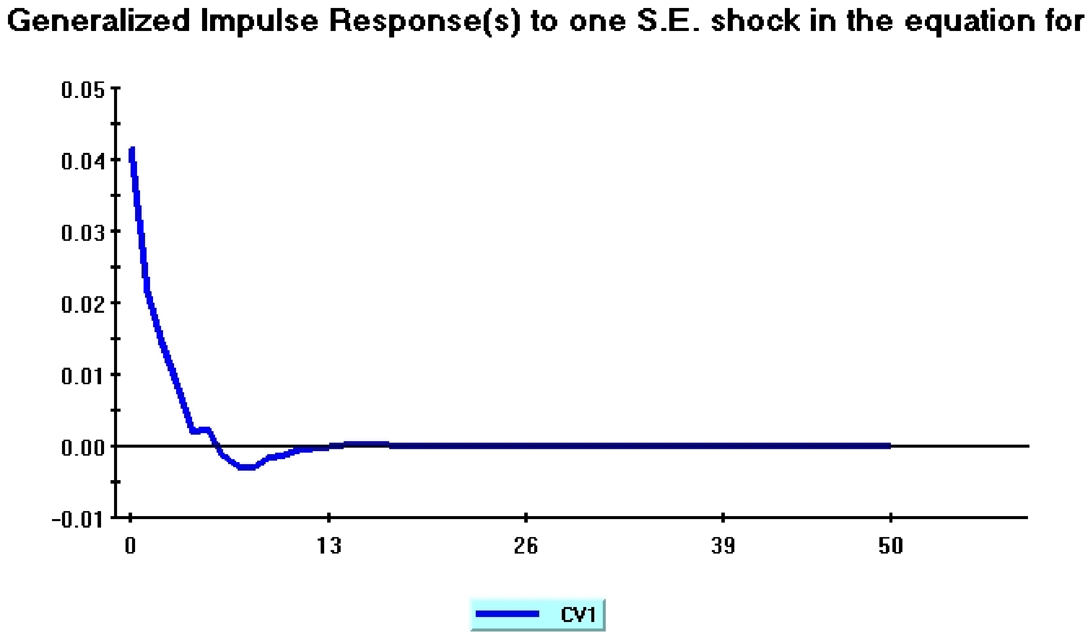
Graph 1 shows Indonesia as a country that receive shock from US and at the same time it pour back the shock to other neighboring countries. From the graph, it seems that it takes about 2 years for Indonesia to reach equilibrium.

Graph 2 (China) : Net Spillover



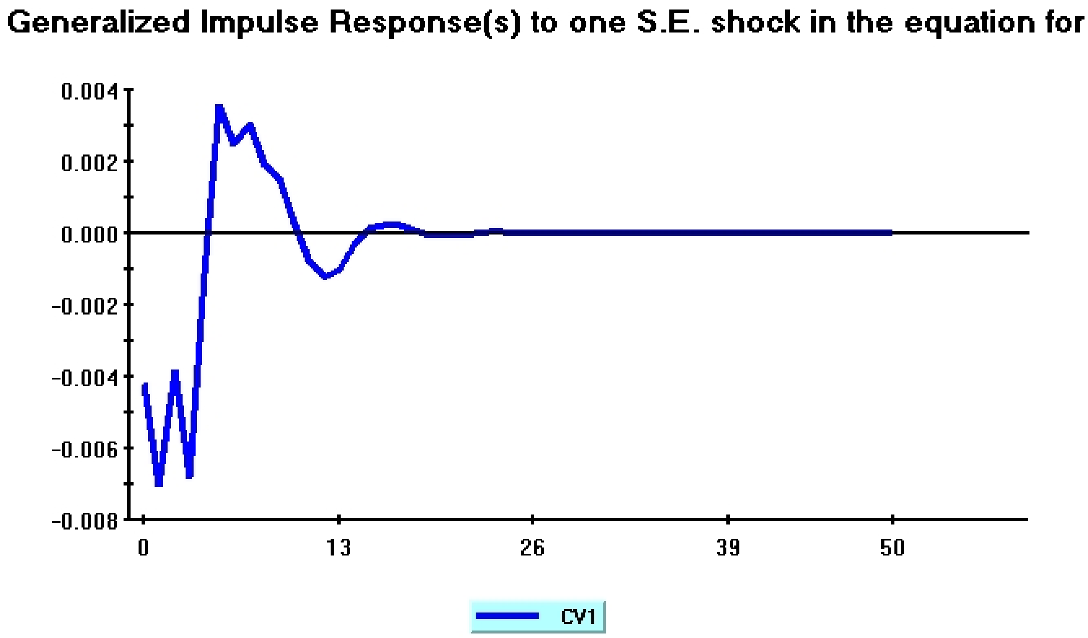
Graph 2 shows that global financial crisis will take along time for China to go back to its equilibrium that is about more than 2 years. Noted that the curve denotes that China as a net spillover.

Graph 3 (Japan): Net Spillover



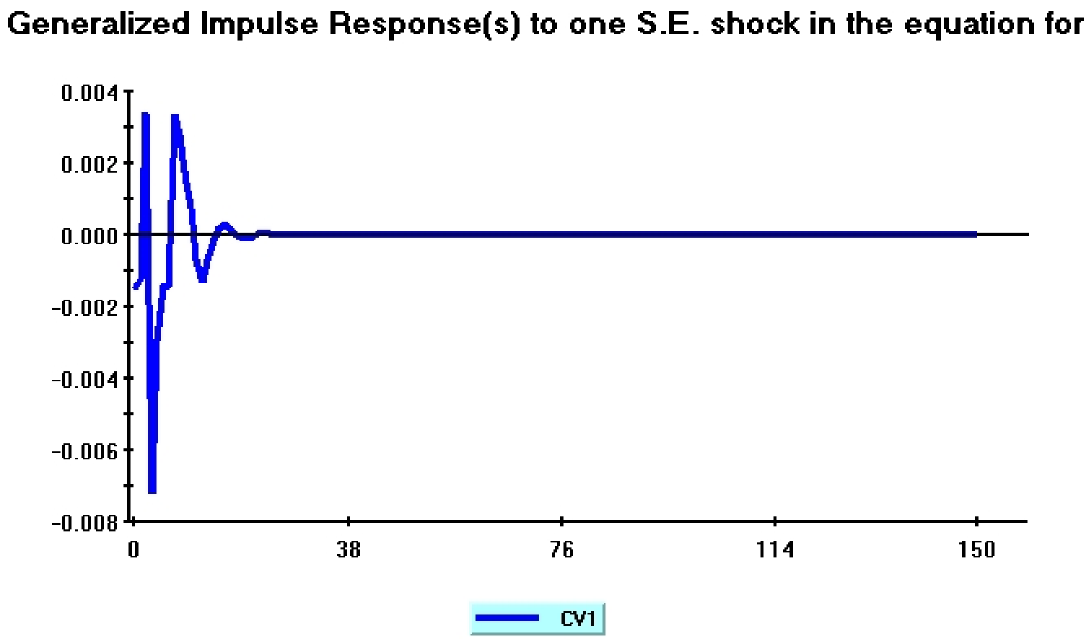
Graph 3 shows the spillover effect that Japan facing from global financial crisis. It takes about 2 years fro Japan to achieve equilibrium.

Graph 4 (Malaysia): Contribution from others



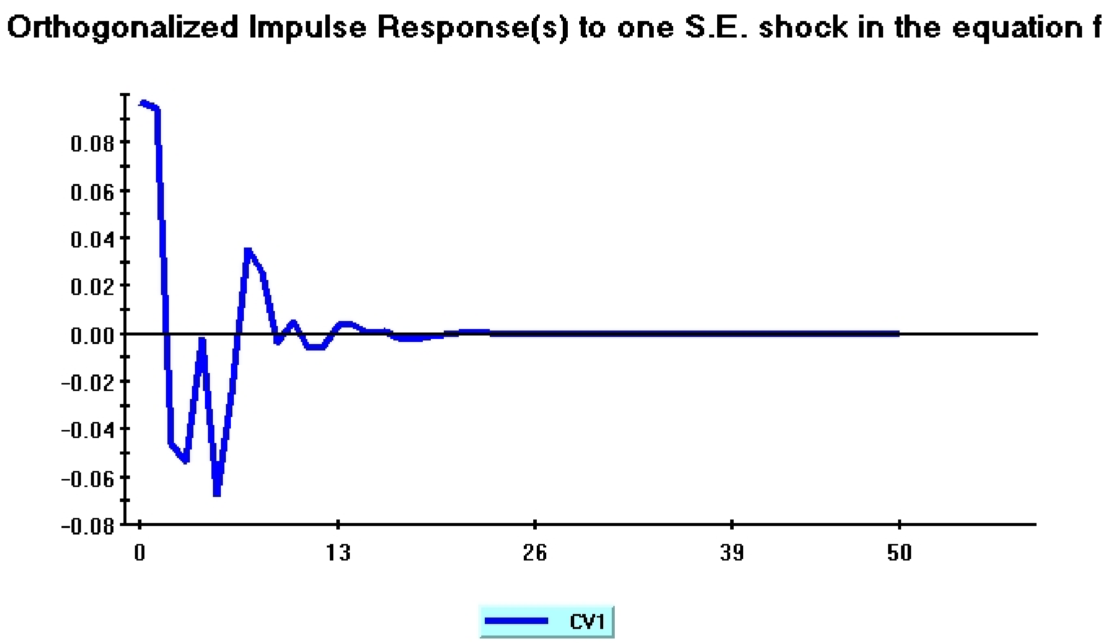
Graph 4 shows Malaysia receive d tremendous shock from global financial crisis. It takes more than 2 and a half years for Malaysia to bounce back.

Graph 5 (Singapore): Contribution from others



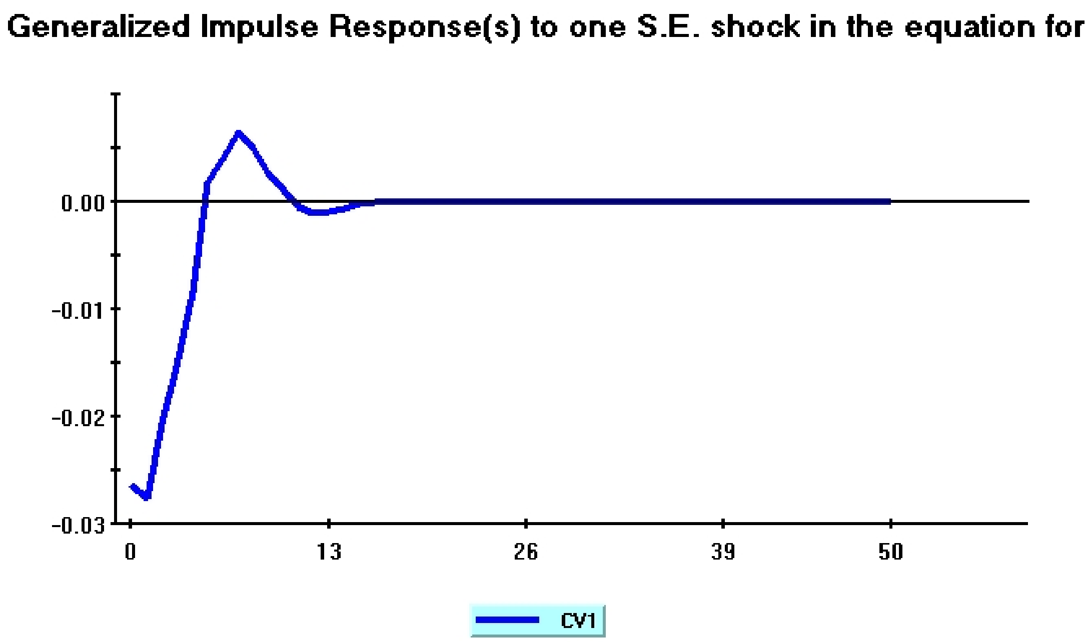
Graph 5 shows volatility of Singapore equity markets when receive shocks. It takes about more than 2 years for Singapore to achieve equilibrium.

Graph 6 (South Korea): Contribution from others



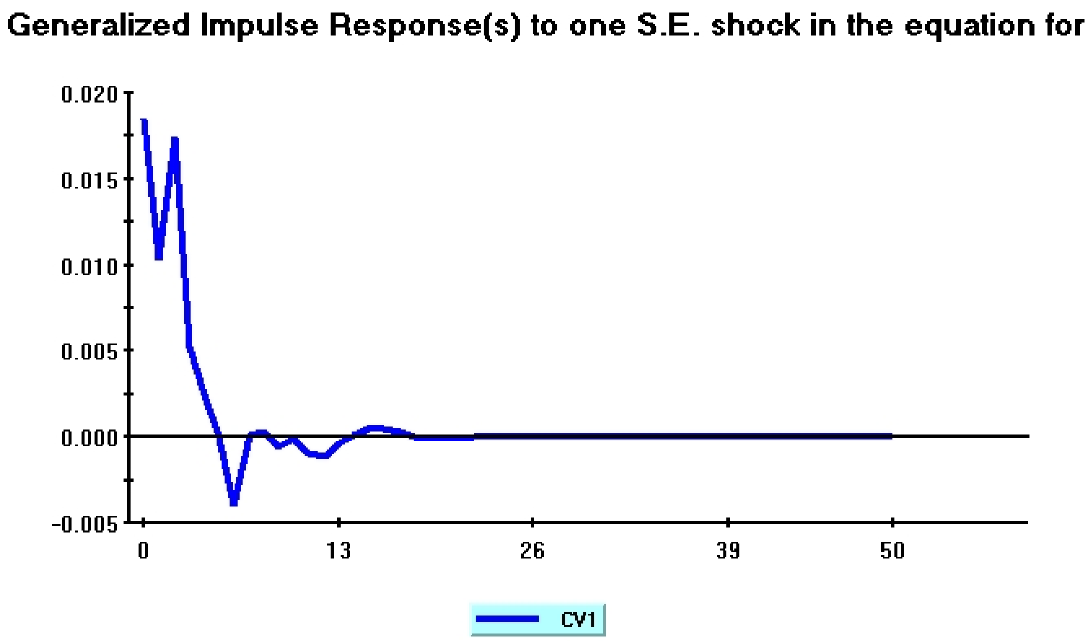
Graph 6 shows equity market volatility on response of global financial crisis. Given proper fiscal and monetary policy, South Korea manage to get back to equilibrium in about 2 years

Graph 7 (Thailand): Contribution from sources.



Graph 7 shows Thailand bounce back to equilibrium in less than 2 years.

Graph 8 (US) : Shock contributor

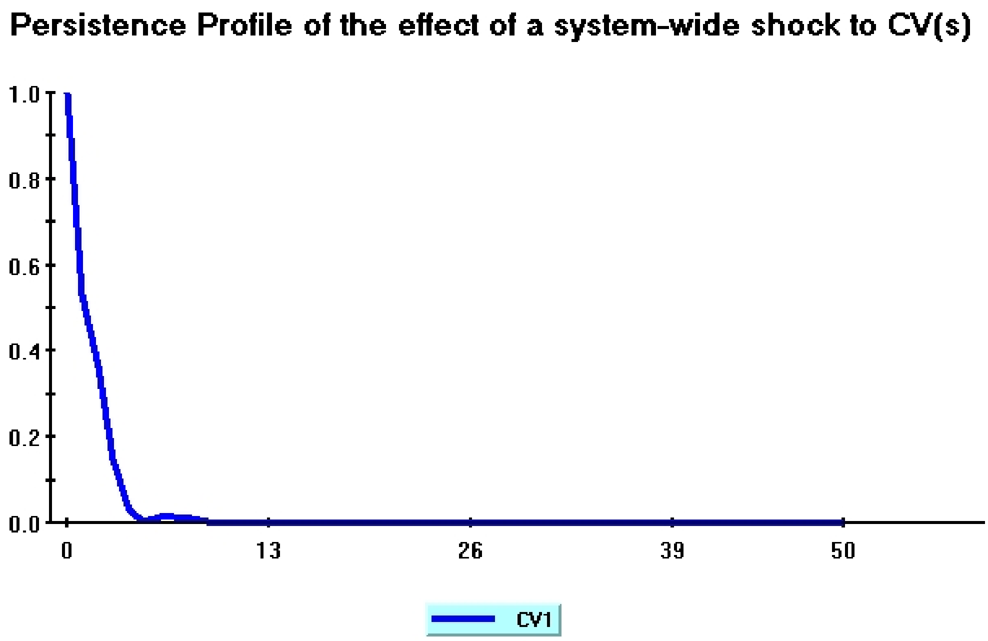


Graph 8 shows US as shock contributor in global financial crisis. US takes much more longer time to achieve equilibrium despite zero interest rate policy that initially may spurs the economic activity. However, US situation is much better now than Eurozone that still does not go out from its sovereign deb crisis.

Step 8: Persistence Profile

The persistence profile illustrates the situation when the entire co-integrating equation is shocked, and indicates the time it would take for the relationship to get back to equilibrium. Here the effect of a system-wide shock on the long-run relations is the focus instead of variable- specific shocks as in the case of IRFs. The chart below shows the persistence profile for the co- integrating equation of this study, the chart indicates that it would take approximately about 2 years' for the co-integrating relationship to return to equilibrium following a system-wide shock.

Graph 8: Persistent Profile



Conclusion and Suggestions/Policy Implications

As financial market becomes more sophisticated, the dynamic connectedness will be much more prevalent. Initially, this study intends to see the effects of global financial crisis shock towards Asian economy. This is because, given Asian financial crisis in 1997, the level of resiliency of Asian countries has increased, and, so it is interesting to study the new pattern of connectedness especially in equity market indices. In fact, as China is becoming more important in the region and at the same time Japan economy seems to be trapped because of ageing society and the un-openness in receiving foreign workers have made that study finding much more interesting.

It is found that the global financial crisis does give shock towards Asian economy in substantial amount. However, given the economy resiliency, most of the countries in this study rebound back in fast manner and able to become agile again despite the conundrums of the shock.

Obviously, it is found that the equity markets become more connected during crisis. The study also found the advanced economies such as China and Japan have increasingly become net 'receiver' (net spillover) of shocks, while emerging market economies, particularly, Malaysia, Singapore, and South Korea have increasingly become much more vulnerable to shock contributions. This finding is also interesting because in the case of China as a big economy, the country does not show any role as a shock transmitter to other economies. This maybe because the China has a large domestic economy able to absorb shock from outside.

However, South Korea is quite different. Korea bouncing effect is fast as we compare it with the shock that happened during the Asian financial crisis. Korean financial marker resiliency may be because they are learning from previous crisis on to overcome financial mismanagement and over leverage.

So, for the future, the policymakers should sit down and need to discuss not just in solo but also in an interconnected ways that involve other neighbor and regional countries in finding ways to reduce shock of dynamic connectedness. This policy formulating process needs more than bilateral or unilateral discussion. A specific platform such as ASEAN and Asia Pacific Economic Cooperation (APEC) is much more suitable because we involve various countries and high level ranking of meeting. This policy formulation is really crucial as Asian region has been predicted to be a fast growing region in more years to come.

On the other hand, emerging market economies especially developing countries like Indonesia, Thailand and Malaysia should not differentiate their real economy and financial market significantly, as this movement of policy may make the countries more vulnerable to the outside shock. Real economies should complement financial markets so that the balance of debt and equity are in tandem with economic activities. Hence, if any future shock emerges through dynamic connectedness, these countries will have their strength to bounce back.

Limitations of study and future research

We found that this study could be expanded in several ways. Future researchers may run a time series in equity indices during Asian financial crisis and compare the spillover effect and shock contributory effect between countries that been affected by Asian Financial crisis and global financial crises. The comparison may contribute to a deeper understanding of dynamic connectedness.

As for certain constraint, this paper does not include other Asian countries that are also important such as India, Hong Kong and Taiwan. Future studies may include these countries and provide a more robust insight into the study.

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