Information Transmission and Price Dynamics
between US and Asia Stock Markets

BY

SHUTING WANG
B.S., University of Science and Technology of China, 2009
M.S., University of Toledo, 2011

THESIS

Submitted as partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Business
Administration in the Graduate College of the
University of Illinois at Chicago, 2016

Chicago, Illinois

Defense Committee:

Stanley Sclove, Chair and Advisor
Houston Stokes, Co-Advisor
Fangfang Wang
John Sparks, Information & Decision Sciences
Yuheng Hu, Information & Decision Sciences

ACKNOWLEDGMENTS

I would like to thank my thesis committee—Professor Houston Stokes, Professor Stanley Sclove, Professor Fangfang Wang, Professor John Sparks, Professor Yuheng Hu--for their sincere support and assistance. They gave me guidance on the development of the proposal and encouraged me all the way towards the accomplishment of my PhD. I want to give special acknowledgement to Professor Houston Stokes and Professor Stanley Sclove, my advisors, for their cordiality to my conduct of this study.

I would like to extend my thanks to a number of other individuals who made important contributions to my proposal, data collection and analysis, and give me warm support during this work. They are my husband Zijie Yan, my mother, and my classmate Fan Wang in the Business Statistics program. Completion of this thesis would never be possible without their help and support.

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SUMMARY

This thesis studies the information transmission and price dynamics among stock markets' movement between US and Asia markets (China and Japan). In particular, the structural change of the stock markets during the 2008 financial crisis period has been analyzed in order to identify the lead-lag relationship between the US stock market and Asia markets. The results show that the co-movement is stronger after the crisis. Although in the long run the US market leads Asian markets and the indices from those three countries have a common nonlinear long term trend for in both pre-crisis and post-crisis period, the analysis shows that China is beginning to play a more important role in the world economies and the international markets are becoming more closely linked after the financial crisis. To gain insight into the co-movement, the role of exchange rate and stock indices has been examined, where the exchange rate can explain part of the dynamic relationship in the data. The international transmission of asset price movement would be adjusted by adding the exchange rate on stock prices. Various statistical methods have been utilized in this work, including Recursive Residuals and the Stock-Watson Test, VAR model and Granger-Causality Test, and co-integration analysis, etc. The results suggest possible unexploited arbitrage and profit opportunities in international portfolios. In addition, these findings can potentially help predict the 2015 Chinese stock market crash and its relationship with US markets.

CHAPTER 1. INTRODUCTION

There was a tremendous stock market drop in August 2015 in both the US and China markets. The Chinese market suffered a big crash in particular. People in the US believed the drastic drop in stock market was largely caused by the market crash in China, while people in China believed their crash was due to the negative international financial environment, especially the bad performance of the US market. This study provides some discussion of this problem. Japan shares common nature with US as they are both developed country; Japan also shares common nature with China as they are both Asian countries. So I would also like to include the Japan market as a variable in this study.

The main purpose of this study is threefold. First, investigate the lead-lag relationship and patterns of stock price co-movements in US stock markets and Asia markets (Japan and China), especially pay attention to the structure change of 2008 financial crisis. Second, examine the role of the foreign exchange rate, whether the exchange rate can explain part of the price dynamics relationship in the data. Third, study if there is a cointegration relationship between these indices.

A consistent and significant dependence among national equity markets reflected in lag relationships could signal unexploited arbitrage and profit opportunities and thus, inefficiencies in the international equity markets. The evidence indicates that a substantial amount of interdependence exists between US markets and Asia markets. The pattern of impulse response emerging from the VAR analysis shows that US market is the most influential one and most of the responses to an innovation are completed within a few days, which supports the notion of informationally efficient international stock markets. While the U.S stock market is found to lead the Asia markets, the analysis shows that China is getting to play a more important role in the world economies and the international markets are getting more closely linked after the financial crisis. Applying cointegration analysis, we can see that in the long run, the stock prices of the US market and Asia markets converge or balance back to an equilibrium. In the short run, there will be more fluctuations in the data.

Furthermore, a structural instability is found between 2008 and 2009. The degree of sensitivity of the Asia stock markets to information from US stock markets increased significantly after the financial crisis period. This finding indicates the internationalization of Asian stock markets and the increased importance of Asia's economy on the world economy, especially China. The role of the prior market to determine stock price was significantly strengthened after the break point. However, the enhanced role of the immediately preceding market in the determination of stock prices suggests a possibility of arbitrage by using the information of preceding market movements. Even though it is assumed that the market is semi-strong efficient or at least weak form efficient, the investor who responds immediately to the innovation of a foreign market will have a chance to benefit since he knows that the markets react positively to each other. Such sensitivity of stock prices to the foreign market's shock, with the consideration of arbitrage opportunity, may stimulate the speed of international transmission of financial disturbance across nations. However, the extent to which investors can actually realize these potential gains depends on the particular investment strategies they adopt (Eun and Resnick (2010)).

This study also emphasizes the role of exchange rate movements on the international stock market study by using two separate time series which are the *local currency* return rate of stock indices and the *dollar* return rate of stock indices. The degree of interdependence between major stock markets becomes more significant when we include the exchange rate factor in the local currency return of stock indices after financial crisis. This evidence suggests that the stock price and exchange rate share deterministic variables. However, the relationship is not very obvious. Therefore, the information transmission of financial disturbance was enhanced throughout the co-movement of stock prices and exchange rates between the US market and Japan and China markets, but the effect is not very apparent because China is a developing country and the exchange rate is decided not only by the market, but more by the governance of the Chinese government.

CHAPTER 2. LITERATURE REVIEW

There has been a lot of research on international portfolio diversification. The fundamental idea is that international diversification allows a total risk reduction with sacrifice. That's why many researchers want to study the correlation between international stock markets and the co-movement structure among them.

The study of portfolio diversification and market interdependence can be traced back to as early as the work of Grubel (1968), Granger and Morgenstern (1970), and Lessard (1976). These early studies made the same observation: national stock indices reflect only their own economies with weak correlations to other stock indices. Among them, Grubel (1968) used the mean-variance model to study the variety of potential gains from international diversification to U.S. investors. He calculated the set of efficient portfolios for eleven different equity markets. He found that the U.S. portfolio is not an efficient one after calculating the efficient set using Moody's industrial index. Therefore, it is likely that the U.S. investors could move to a more efficient portfolio when the barriers in the international equity market are removed, so they can use the advantage of international diversification. It is worth noting that the rising opening of free exchange market plays an important act in the international investment and portfolio diversification (Huang, Yang et al. (2000)).

Hilliard (1979) used spectral analysis to examine the international equity market indices during an international financial crisis. He examined daily average data from ten world markets (Amsterdam, Frankfurt, London, Milan, New York, Paris, Sydney, Tokyo, Toronto, and Zurich) from July 7, 1973 to April 30, 1974, which included the October 1973 Arab-Israeli war and the resulting oil embargo. He concluded that world markets reacted independently to the financial crisis despite the existence of some contemporaneous correlations between the intra-continental markets. Furthermore, Hilliard's tests ruled out a lead-lag relationship between the financial markets with the exception of New York leading Amsterdam by one day. Also, Hilliard did not use his results to draw any inferences about the pricing of assets in an international context.

Subsequently, Eun and Shim (1989) found that innovations in the U.S. quickly spread to other markets in a distinctly recognizable way, and no individual foreign market can substantially clarify the movements of the U.S. market. To understand the route of international transmission of stock market movements, they investigated the scheme of dynamic responses to innovations in an individual market using the responses of estimated VAR system. The resulting response patterns are largely consistent with the view of information efficient international stock markets. This suggests that making unusual profits would be difficult just by investing in a specific market using the noticed developments in other markets. Since no prior restriction is imposed, the VAR analysis enables location of all the main channels of transmission via simulated responses.

Outcomes reported in the empirical literature show that since 2000 the correlations among financial markets have been increasing and more perceptible among developed countries (Silvennoinen and Teräsvirta (2005); Cappiello, Engle et al. (2006); Savva, Osborn et al. (2009); Aslanidis, Osborn et al. (2010)). The observations indicate that the portfolio diversification is no long a significant benefit for investors transacting in developed markets. As a result, those investors should try to find markets that have low or even negative correlations with international financial markets, and especially emerging markets that have high potential for high-speed growth.

A popular alternative seems to be China. In the last 10-20 years, emerging markets, especially China are developing really fast. Chinese stock market's market capitalization and trading volume and number of investors are growing rapidly. China also did a lot of financial reforms to allow more freedom in international financial market investment. International investors have been thus attracted by the enormous opportunities in all economy areas of China due to its great scale and remarkable growth rate of economy (Öztek and Öcal (2015)).

Huang, Yang et al. (2000) studied the cointegration and causality relationships among three stock markets, including U.S., Japan and the South China Growth Triangle (SCGT) region. Using unit root and cointegration techniques to treat the breaks, they investigated the data period from 10/2/1992 to 6/30/1997. Except relationships between Shanghai and Shenzhen in SCGT, they did not find apparent cointegration among these markets. However, they found that the stock returns of the Hong Kong and U.S. markets were contemporaneous. Furthermore, the price variations in the US could be utilized to forecast markets of Hong Kong and Taiwan on next day based on the Granger causality test. Similarly, the Hong Kong stock market led the Taiwan market by one day in terms of price changes.

More recently**,** the paper by Öztek and Öcal (2015) presents a comprehensive analysis of time-varying return co-movements between stock markets of several countries, including China, Japan, France, UK, and USA. They used two models focusing especially on the role of domestic and international volatility and news. Their first model is a smooth transition conditional correlation (STCC-GARCH) model, and the second one is double STCC-GARCH model. The results indicate perceptible rising trends in conditional correlations among those markets, especially following the financial restructurings in China. Furthermore, they suggested that Chinese stock markets may be safe harbors during global financial crises.

Further, Guidi, Savva et al. (2016) examined the extent of short-run co-movements and long-run dynamics among the stock markets of US, UK, Mainland China, Hong Kong, and Taiwan. Their paper is based on a fixed rolling period of 160 weeks using an asymmetric dynamic covariance approach. The dynamic analysis reveals only intermittent occurrences of long-run co-movements. They also found positive yet insignificant conditional correlations between stock market returns. These results reveal opportunity for diversification benefits with the scope to be estimated based on different portfolio choices. Finally, they suggested that both UK and US investors should expect higher returns by choosing diversified portfolio**s.**

CHAPTER 3. DATA

3.1 Data Description and Time Zones

The data for this study ranges from 01/01/2002-12/31/2014. The data in US stock market is the adjusted daily close price of SP500 index. The SP500 index is an index of the US stock market based on the market capitalization of 500 large companies with common shares listed on the NYSE or NASDAQ. It is a free-float capitalization-weighted index. The data from the Japan stock market is the adjusted daily close price of Nikkei225, a price-weighted index representing the Tokyo Stock Exchange (TSE). The data from the China stock market is the adjusted daily close price of Shanghai Stock Exchange (SSE) composite, including A shares and B shares traded at SSE. All raw data of stock indices from the above three countries are downloaded from yahoo finance website. The daily exchange rate data of the above 3 countries is downloaded from IMF website.

Interpretation of the time of day has to be taken into account when using daily indices from the world's stock markets. The indices are closing prices of their respective markets. So it is important to keep in mind the differences of three national markets' trading time and closing time due to time zones difference before we conduct any specific study on it.

The three countries analyzed in this thesis are listed in Table 1 based on their market closing times in a calendar day.

Table 1. Time Zone Description

World exchanges	Time zone	Local time	UTC

Tokyo Stock Exchange	TSE	Japan	JST	+9		09:00	15:00	11:30–12:30	00:00	06:00	02:30–03:30
Shanghai Stock Exchange	SSE	China	CST	+8		09:30	15:00	11:30–13:00	01:30	07:00	03:30–05:00
New York Stock Exchange	NYSE	United States	EST	−5	Mar–Nov	09:30	16:00	No	14:30	21:00	No

On a given calendar day, the Japan market is closed one hour before Chinese market closes. The Chinese market is closed before U.S. market opens. So the daily returns of U.S. markets, even before opened, are actually influenced by the return realized in Japan or China earlier on the same calendar day. This implies that the system of these three markets shows recursive joint determination of daily closed-to-closed returns. For example, if Japan and the United States show a significant relationship on the same day, it actually reflects a Japanese lead of about 15 hours in real time (DST). Similarly, if the US leads Japan by a calendar day using this date, it in fact shows a lead of less than a day in real time (i.e., 9 hours, DST in US). Since the US is the last one to close among these markets, if any other one shows a lead of one day to the US market, the real lead is actually more than one day in real time. Therefore, the data analysis must consider these timing issues.

3.2 Data Preliminary Analysis

The data sets contain some missing observations since each country has different holidays. So, I did several things to clean the data.

First, I transformed the date data in the dataset. In order for the data to be read and analyzed easily in the software, I transformed the date data in to the serial date, or serial date-time, which is used in Excel software. Detailed explanation of this transformation can be found at http://www.cpearson.com/excel/datetime.htm. Thus, the start date of the data 1/2/2002 (because no countries traded on 1/1/2002) is read as 37258 and the end date of the data 12/31/2014 is read as 42004 from Excel into statistical software.

Secondly, I cleaned the missing data across the country since different countries have different holidays and no trading days. For those dates where no countries have trading data, I just deleted that date. Five (5) dates were deleted in total; that accounts for only 0.15% of the data. After deleting the missing data, I have a total dataset of 3386 data points where at least there is one country has trading data on the given date. Since 99.85% of the data was kept, this cleaning won't change the lag structure of the data. Then I imputed those missing data in the data series with its own trend using linear imputation method. This has been done for each of the three countries' stock indices and exchange rate data, respectively.

The raw data of stock indices in their local currencies from the above three countries are shown in Figure 1. We can clearly see that there seems to be a structural breakpoint in all three data series; we will discuss this further in chapter 5.

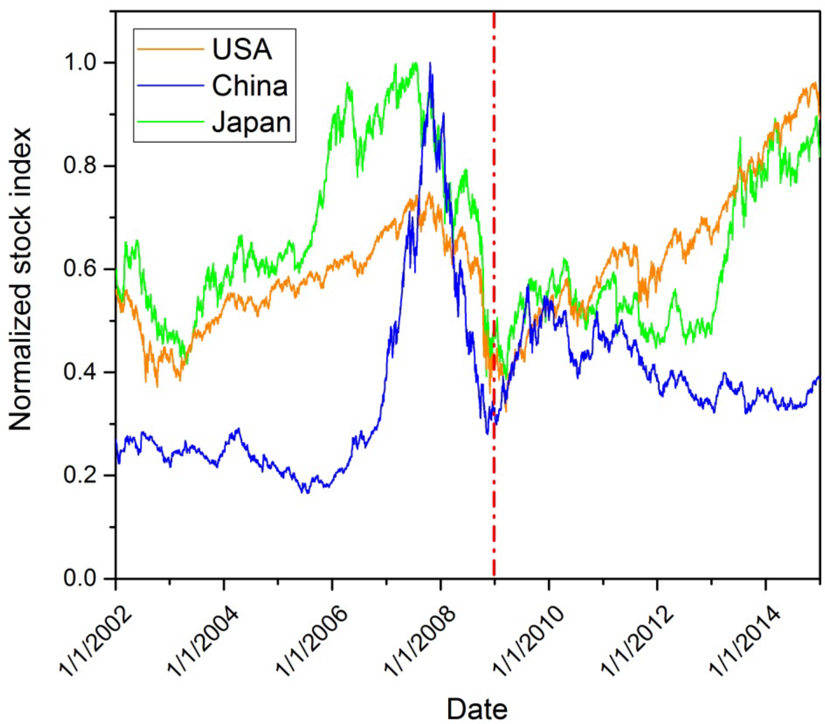


Figure 1. Trend of stock indices in 3 countries from 2002 to 2014.

In order to analyze the role of exchange rate, in addition to study the stock price in the countries' own currency, we also adjust the prices of China and Japan by their exchange rate to dollars, which gives us the stock price in dollar currency as $\frac{P_t}{EX_t}$, denoted by CNd and JAd.

We conducted the augmented Dickey–Fuller test (ADF) test on stock prices of both the local currency and dollar currency to test whether the series have a unit root. The model underlying the ADF test is as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t, \tag{1}$$

where α is a constant, β *is* time coefficient and *P* is autoregressive lag order. If we impose the constraints $\alpha = 0$ and $\beta = 0$, the model above will be reduced to a random walk model.

Therefore, there are three main versions of the test, discussions about whether to include the intercept and deterministic time trend terms in the test equation are omitted here.

The unit root test uses the test statistic $DT_{\tau} = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$ to test the null hypothesis $\gamma = 0$ against the alternative hypothesis $\gamma < 0$. After computing the value of the test statistic, it can be compared to the Dickey–Fuller Test and get the p-value to see whether the null hypothesis is rejected.

The results of the ADF test on both local currency and dollar currency series are shown in Appendix A, Table A.1. The ADF test shows that, the p-value for **the** US index is 0.949, the p-value for **the** Japan index is 0.8886, and the p-value for **the** China index is 0.6589. All of the above p-values indicate that the price series for these indices have a unit root, therefore are not stationary. Thus, we introduce the return rate (rate of return) of the stock index. The return in local currency over a single period is:

$$\mathrm{R}_{\mathrm{t}} = \frac{\mathrm{P}_{\mathrm{t}} - \mathrm{P}_{\mathrm{t-1}}}{\mathrm{P}_{\mathrm{t-1}}} \qquad (2)$$

Similarly, the return in dollar currency over a single period is:

$$Rd_t = \frac{\frac{\mathrm{P}_t}{EX_t} - \frac{\mathrm{P}_{t-1}}{EX_{t-1}}}{\frac{\mathrm{P}_{t-1}}{EX_{t-1}}} \qquad (3)$$

where:

P_{t} or $\mathrm{P}_{\mathrm{t-1}}$ = stock price at time t or t-1

EX_t or EX_{t-1} = spot exchange rate at time t or t-1

The same ADF tests show that the return rates are all stationary in Table A.2 in Appendix A. Thus, from now on, we will use the stock market return rates of the above three countries in terms of both their local currency and dollar currency. The return series will then contain 3385 observations.

CHAPTER 4. THEORETICAL ANALYSIS

<u>4.1 International Portfolio</u>

General financial theory implies that there are two kinds of risk involved in investment decisions. The first risk is called *unique risk*, and it may be removed by diversification. It is due to unique factors associated with a company. The second risk is termed *market risk*. It is due **to** economy-wide factors that influence all businesses. *Market risk* is the reason for mutual fluctuations of stocks; it affects all capital assets and cannot be entirely excluded from the fluctuations of portfolio return rate. *Market risk* is a systematic risk and the source for risk premium of return over and above interest rate.

The scheme of international finance theory largely reflects that of domestic financial theory. No matter if there are one or more capital markets, the analytical sequence is always the same. In international finance, we can redefine market risk as domestic market risk that cannot be avoided within domestic boundaries but can be avoided by international investment. We add one more concept of risk, namely***, international market risk*.** International market risk originates from the fact that there exists worldwide economic risk that hurts the economy of most part of the world by causing a co-movement of international stock indices. Distinguishing between systematic and non-systematic portions of the risk is crucial in estimating international market risk. Investors usually behave as if they consider only the systematic risk when making decisions. Yet if we assume that the domestic stock return is influenced by international market factors, the individual asset returns will be affected by the daily foreign stock return and its lags.

There are several theoretical explanations of why we should expect national equity markets to be connected. Ripley (1973) gives three main reasons: (1) Stock prices of countries may be indirectly associated with mutual movements in national income and expectations. (2) Real interest rates tend to match among countries via international capital flow, thus motivating co-variation in equity prices. (3) There has been rising dominance of multinational companies whose stocks are traded in several national markets. Additional reasons for growing correlation are the increasing speed and efficiency of information flow worldwide, and a heightened investor's sensitivity to relevant information that facilitates the understanding of what is happening in the markets. Thus, a short-run correlation in stock price movements across the world is expected to be an increasing function of time.

Co-movements between stock prices in different countries are of interest to forecasters and policy makers because stock movements affect domestic consumption and investment expenditures (Shiller, Fischer et al. (1984)). The wealth of consumers is affected by changes in stock prices and changes in wealth affect consumption decisions. **Co-movement** between stock indices may arise in many ways. It may reflect similarities of stock market structure between nations, or show co-movement of economic variables in countries. For example, countries whose interest rates move in a similar way may have stock prices that also move in similar way. Movements in interest rates affect expectations about future economic developments, thus similar movements in two countries may cause an indirect link between their stock prices. If the shares of the same group of multinational companies are in trade in two countries, market expectations about their future can be similar in these countries.

4.2 Relationship between Stock Price and Exchange Rate

Historic evidence shows that stock prices and exchange rates can be explained by various factors that affect domestic monetary and financial conditions and expectation. It also indicates that exchange rates factor in international diversification of stock can be important to determine the true result of the international investment. The return value of portfolio measured by the home currency of an international investor is the combination of the assets' returns and currency movements, so the investor has risk from both markets and the currency. Therefore, the investor needs to consider the change of an asset's price with the currency. Although the relationship among national stock markets has been analyzed in a series of studies since Grubel (1968) studied the benefit from international portfolio diversification, previous studies did not consider the effect of currency movements as an important factor when they studied the international co-movement of stock markets. In determination processes of exchange rate and stock price, monetary economic factors and expectations play an important role. This suggests that short term analysis of exchange rate and stock price should be conducted in a common macroeconomic framework. At the same time, an increase in the expected inflation rate would depreciate in terms of foreign exchange, which is caused by decreasing the attractiveness of holding domestic currency relative to holding foreign currency. Consequently, the stock price and exchange rate move together.

Therefore, both asset prices and exchange rates are affected by an integrated process that includes changes in supply of and demand for money and financial assets; economic and financial conditions and developments; and monetary and fiscal policy, market expectations, and efficient market behavior. Therefore, along with close relationships between asset price and macroeconomic variables and between exchange rate and macroeconomic variables, the similarity of movement between stock price and exchange rate shows the important role of exchange rate in international asset investment. The international transmission of asset price movement would be increased by adding the exchange rate movements on stock prices. However, this approach is mainly relevant for countries that have well-developed capital and money markets coupled with relatively free exchange markets where arbitrage between domestic and foreign assets is allowed. In countries where such arbitrage is limited or nonexistent, the exchange rate is determined by supply and demand in goods markets and official intervention.

Overall, stock prices have a negative relationship with exchange rates throughout the macroeconomic variables. Stock price is negatively related to changes in interest rate and the inflation rate and positively related to changes in the expected level of real production. On the other hand, foreign exchange rates are related by those macroeconomic factors. Raising the domestic interest rate and inflation will cause an appreciation of exchange rate. Increase in real production in domestic economy will lower the exchange rate. Theory suggests that there is a negative relationship between stock prices and exchange rates.

Therefore, currency movement is an important factor in examining the nature of the interdependence of the international stock markets. It is more likely for currency movement to be a significant part of total portfolio return when a flexible exchange rate regime began to start for Asian countries.

Since there are economic variables that affect both exchange rate and stock returns, we believe that a movement of stock return accompanies a movement of exchange rate.

Next, we will discuss the relationship between stock price and macroeconomic variables, between exchange rate and macroeconomic variables, and, as a result, between exchange rate and stock price.

4.2.1 Relationship between Stock Prices and Economic Variables

Market prices of stocks are represented as the expected cash flows (E(CF)) divided by the present discount rate:

$$P = E\left(CF\right)/r \tag{4}$$

where CF is the **cash flow/ dividend stream** and ***r*** is the **discount rate**. Hence, it indicates that macroeconomic factors that shift discount rates or expected cash flows can affect stock returns.

The discount rate is a time-averaged rate. Expected inflation should affect real discount rates, but it may also affect cash flows. For instance, if expected inflation increases, stock prices fall because of the decrease in anticipated future real cash flows. Of these variables, the real interest rate and inflation rate provide a consistent explanation of stock price movements.

The empirical evidence indicates a negative relationship between stock returns and inflation. Using monetary links between inflation and real economic activity, the following two theories show that stock price indicates future changes in real economic activity.

Fama (1981) used a traditional quantity theory based on money demand to explain the high inflation rates during the post-1953 period. The theory shows lower real stock return is linked to lower anticipated growth rates of real activity. Negative correlations between inflation and real activity can introduce the same trend of relationship between real stock return and inflation.

According to Geske and Roll (1983) money supply explanation, a reduction in economic activity leads to a reduction in fiscal government revenues. If expenditures remain constant, increased budget deficit and inflation can be expected. Furthermore, since a government will borrow to finance the deficit, the real interest rate might increase.

4.2.2 Relationship between Exchange Rate and Macroeconomic Variables

Foreign exchange rates can be explained by various factors that affect international transactions in goods, services, and financial assets, as well as domestic monetary and financial conditions and expectation.

There is a wide spectrum of exchange rate theories and models, and along this spectrum each model emphasizes a different cause and effect as well as different transmission channels. While there is no one generally accepted theory or model of exchange rate determination, there are several main approaches or theories that provide a general framework for analysis of exchange rates.

First, the traditional analysis of exchange rate determination emphasizes effects of supply and demand in goods markets, that is, the development in the current account. Secondly, monetary and asset market theories of exchange rate determination emphasize the role of markets for money and securities in the determination process; views the exchange rate as a relative price of two national assets or monies, determined primarily by the demand for and supply of the stocks of various national monies and expectations; considers the exchange rate as endogenously determined by stock equilibrium conditions in markets for national monies; and maintains that the equilibrium currency rate is attained when the existing stocks of the two national monies are willingly held.

As a complete and exclusive analysis of the foreign exchange, the traditional theories are regarded as incomplete when they explain the short term movement of exchange rate. In the short term, exchange rates are determined mainly by the monetary asset-market mechanism and expectation; and expectations of future exchange rates or real and monetary economic factors and policies that determine the trade balance and relative prices. In other words, the asset-market approach suggests that an analysis of exchange rates should be conducted in a general macroeconomic framework. An integrated exchange rate model assumes relationships among exchange rates, interest rates, and relative prices. Accordingly, in equilibrium under perfect conditions interest rates, prices, and forward and spot exchange rates are interdependent in a manner such that the purchasing power parity, interest rate parity, and the expectations of the forward exchange rate are maintained.

According to the monetary theory of exchange rates, variables that lead to an increase in the demand for domestic currency should lead to an increase in the price of domestic currency on the foreign exchange market. Factors that would increase the demand for domestic currency balances are an increase in domestic income and increase in domestic interest rates. Therefore, monetary theory suggests that these factors should cause the domestic currency to appreciate on the foreign exchange market.

As we regard the exchange rate as the relative price of two national monies, or two assets, the exchange rate can be analyzed within a context that is appropriate for the analysis of asset prices. Alternatively, the exchange rate represents equilibrium between the desire to hold stocks of assets denominated in that currency and the available supply of such assets.

The asset market approach does not deny that there is a demand for currency as a medium of exchange. However, the stock of financial assets is largely relative to the volume of money in circulation or transaction balances needed for current transaction. Furthermore, since assets can be exchanged relatively easily, while it takes time to benefit from improved international competitiveness in trade, it is likely that factors influencing the attractiveness of different assets held will, in the short run, play a great role in determining exchange rate movement.

Since exchange rate movements are usually brought by imbalances between demand and supply in different money markets, an analysis of exchange rates must include comparisons of factors affecting the demand for and supply of money. For instance, an increase in the expected inflation rate would decrease the attractiveness of holding domestic money relative to holding foreign money, implying a tendency for domestic money to depreciate in terms of foreign exchange.

4.2.3 Relationship between Exchange Rate and Stock Price

In determining processes of exchange rate and stock price, monetary economic factors and expectations play an important role. It suggests that short term analysis of exchange rate and stock price should be conducted in a common macroeconomic framework.

For example, an increase in the expected inflation rate would decrease the stock price. At the same time, an increase in the expected inflation rate would depreciate in terms of foreign exchange, which is caused by decreasing the attractiveness of holding domestic currency relative to holding foreign currency. Consequently, the stock price and exchange rate move together.

Therefore, both asset prices and exchange rates are affected by an integrated process that includes changes in supply of and demand for money and financial assets; economic and financial conditions and developments which include interest rates, inflation, etc.

Therefore, along with close relationships between asset price and macroeconomic variables and between exchange rates and macroeconomic variables, the similarity of movement between stock price and exchange rate shows the important role of exchange rate in international asset investment. The international transmission of asset price movement would be increased by adding the exchange rate movements on stock prices.

CHAPTER 5. STRUCTURAL BREAKPOINT

5.1 Recursive Residuals

We begin our analysis with the test for structural stability of data series for the return rate. This step is the most crucial because the estimates can be severely biased if the time series are not stable processes.

Tests for structural stability are much discussed in the literature. Nyblom (1989) proposed the sup-F test to detect possible changes in parameters. Brown, Durbin et al. (1975) made an important contribution by assessing the constancy of regression coefficients. Stokes (1997) discussed thoroughly the Recursive Residuals (RR) procedure to detect the locations of potential structural breaks in a series. For an Ordinary Least Squares (OLS) procedure, the OLS residuals can be heteroscedastic and auto-correlated even when the true errors are white noise. The Recursive Residuals procedure transforms the OLS residuals, since they are not BLUE (Best Linear Unbiased Estimates) so that they do satisfy the OLS assumptions. The technique begins with estimating OLS and then computing updated coefficient vectors when extra data are added to the regression, while the recursive residuals satisfy OLS properties, and are identically and independently distributed as normal with mean and standard deviation σ, which we will denote as i.i.d.~ $N(0, \sigma)$. Stokes (1997) mentioned that the cumulated sum of recursive residuals test (CUSUM), cumulated sum of squared standardized recursive residuals test (CUSUMSQ) and the Harvey and Collier (1977) test are the three most important summary tests for parameter stability. The CUSUM test and CUSUMSQ test were proposed by Brown, Durbin et al. (1975). If the break is not known, CUSUM and CUSUMSQ will be more appropriate. Also, the Quandt log-likelihood ratio test (QLR) is another important technique suggested by Quandt (1960) to detect the unknown breakpoint. This is especially useful if there is only one break.

Here, we will use CUSUM, CUSUMSQ and QLR tests to perform the breakpoint analysis. The CUSUM test was proposed by Brown, Durbin et al. (1975) to check the parameter stability. The test is based on calculating the quantity

$$\Gamma_i = \sum_{j=K+1}^{i} w_j / \hat{\sigma}. \tag{5}$$

w_j is the standardized recursive residual, $\hat{\sigma}$ is estimated variance of w_j .

The CUSUM test is especially good at detecting systematic departure of the β_i coefficients that results in a systematic sign on the first step ahead forecast error. The CUSUMSQ test can be used when the variation of β_i from constancy is haphazard but that there involves a systematic change in the accuracy of the estimated equation as observations are added. The CUSUMSQ test involves a plot of Γ_i^* defined as

$$\Gamma_i^* = \sum_{j=K+1}^{i} w_j^2 / \sum_{j=K+1}^{T} w_j^2. \tag{6}$$

Boundaries for Γ_i and Γ_i^* are typically 1 and 0 for upper-right- and lower-left-hand values in a rectangular plot (Brown, Durbin et al. (1975)). A plot lying above the diagonal indicates poor regression tracking in the early subsample while that below the diagonal suggests better regression tracking.

The Quandt log-likelihood ratio test is defined as

$$\lambda_i = 0.5i\ \ln(\sigma_1^2) + 0.5(T - i)\ln(\sigma_2^2) - 0.5\ T\ \ln(\sigma^2) \qquad (7)$$

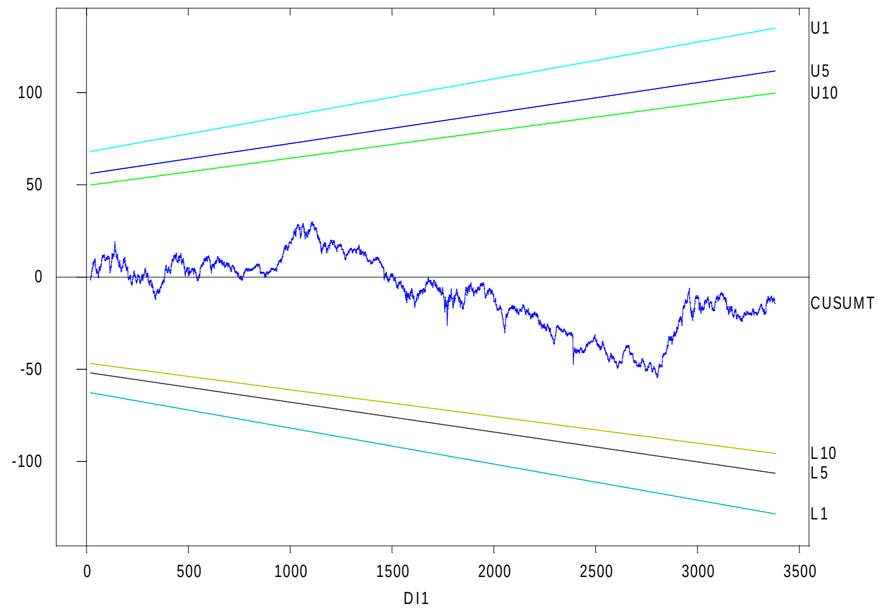
where $\boldsymbol{\sigma}_1^2$ is the variance of regressions for the first i observations, $\boldsymbol{\sigma}_2^2$ is for the last T - i data and σ^2 is for the whole data. The break of the sample can be identified by the minimum of λ_i.

All these test statistics can be plotted in graphs, so it is easy to test their significance and also identify the possible break time point.

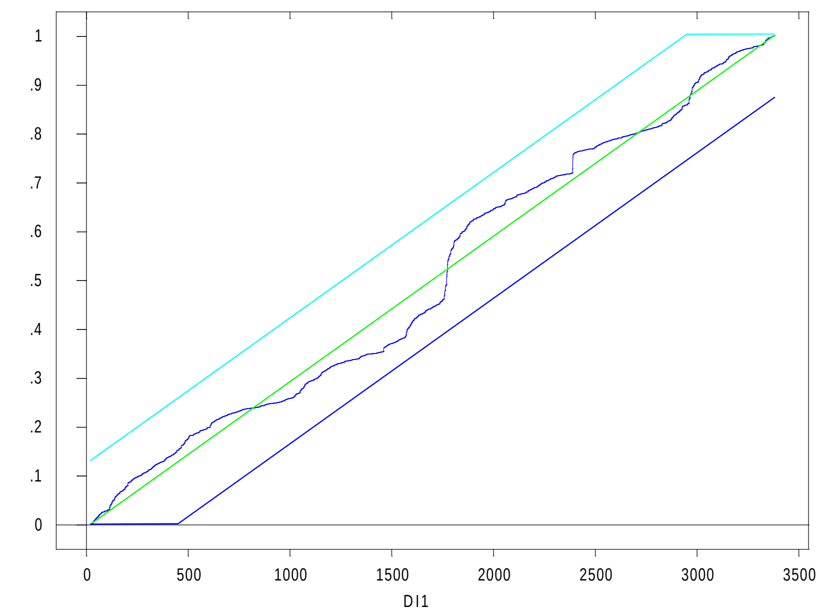
5.2 Recursive Residuals Results

Let's start with the Japanese market. From Figure 2, we can see that the plot is within the bound in CUSUM and CUSUMQ plot. But, by taking a look at the QLR plot, we can see there is a tremendous drop around n=1400 to n=1700 which indicates a structure breakpoint. In a word, for Japanese market return series, there should be a breakpoint between around n=1400 to n=1700, which is June 2007 to July 2008. Here n is the number of observations. Recall that we have 3385 return observations in total.

Plot of Cusum Test



Plot of Cusumsq Test



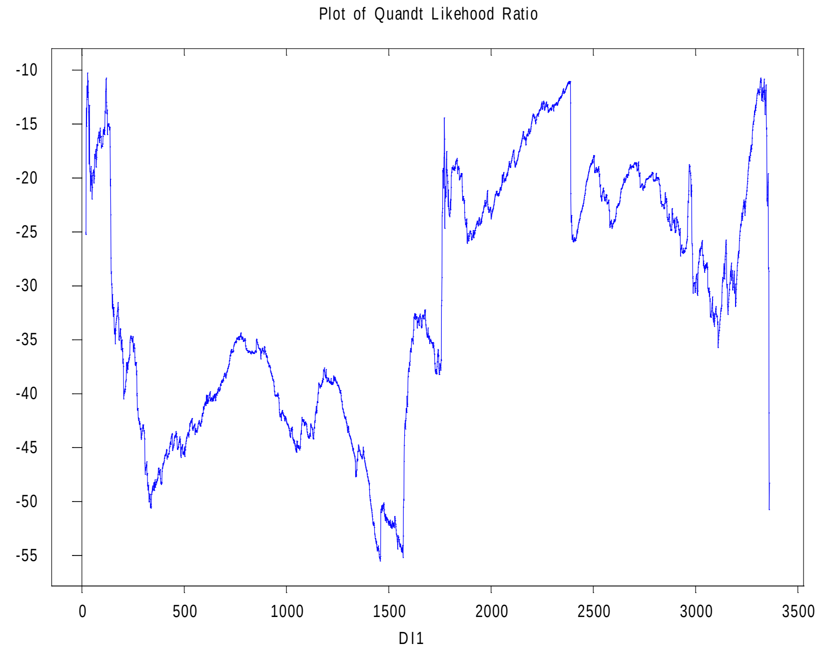


Figure 2. CUMSM, CUMSMSQ, and QLR plots for Japanese market return.

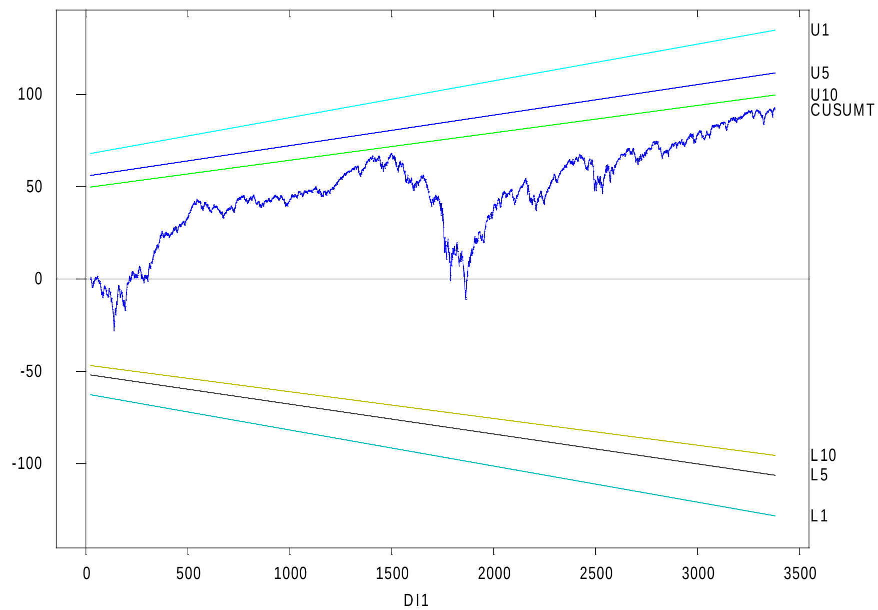
Plots in Figure 2 are based on the OLS model (8)

$$\begin{aligned} JAR_t = {} & 0.210 * USR_t + 0.632 * USR_{t-1} + 0.144 * USR_{t-2} + 0.067 * USR_{t-3} + 0.056 * USR_{t-5} \\ & + 0.14 * CNR_t - 0.046 * CNR_{t-1} - 0.122 * JAR_{t-1} - 0.049 * JAR_{t-3} \end{aligned} \tag{8}$$

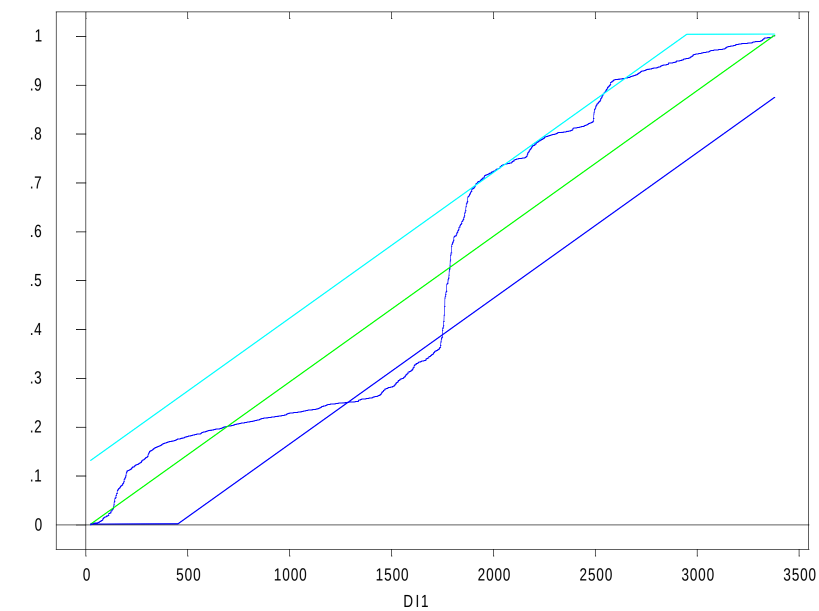
(t=12.65) (t=36.53) (t=7.04) (t=3.24) (t=2.81)

(t=10.29) (t=-3.35) (t=-7.07) (t=-2.82)

Plot of Cusum Test



Plot of Cusumsq Test



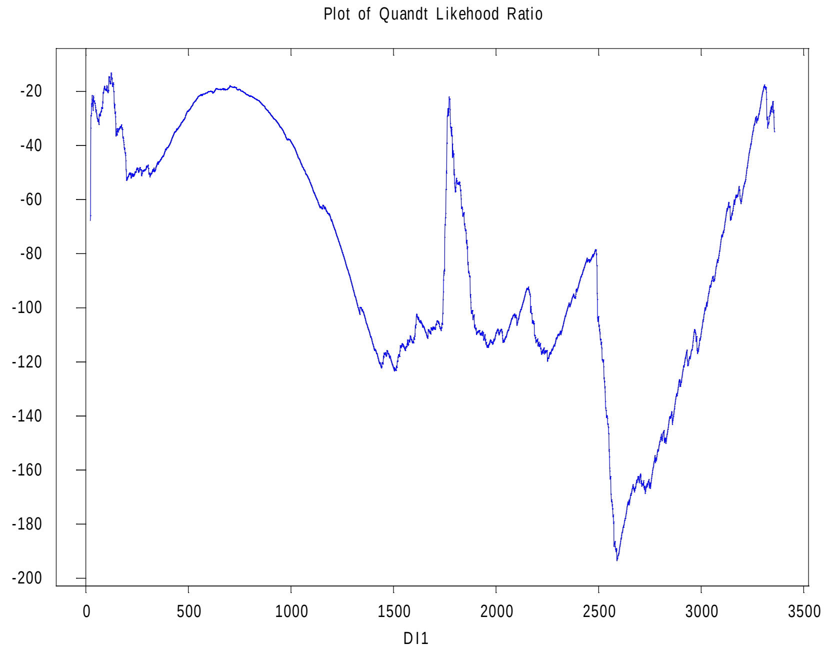


Figure 3. CUMSM, CUMSMSQ, and QLR plots for US market return.

Plots in Figure 3 are based on the OLS model (9)

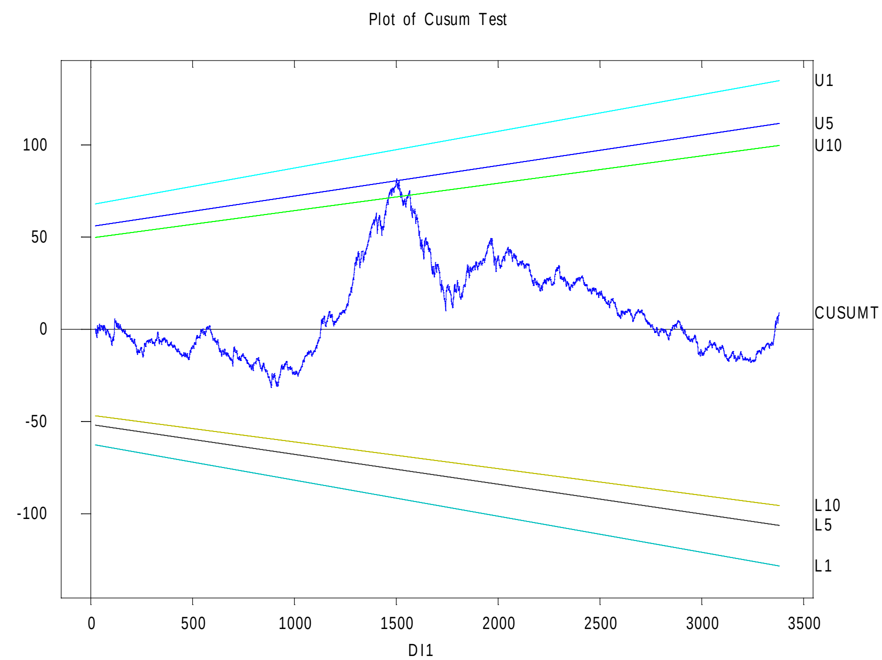
$$\begin{aligned} USR_t = & -0.24 * USR_{t-1} - 0.087 * USR_{t-2} - 0.048 * CNR_{t-5} \\ & + 0.215 * JAR_t + 0.040 * JAR_{t-1} - 0.033 * JAR_{t-6} \end{aligned} \qquad (9)$$

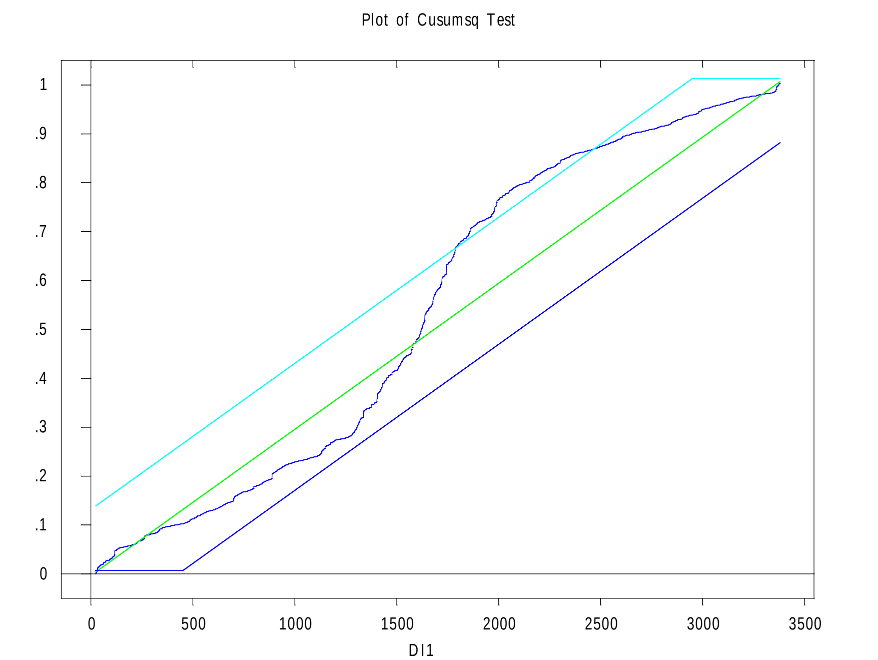
(t=-11.64) (t=-4.16) (t=-3.43)

(t=12.59) (t=2.25) (t=-2.21)

From Figure 3, which depicts the US market, we can see that the plot is within the bound in CUSUM plot. But by taking a look at the CUSUMQ plot, we can see that the plot gets out of the bound when n is around 1400 to 1800. These indicate the instability in the data series. Besides, by taking a look at the QLR plot, we can see there is a tremendous drop around n=1500 and n=2600 which indicates a structure breakpoint.

Thus, from the above three plots, it seems like the US market return data series is not stable from time period n=1500 to n=2600, which is Oct. 2007 to Jan 2012.





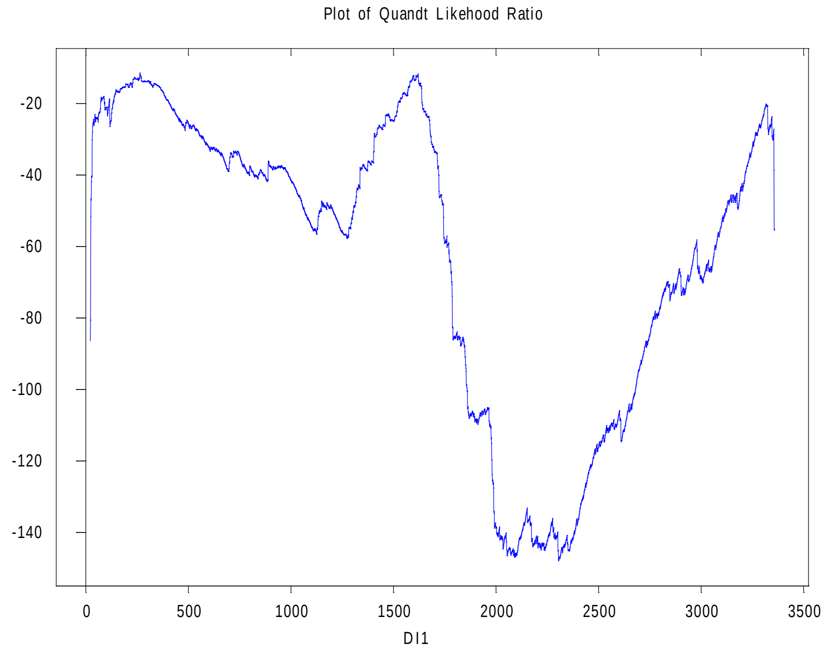


Figure 4. CUMSM, CUMSMSQ, and QLR plots for Chinese market return.

Plots in Figure 4 are based on the OLS model (10)

$$
\begin{aligned}
CNR_t = {} & 0.564*USR_{t-1} + 0.068*USR_{t-2} + 0.096*USR_{t-6} + 0.041*CNR_{t-3} \\
& + 0.036*CNR_{t-4} + 0.219*JAR_t - 0.072*JAR_{t-1} - 0.459*JAR_{t-5}
\end{aligned} \tag{10}
$$

(t=2.20) (t=2.64) (t=3.60) (t=2.36)

(t=2.08) (t=10.27) (t=-3.30) (t=-2.11)

From Figure 4, which depicts the Chinese market, we can see that the plot gets out of the 5% bound in CUSUM plot when *n* is around 1500. This is also consistent with the results by taking a look at the CUSUMQ plot. We can see that the plot gets out of the bound when n is around 1800 to 2200. These indicate the instability in the data series. Besides, by taking a look at the QLR plot, we can see there is a tremendous drop around n=2000 to n=2400 which indicates a structure breakpoint. Thus, from the above three plots, it seems like the US market return data series has a breakpoint from n=1500 to n=2200, which is Oct.2007 to June 2010.

Based on the analysis above, we can see that there should be a breakpoint for all the three countries' return series around the beginning of 2008 to the end of 2010. This is consistent with the time frame of the financial crisis. See Appendix B for the chronological order of financial crisis events.

The same analysis with the return series in dollar currency gives us similar results. And we can also see from the original data itself (refer to Figure 1), the price experienced a drastically drop from the beginning of 2008 to the end of 2010 in all the three countries.

Therefore, there are two methods that I am going to deal with the breakpoint of the data structure.

First attempt: For simplicity of the analysis, we choose the breakpoint to be at 12/31/2008 and separate the data into two sub-periods: pre-crisis period and post-period crisis period. This kind of separation is also consistent with the chronology events and literature as provided in Appendix B. Therefore, from now on, we will conduct our analysis on all of the 4 subsets defined as follows:

- M1-Subsample Set 1: Pre- Crisis Local Currency

  For US: USR from 01/01/2002-12/31/2008

  For China: CNR from 01/01/2002-12/31/2008

  For Japan: JAR from 01/01/2002-12/31/2008

- M1-Subsample Set 2: Pre-Crisis Dollar Currency

  For US: USRd from 01/01/2002-12/31/2008

For China: CNRd from 01/01/2002-12/31/2008

For Japan: JARd from 01/01/2002-12/31/2008

- M1-Subsample Set 3: Post- Crisis Local Currency

  For US: USR from 01/01/2009-12/31/2014

  For China: CNR from 01/01/2009-12/31/2014

  For Japan: JAR from 01/01/2009-12/31/2014

- M1-Subsample Set 4: Post-Crisis Dollar Currency

  For US: USRd from 01/01/2009-12/31/2014

  For China: CNRd from 01/01/2009-12/31/2014

  For Japan: JARd from 01/01/2009-12/31/2014

Second attempt: Since the structure during the financial crisis period is too unsteady, it is difficult to model the data structure during the financial crisis period. In order to minimize the impact the unstable structure did to the pre-crisis period or the post-crisis period. We take out the data series from 07/01/2008 to 06/30/2009 as shown in Figure 5.

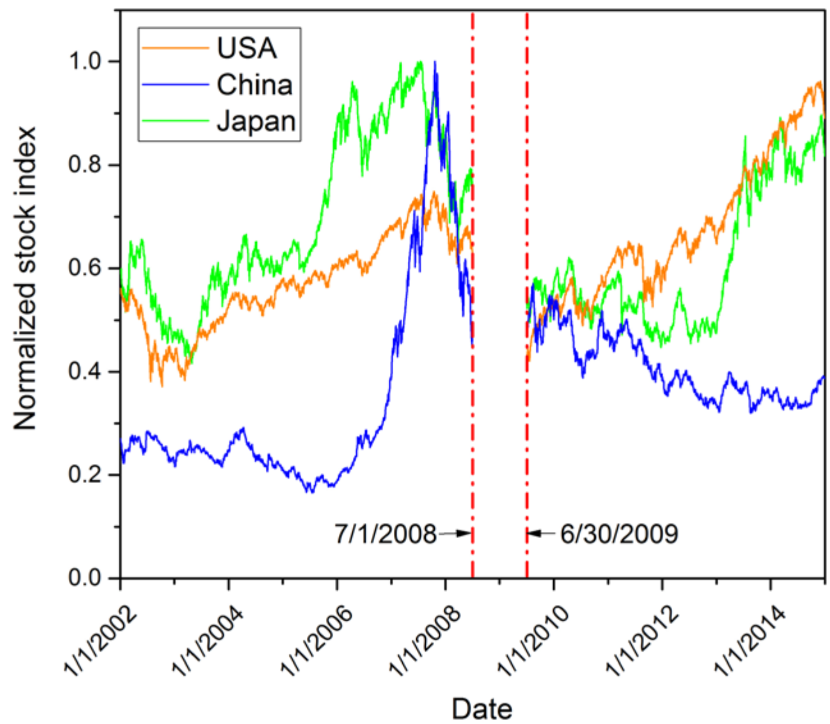


Figure 5. Stock indices in 3 countries from 2002 to 2014 with a take out from 7/1/2008 to 6/30/2009 used for data analysis in method 2.

Therefore, we will conduct our analysis on all of the 4 subsets defined as follows:

- M2-Subsample Set 1: Pre- Crisis Local Currency

  For US: USR from 01/01/2002-06/30/2008

  For China: CNR from 01/01/2002-06/30/2008

  For Japan: JAR from 01/01/2002-06/30/2008

- M2-Subsample Set 2: Pre-Crisis Dollar Currency

  For US: USRd from 01/01/2002-06/30/2008

  For China: CNRd from 01/01/2002-06/30/2008

  For Japan: JARd from 01/01/2002-06/30/2008

- M2-Subsample Set 3: Post- Crisis Local Currency

For US: USR from 07/01/2009-12/31/2014

For China: CNR from 07/01/2009-12/31/2014

For Japan: JAR from 07/01/2009-12/31/2014

- M2-Subsample Set 4: Post-Crisis Dollar Currency

  For US: USRd from 07/01/2009-12/31/2014

  For China: CNRd from 07/01/2009-12/31/2014

  For Japan: JARd from 07/01/2009-12/31/2014

CHAPTER 6. VAR ANALYSIS

In this chapter, we now use some time series analysis methods to study the patterns of stock return movements in US, Japan and China. We also want to examine the role of the foreign exchange rate on the dynamic relationships of the stock markets. More specifically, we want to analyze the extent to which a variation of one country's stock price index applies an influence on that of other countries. If a lead-lag relationship was found among the stock returns that would imply a consistent and significant interdependence between US and Asia equity markets, which could signal unexploited arbitrage and profit opportunities and thus, inefficiencies in the international equity markets.

VAR (Vector Autoregression) analysis is widely used in the empirical investigation of economic and financial data. The purpose of VAR analysis is to determine the structure or form of models based on empirical evidence. Thus, the causal relationships between stock markets and exchange rate could be discovered. One advantage of VAR analysis is that it studies the dynamic response or relationships of a system instead of simple relationships.

The VAR models studied includes three variables---return rate of US, China and Japan markets, both in their local currency and dollar and both in pre-crisis period or post-crisis period as we discussed before. The models for the four different datasets in both method 1 (M1) and method 2 (M2) would be as follows:

$$\begin{pmatrix} G_{11}(B) & G_{12}(B) & G_{13}(B) \\ G_{21}(B) & G_{22}(B) & G_{23}(B) \\ G_{31}(B) & G_{32}(B) & G_{33}(B) \end{pmatrix} \begin{pmatrix} preUSR_t \\ preCNR_t \\ preJAR_t \end{pmatrix} = \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{11}$$

$$\begin{pmatrix} \tilde{G}_{11}(B) & \tilde{G}_{12}(B) & \tilde{G}_{13}(B) \\ \tilde{G}_{21}(B) & \tilde{G}_{22}(B) & \tilde{G}_{23}(B) \\ \tilde{G}_{31}(B) & \tilde{G}_{32}(B) & \tilde{G}_{33}(B) \end{pmatrix} \begin{pmatrix} preUSRd_t \\ preCNRd_t \\ preJARd_t \end{pmatrix} = \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{12}$$

$$\begin{pmatrix} D_{11}(B) & D_{12}(B) & D_{13}(B) \\ D_{21}(B) & D_{22}(B) & D_{23}(B) \\ D_{31}(B) & D_{32}(B) & D_{33}(B) \end{pmatrix} \begin{pmatrix} postUSR_t \\ postCNR_t \\ postJAR_t \end{pmatrix} = \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{13}$$

$$\begin{pmatrix} \tilde{D}_{11}(B) & \tilde{D}_{12}(B) & \tilde{D}_{13}(B) \\ \tilde{D}_{21}(B) & \tilde{D}_{22}(B) & \tilde{D}_{23}(B) \\ \tilde{D}_{31}(B) & \tilde{D}_{32}(B) & \tilde{D}_{33}(B) \end{pmatrix} \begin{pmatrix} postUSRd_t \\ postCNRd_t \\ postJARd_t \end{pmatrix} = \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{14}$$

Here B is the backshift operator.

There are some obvious benefits in using VAR model to fit the data. VAR model does not have exogenous variables. Each variable is forecasted by the lagged values of its own and of other variables. We can determine the cause and effect relationship from the available data itself through the VAR model instead of using prior information. Previously, economic theory usually has to provide a model that postulates the direction of causality, now we can examine models including the causal direction with statistical tools.

The following five parts of analyses will be performed in this Chapter.

1) VAR model order Selection
2) Granger Causality Test
3) Impulse Response Function
4) Correlation Matrix of Residuals

6.1 VAR Order Selection

In order to fit the VAR model, the first step is to select appropriate lag order for the above 4 models in both method 1 (M1) and method 2 (M2). Lag selections for those 4 models are tested by AIC, HQ, SC, FPE. The test results are reported in Appendix C. Table 2 summarizes the lag selection results by using different criteria.

The information criteria and prediction error are calculated as below:

$$AIC(n) = \ln\det(\tilde{\Sigma}_u(n)) + \frac{2}{T} nK^2 \tag{15}$$

$$HQ(n) = \ln\det(\tilde{\Sigma}_u(n)) + \frac{2\ln(\ln(T))}{T} nK^2 \tag{16}$$

$$SC(n) = \ln\det(\tilde{\Sigma}_u(n)) + \frac{\ln(T)}{T} nK^2 \tag{17}$$

$$FPE(n) = (\frac{T+n^*}{T-n^*})^K \det(\tilde{\Sigma}_u(n)) \tag{18}$$

with $\tilde{\Sigma}_u(n) = T^{-1}\sum_{t=1}^{T}\hat{e}_t\hat{e}_t^{'}$ and n^* is the total number of the parameters in each equation and n assigns the lag order, K is number of variables in the Y vector.

Table 2. VAR Lag Selection Results

M1

Data Sets	AIC	HQ	SC	FPE
Pre-Crisis Local	8	2	1	8
Pre-Crisis Dollar	8	2	2	8
Post-Crisis Local	2	1	1	2
Post-Crisis Dollar	3	2	1	3

M2

Data Sets	AIC	HQ	SC	FPE
Pre-Crisis Local	1	1	1	1
Pre-Crisis Dollar	4	1	1	4
Post-Crisis Local	3	1	1	3
Post-Crisis Dollar	3	2	1	3

Since the orders selected by different criteria are not even close, we would like to discuss other diagnostic aids—CCF (cross correlation matrix plot) and M statistics.

I checked CCF plots for all those datasets both in method 1 and method 2. It seems like the CCF plot can only be cleaned after 8-12 lags or even more, except for M2 Pre-Crisis Dollar dataset， where the CCF plot is cleaned using lag order 4. Since these datasets have already be been differenced and are stationary, I think taking lag orders of 8-12 or even more would be overfitting the data. So I decided to adopt lags suggested by those information criteria and use M statistics to make further decision on what lag order I should choose.

The output of each order of the VAR model includes the residual covariance matrix S(j), the eigenvalues, eigenvectors, determinant and reciprocal of S(j), and the residual correlation matrix RS(j). Zero eigenvalues in S(J) imply that the number of innovation series is less than k. Alternatively, we can calculate $\mathrm{M}(i)$ for $i \in \{1, \cdots, \mathrm{p}\}$, which is distributed as chi-square with k^2 degrees of freedom (Tiao and Box (1981))

$$\mathrm{M}(i) = -(\mathrm{T} - .5 - 1 - ki)\ln(|\,\mathrm{S}(i)\,| \,/\, |\,\mathrm{S}(i-1)\,|) \tag{19}$$

$\mathrm{M}(j+1)$ will not be significant if j is the right maximum order, because $\ln(|\,\mathrm{S}(j+1)\,|/|\,\mathrm{S}(j)\,|)$

approaches zero when |S(j+1)| approaches |S(j)|.

Hence, the results of M-statistics computed for different lags are reported below:

Table 3. M-statistics outputs of lag order

M1

Data Sets\M	**1**	**2**	**3**	**4**	**5**	**6**
Pre-Crisis Local	633.47	**58.26**	28.93	26.66	24.82	23.02
M1Pre-Crisis Dollar	390.25	**74.98**	22.74	26.41	20.95	18.78
M1Post-Crisis Local	567.15	**25.7**	14.25	9.44	9.48	12.41
M1Post-Crisis Dollar	459.42	46.31	**27.08 (0.0014)**	16.3 (0.0610)	11.24	12.56

M2

Data Sets\M	**1**	**2**	**3**	**4**	**5**	**6**
Pre-Crisis Local	**390.65**	14.73	11.63	24.91	12.98	12.75
Pre-Crisis Dollar	255.24	18.89 (0.0261)	11.96 (0.2158)	**26.50 (0.0017)**	9.99 (0.3512)	9.91
Post-Crisis Local	444.49	28.88 (0.0007)	**21.02 (0.0126)**	4.33 (0.8882)	11.63	9.16
Post-Crisis Dollar	369.20	45.54	**27.11 (0.0013)**	11.03 (0.2739)	12.44 (0.1869)	8.45

As we can observe from Table 3, M statistics drops drastically after the lag in bold. Combined with the results we got from Table 2, in method 1, we use lag orders equal 2 for pre-crisis local currency, pre-crisis dollar currency, post-crisis local currency data sets and lag order equals 3 for post-crisis dollar currency data set.

Similar analysis could be used in the four datasets in M2 as well. In this method 2, we use lag order equals 1 for pre-crisis local currency. Lag order equals 4 for pre-crisis dollar currency, another support for this selection is that CCF (cross correlation plot) are all clean using lag order equals 4. Lag order equals 3 for post-crisis local currency. Lag order equals 3 for post-crisis dollar currency.

6.2 Granger Causality Test

In this section, we are going to investigate the causal relationships and feedbacks between the three series.

One useful tool of investigating this kind of relationship is the **Granger-Causality test** which was proposed by Granger (1969). The basic idea of Granger Causality is that for series x_t and y_t , if y_t could be better predicted using the information y_{t-i} of and x_{t-i} , (i=1,2,…) than just using y_{t-i} alone, then we say that variable X Granger-causes variable Y.

Granger (1969) suggested the Causality testing based on a bivariate VAR representation:

$$y_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i y_{t-i} + \sum_{j=1}^{n} \beta_j x_{t-j} + e_{ty} \quad (20)$$

$$x_t = \beta_0 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{j=1}^{n} \beta_j y_{t-j} + e_{tx} \quad (21)$$

Here y_t represents any of the three return series, x_t is any one of the rest two return series. x_{t-j} and y_{t-j} contains information which is statistically significant to predict the value of y_t and x_t, respectively. If $\beta_j \neq 0$, that means x_t and y_t will be helpful in estimating y_t in (20) and x_t in (21), respectively. In other words, if $\beta_j \neq 0$, the variance of e_t produced by (20) and (21) will be significantly lower than the var(e_t) produced when restricting $\beta_j = 0$.

Testing that X Granger-causes Y is based on equation (20) and Y Granger-causes X on (21). The null hypothesis for Granger Causality F-test is $H_0 : \beta_1 = \beta_2 = ... = \beta_n = 0$. Similarly, the Granger-Causality concept and models can be extended to three variables. Tables 4-7 report the F-statistics and significance of the Granger Causality test results for the four different data subsets in the two methods we discussed above.

Table 4. Granger-Causality F-test results for pre-crisis local currency

M1: 2 Lag used

Causality Relation	F-statistics	p-value	Significance
CN-->US	1.03	0.3566	
JP-->US	0.13	0.8783	
US-->CN	15.38	0.0000	***
JP-->CN	4.42	0.0122	**
US-->JP	330.61	0.0000	***
CN-->JP	2.91	0.0545	*
JP,US-->CN	8.16	0.0000	***
JP,CN-->US	0.67	0.6106	
US,CN-->JP	167.10	0.0000	***

M2: 1 Lag used

Causality Relation	F-statistics	p-value	Significance
CN-->US	0.089	0.7649	
JP-->US	2.26	0.1327	
US-->CN	10.46	0.0012	***
JP-->CN	0.0091	0.9241	
US-->JP	405.38	0.0000	***
CN-->JP	1.70	0.1926	
JP,US-->CN	5.27	0.0052	***
JP,CN-->US	1.13	0.322	
US,CN-->JP	204.00	0.0000	***

*p<0.1; **p<0.05;***p<0.01

In Table 4, in both method 1 and method 2, the F-test is not significant for China Granger causes US, Japan Granger causes US. F-test is also not significant for Japan and China jointly Granger causes US. However, F-test is significant at 1% level for US Granger causes China, US Granger causes Japan, Japan and US jointly causes China, US and China jointly causes Japan. In method

1 only, F-test is significant at 5% level for Japan Granger causes China. F-test is significant at 10% level but not significant at 5% level for China Granger causes Japan. These two F-tests are not significant in method 2. Because Japan market closes first, then China market closes. US market closes at last on the same calendar. The significance for Japan Granger causes China may be due to the fact that Japan market closes one hour before China market. We can positively say that in both methods US market leads Asia markets—China and Japan; China and/or Japan markets do not Granger cause US market at pre-crisis period in their local currency. Whether China market leads Japan market would be a judgmental call in method 1.

In Table 5, we would have similar conclusions for the causal relationships and feedbacks. We can positively say that in both methods, US market leads Asia market; China and/or Japan markets do not Granger cause US market at pre-crisis period in their dollar currency. There isn't too much difference in the results by adding the exchange rate in both methods.

Table 5. Granger-Causality F-test for pre-crisis dollar currency

M1: 2 Lag used

Causality Relation	F-statistics	p-value	Significance
CN-->US	0.99	0.3729	
JP-->US	0.67	0.5132	
US-->CN	14.85	0.0000	***
JP-->CN	4.14	0.0161	***
US-->JP	197.18	0.0000	***
CN-->JP	2.58	0.0764	*
JP,US-->CN	7.95	0.0000	***
JP,CN-->US	0.95	0.4341	
US,CN-->JP	99.85	0.0000	***

M2: 4 Lag used

Causality Relation	F-statistics	p-value	Significance
CN-->US	0.98	0.4179	
JP-->US	1.21	0.3056	
US-->CN	4.92	0.0006	***
JP-->CN	1.37	0.2420	

US-->JP	68.19	0.0000	***
CN-->JP	0.98	0.4180	
JP,US-->CN	3.08	0.0018	***
JP,CN-->US	1.12	0.3482	
US,CN-->JP	34.46	0.0000	***

*p<0.1; **p<0.05;***p<0.01

In Table 6, we would also have similar conclusion for the causal relationships and feedbacks. In both methods, we can positively say that US market leads Asia market; China and/or Japan markets do not Granger cause US market at post-crisis period in their local currency. Whether the China market leads Japan market or Japan leads China market would be a judgmental call.

Table 6. Granger-Causality F-test for post-crisis local currency

M1: 2 Lag used

Causality Relation	F-statistics	p-value	Significance
CN-->US	0.49	0.6111	
JP-->US	1.9	0.1501	
US-->CN	32.05	0.0000	***
JP-->CN	5.44	0.0043	***
US-->JP	313.4	0.0000	***
CN-->JP	2.56	0.0776	*
JP,US-->CN	16.66	0.0000	***
JP,CN-->US	1.04	0.3829	
US,CN-->JP	156.74	0.0000	***

M2: 3 Lag used

Causality Relation	F-statistics	p-value	Significance
CN-->US	1.71	0.1635	
JP-->US	0.58	0.6301	
US-->CN	18.68	0.0000	***
JP-->CN	3.38	0.0176	
US-->JP	165.09	0.0000	***
CN-->JP	3.22	0.0221	**
JP,US-->CN	10.04	0.0000	***
JP,CN-->US	1.03	0.5993	
US,CN-->JP	83.53	0.0000	***

*p<0.1; **p<0.05;***p<0.01

In Table 7, in method 1, we have something different in the result of causal relationships and feedbacks. F-test is not significant for China Granger causes US. However, F-test is significant at

1% level for US Granger causes China, US Granger causes Japan, Japan and US jointly causes China, US and China jointly causes Japan. The F-test is significant at 5% level for Japan Granger causes US and Japan Granger causes China. The F-test is significant at 10% level but not significant at 5% level for China Granger causes Japan and Japan and China Granger causes US. Still, we can only positively say US market leads Asia markets. Because Asia markets close before US market on the same calendar day, those indications of Asia market cause US market may be due to the time zones difference and can't be concluded. But we can clearly see that at post-crisis period, Japan and China markets can also impact more about US market now. This is also a support for the saying that international markets are getting more closely linked. In addition to that, this result can only be seen using dollar currency but not the local currency return of the series, which also indicates that the international transmission of asset price movement would be increased by adding the exchange rate movements on stock prices.

Table 7. Granger-Causality F-test for post-crisis dollar currency

M1: 3 Lag used

Causality Relation	**F-statistics**	**p-value**	**Significance**
CN-->US	1.15	0.3291	
JP-->US	3.23	0.0216	**
US-->CN	23.17	0.0000	***
JP-->CN	3.18	0.0233	**
US-->JP	162.57	0.0000	***
CN-->JP	2.06	0.1032	*
JP,US-->CN	12.02	0.0000	***
JP,CN-->US	2.015	0.0602	*
US,CN-->JP	81.54	0.0000	***

M2: 3 Lag used

Causality Relation	**F-statistics**	**p-value**	**Significance**
CN-->US	1.85	0.1355	

JP-->US	1.83	0.1403	
US-->CN	21.06	0.0000	***
JP-->CN	3.02	0.0289	**
US-->JP	130.80	0.0000	***
CN-->JP	2.26	0.0835	*
JP,US-->CN	11.01	0.0000	***
JP,CN-->US	1.65	0.129	
US,CN-->JP	65.73	0.0000	***

*p<0.1; **p<0.05;***p<0.01

In method 2, comparing post-crisis local currency and dollar currency, we see that in post-crisis local currency, China Granger causes Japan at 5% level, while after being adjusted for exchange rate, China Granger causes Japan at 10% level, Japan also Granger causes China at 5% level. Those two are not seen in pre-crisis local or dollar currency. These suggests that the China and Japan markets are getting more linked after financial crisis, especially after being adjusted for exchange rate. Since Japan market closes before China market, we can only say after financial crisis, China is getting important, it Granger causes Japan market now. By looking at it in another way, this relationship is not seen before the crisis, it also suggests the impact of US market to Japan and China markets are getting less after the financial crisis. The impact between Japan and China market are being overlooked or covered by the impact US market did to the two Asia markets, now the impact began to show as US market is having less impact to Asia markets after financial crisis.

In addition, if we compare the results between method 1 and method 2, we see that the two Asia markets are generally more active in method 1 than in method 2. I think that’s partly due to the fact that we include the financial crisis period 07/01/2008-06/30/2009 in method 1. This may also imply that during financial crisis period, the two Asia markets are more influential in the world economy than a rather stable period.

Based on the discussions above about the Granger-Causality test, the causal relationships and feedbacks between US, Japan and China markets would be suggested to be as follows:

Before the financial crisis, US market leads Japan and China markets. After financial crisis, the interaction became more complicated. US market still leads Japan and China markets, but Japan and China markets are getting more linked while the impact of US market are getting less especially when we adjusted the return for exchange rate. International markets are getting more closely linked. During financial crisis period, the two Asia markets are more influential in the world economy than a rather stable period.

6.3 Impulse Response Function

To get more information about the international transmission of stock market movements, we now use the simulated response of VAR system to study the dynamic responses of each of the three markets to innovations in a specific market.

Investigation of the innovation pattern and responses in different markets can be accurately implemented by the analysis of impulse response function. The VAR form of (11) to (14) can be transformed to a **vector moving average** form (VMA) to estimate the impulse response in the shocks, and VMA allows the measurement of shock going in two ways.

In both method 1 and method 2, let's take VAR model (11) as an example. Provided $G(B)=\begin{pmatrix} G_{11}(B) & G_{12}(B) & G_{13}(B) \\ G_{21}(B) & G_{22}(B) & G_{23}(B) \\ G_{31}(B) & G_{32}(B) & G_{33}(B) \end{pmatrix}$ are convertible, (11) can be transformed in form of VMA model

$$\begin{pmatrix} preUSR_t \\ preCNR_t \\ preJAR_t \end{pmatrix} = \Theta(B) \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{22}$$

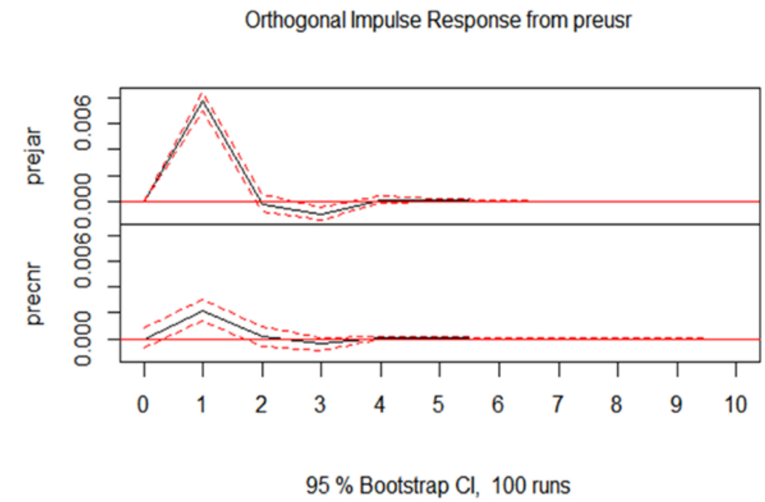
where $\Theta(B) \equiv \left[G(B)\right]^{-1}$. $\Theta(B)$ measures the dynamic responses of the return rate of preUSR, preCNR, preJAR to a shock in the model. (22) can be expanded to

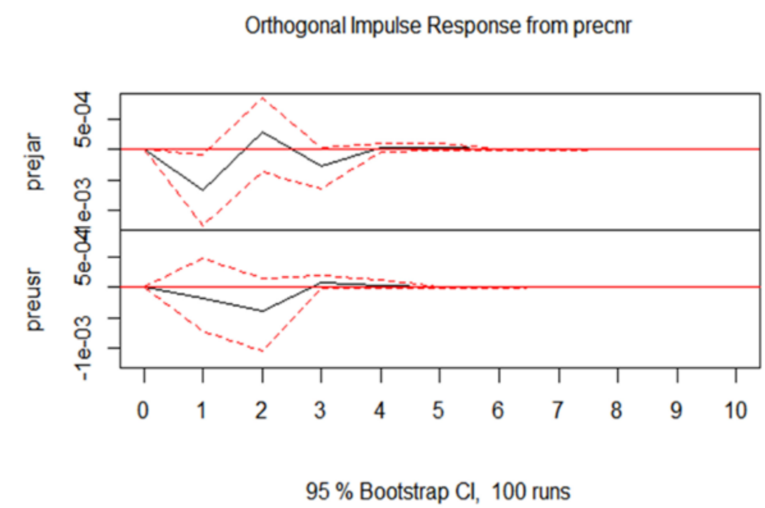
$$\begin{pmatrix} preUSR_t \\ preCNR_t \\ preJAR_t \end{pmatrix} = \begin{pmatrix} \theta_{11}(B) & \theta_{12}(B) & \theta_{13}(B) \\ \theta_{21}(B) & \theta_{22}(B) & \theta_{23}(B) \\ \theta_{31}(B) & \theta_{32}(B) & \theta_{33}(B) \end{pmatrix} \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} \tag{23}$$

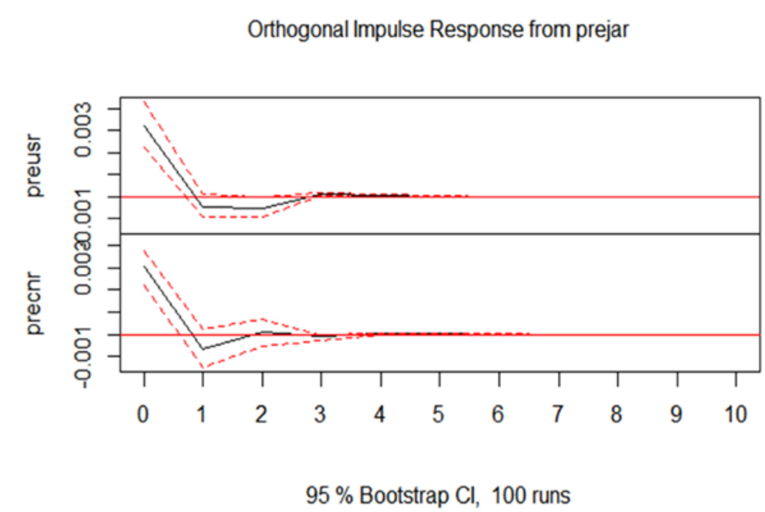
To be specific, $\theta_{12}(B)$ measures the effect of shocks in preCNR on price of preUSR. $\theta_{13}(B)$ measures the effect of shocks in preJAR on the price of preUSR. $\theta_{21}(B)$ measures the effect of shocks in preUSR on the price of preCNR. $\theta_{23}(B)$ measures the effect of shocks in preJAR on the price of preCNR. $\theta_{31}(B)$ measures the effect of shocks in preUSR on the price of preJAR. $\theta_{32}(B)$ measures the effect of shocks in preCNR on the price of preJAR (Koop, Pesaran et al. (1996)).

The orthogonalized impulse response coefficients for those 4 data sets of both methods are provided in Appendix D. The coefficients are plotted in the figures below. We also computed and plotted 95% confidence bands using bootstrap method. Figure 6-Figure 9 are based on the transformed VMA model of (11)-(14) with the lag orders selected in section 6.1.

(a) Method 1


Orthogonal Impulse Response from preusr
prejar
0.000
0.006
precnr
0.000
0.006
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


Orthogonal Impulse Response from precnr
prejar
-1e-03
5e-04
preusr
-1e-03
5e-04
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


Orthogonal Impulse Response from prejar
preusr
-0.001
0.003
precnr
-0.001
0.003
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs

(b) Method 2

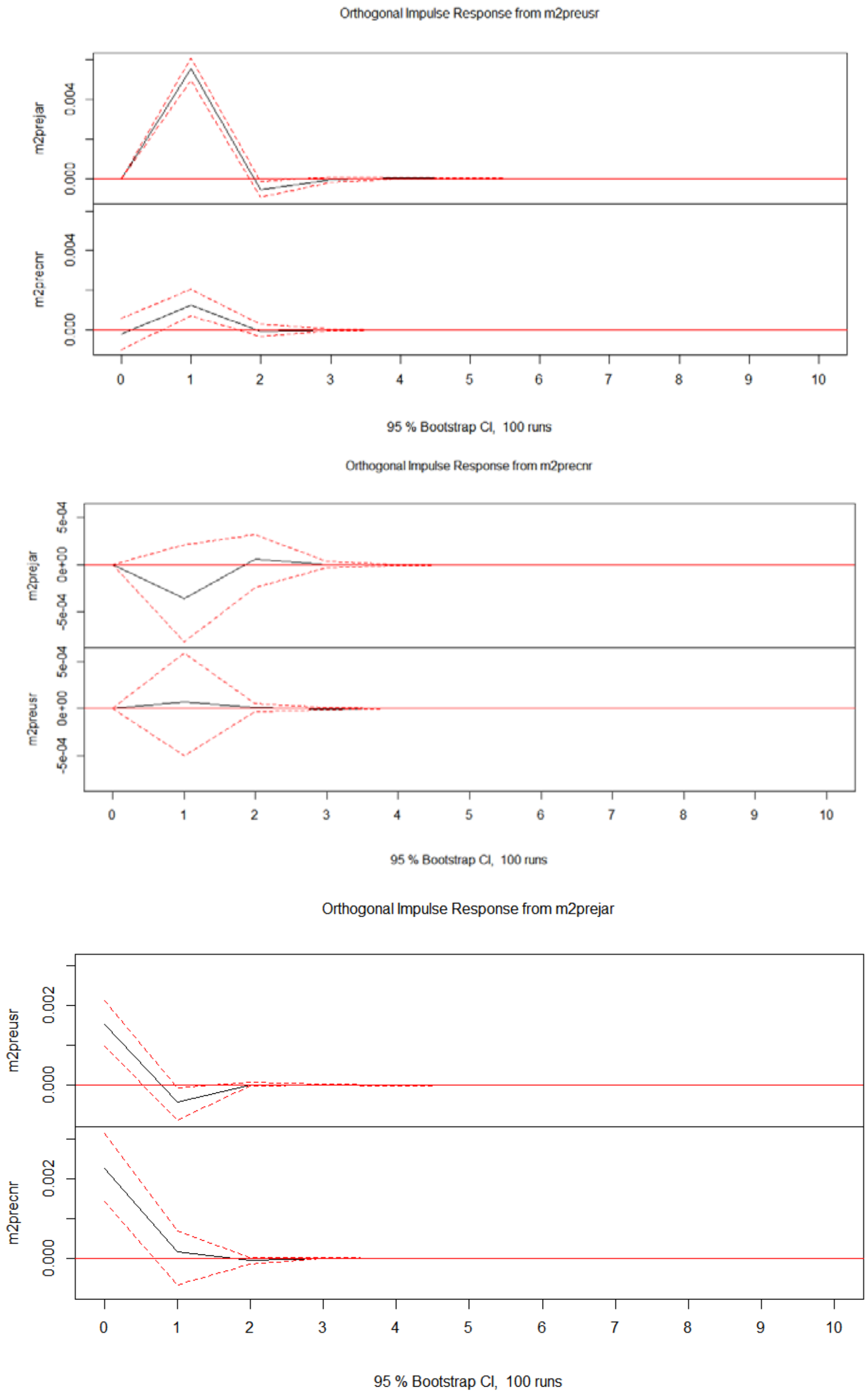
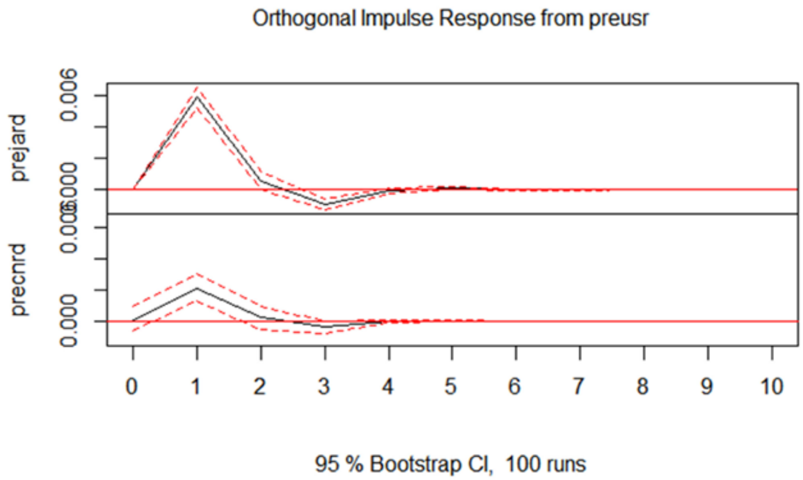
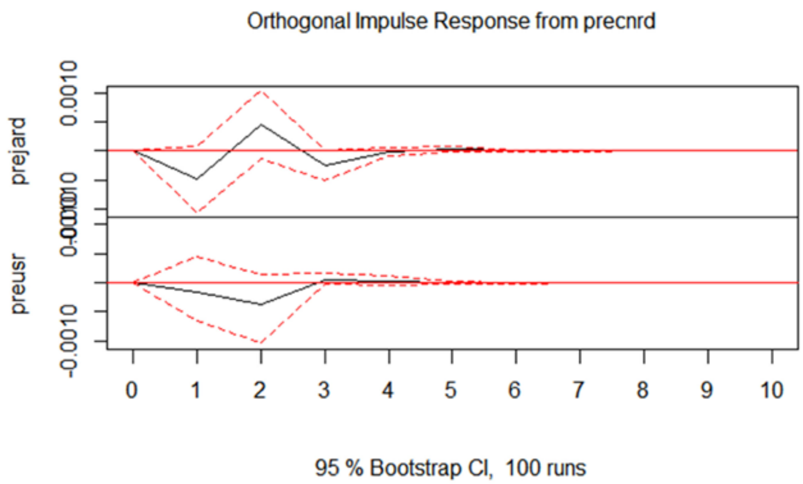
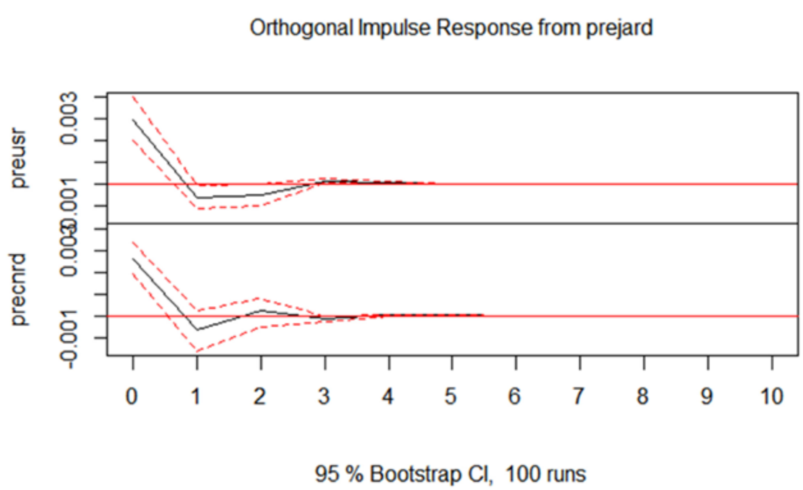


Figure 6. Impulse response function for pre-crisis local currency dataset

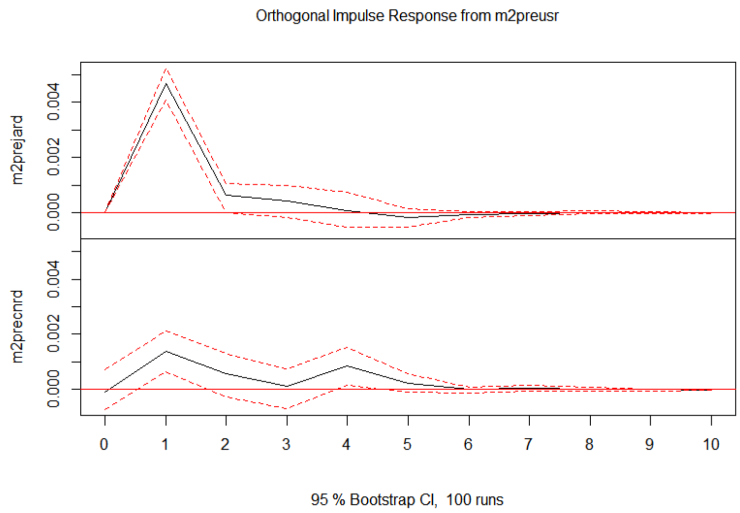
(a) Method 1

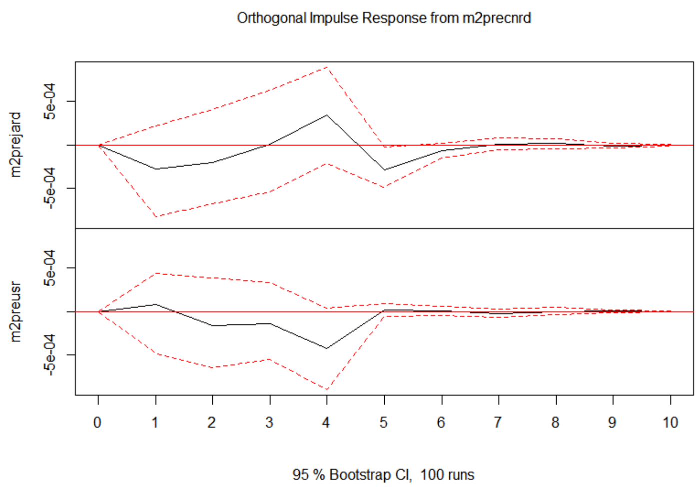

Orthogonal Impulse Response from preusr
prejard
precnrd
0.006
0.000
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


Orthogonal Impulse Response from precnrd
prejard
preusr
0.0010
-0.0010
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


Orthogonal Impulse Response from prejard
preusr
precnrd
0.003
-0.001
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs

(b) Method 2





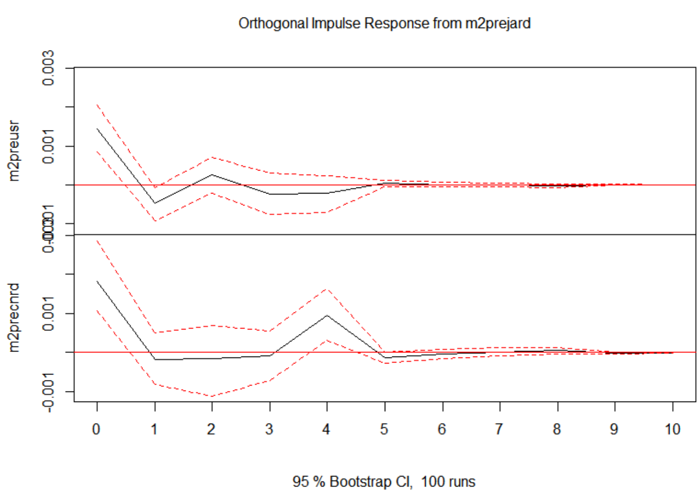
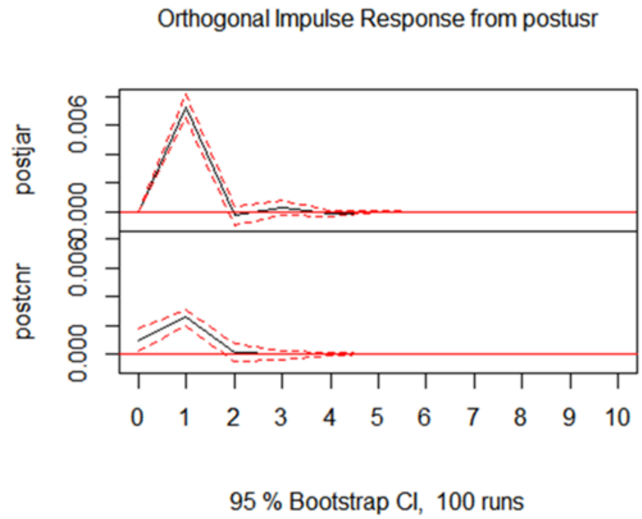
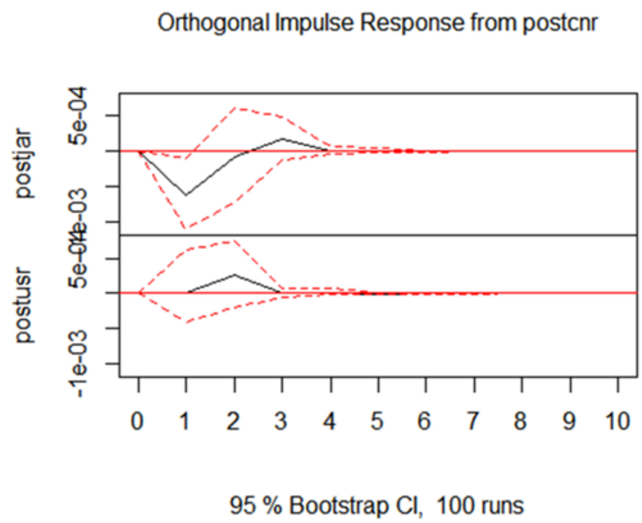


Figure 7. Impulse Response Function for pre-crisis dollar currency dataset

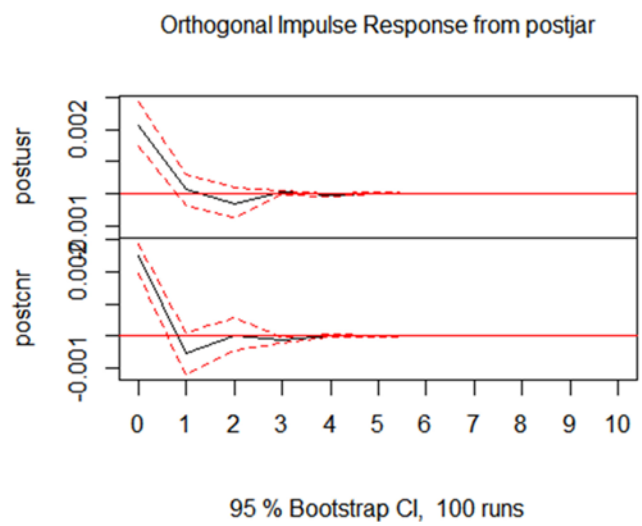
(a) Method 1



Orthogonal Impulse Response from postusr
postjar
postcnr
0.000
0.006
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs

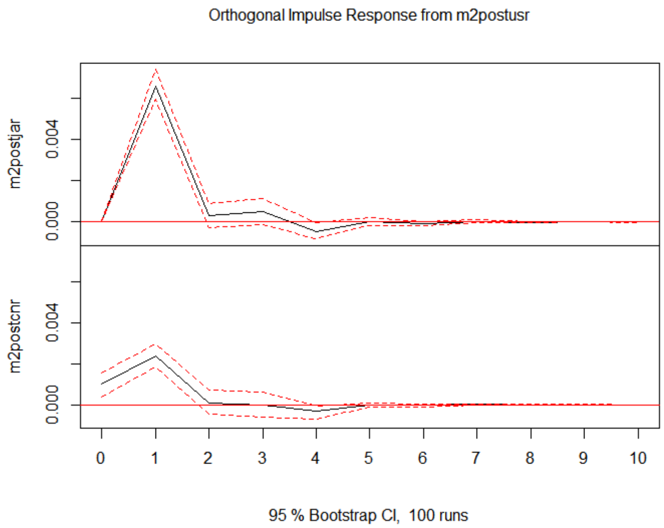


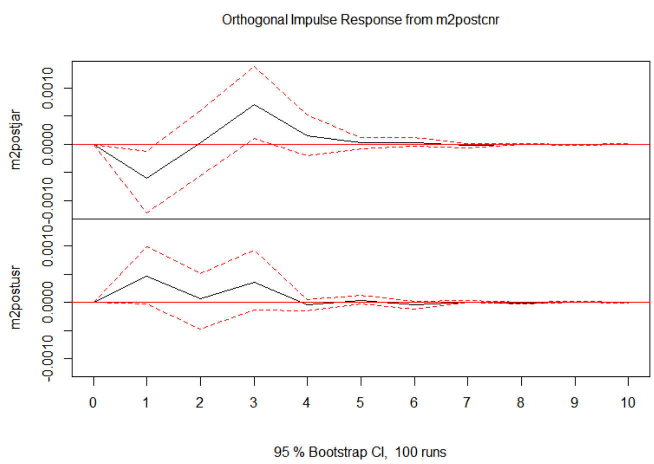
Orthogonal Impulse Response from postcnr
postjar
postusr
5e-04
-1e-03
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs



Orthogonal Impulse Response from postjar
postusr
postcnr
0.002
-0.001
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs

(b) Method 2





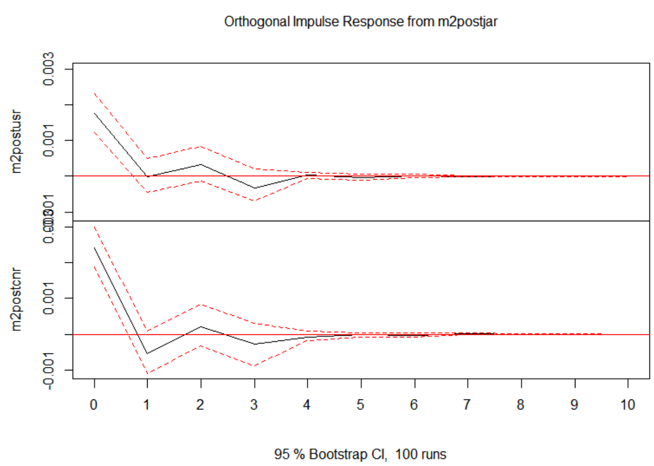
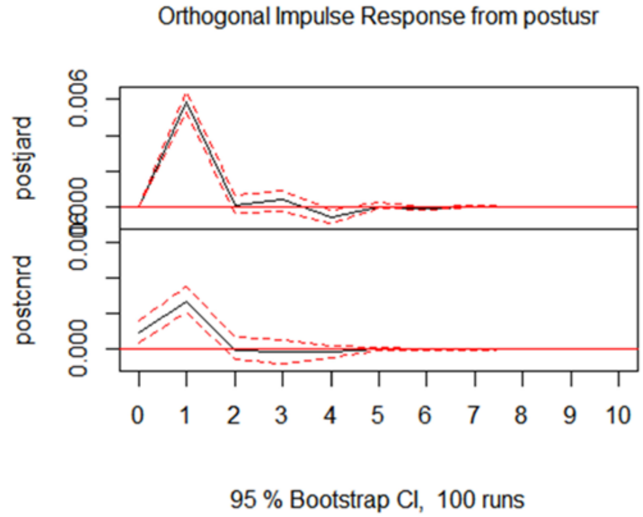
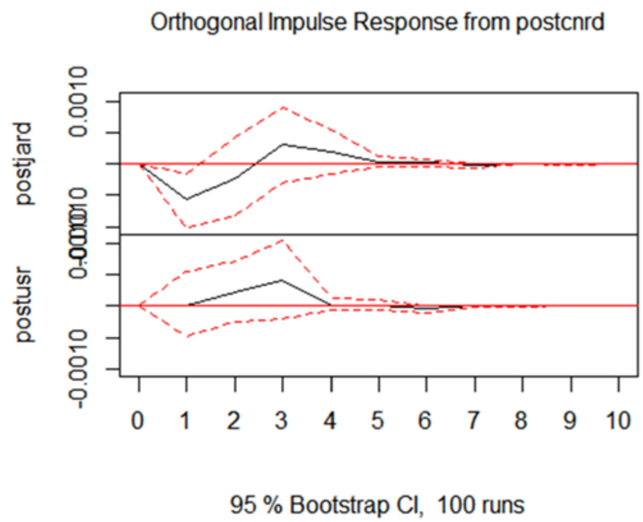
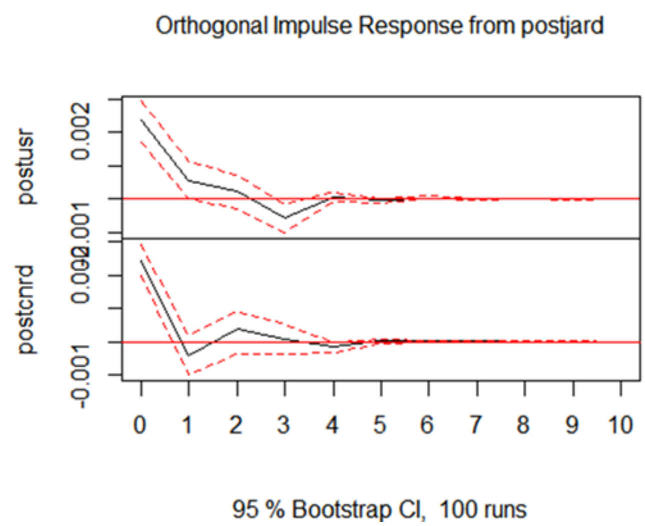


Figure 8. Impulse Response Function for post-crisis local currency dataset

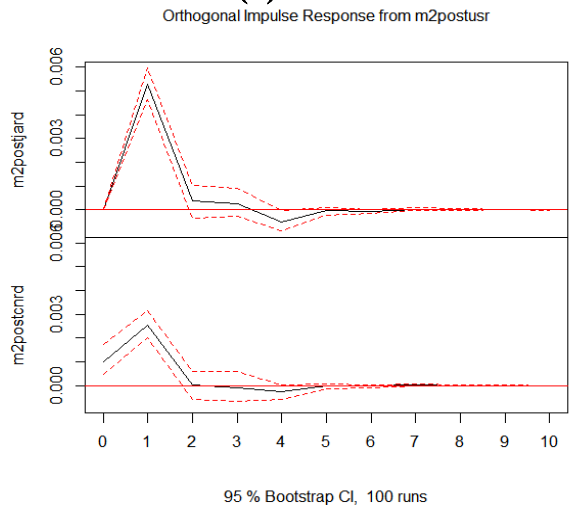
(a) Method 1

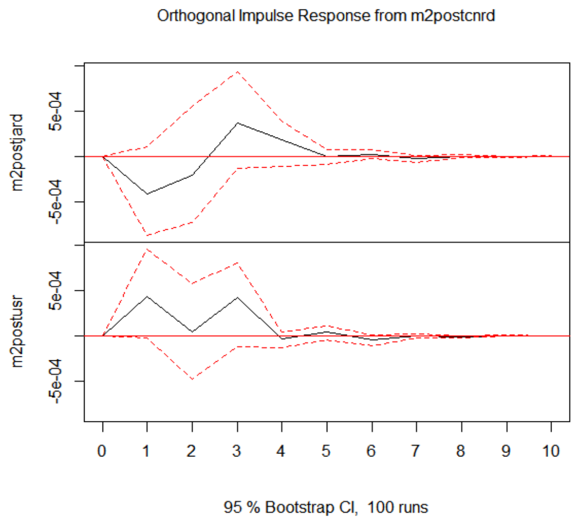

Orthogonal Impulse Response from postusr
postjard
postcnrd
0.006
0.000
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


Orthogonal Impulse Response from postcnrd
postjard
postusr
0.0010
-0.0010
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


Orthogonal Impulse Response from postjard
postusr
postcnrd
0.002
-0.001
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs

(b) Method 2





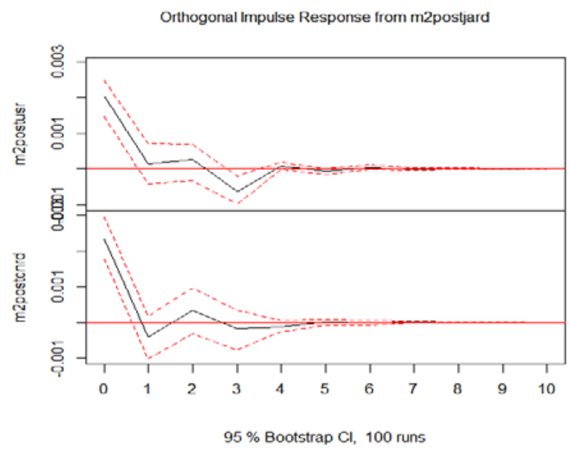


Figure 9. Impulse response function for post-crisis dollar currency dataset

Let’s take Figure 6 and Appendix C(1), which describe pre-crisis local currency period as an example. In method 1, it is clear from the above models that the U.S. market leads the other two markets, but none of these other countries leads the U.S. Market. As can be seen from Figure 6 , innovations in the U.S. Stock market are transmitted to the other markets within one day and the responses rapidly die off. The Chinese and Japanese impulse response to a U.S. shock is 0.00214 and 0.00779 respectively on day 1, followed by 1.912*10^(-4) and -2.197*10^(-4) on day 2. This implies that the Japan and China markets react intensely to the U.S. shock on day 1 when a shock occurs in the U.S., and the adjustments are largely finished by day 2. In method 2, we have similar results, the impulse response from US market to Japan and China markets starts as positive, 5.56*10^(-3) and 1.26*10^(-3) respectively. While the impulse response from China market to Japan starts as negative -3.63*10^(-4). The impulse response from China to US markets is much closer to 0 as 7.36*10^(-5). The impulse response from Japan to US and China markets starts with a positive number on day 0, which may due to the fact that Japan market opens first, and then dies off quickly around day 2.

Since the Asia markets are already closed when the U.S. market opens, these two markets should react to the U.S. innovation with a one-day lag, which is what we found in Figure 6 and Appendix C(1). Unlike the case of the U.S. shock, the reaction of the other markets to a Japan shock is found to be relatively weak. On the other hand, even though the reaction of the U.S and China market to the Japan shock is also low, the Japan stock market still influence on U.S and China market, since most of the responses of U.S. and China market to a Japan shock take place on day 0, even though some of the explanations may be due to the time zones difference. The low response of the U.S. stock market to a Japan stock implies that the stock price of the U.S. market is not determined by the Japan stock market.

Similar conclusions can been seen for Figure 7, Figure 8, Figure 9 and Appendix C(2)-C(4), which support our findings in VAR lag order selection and the Granger-Causality test sections.

6.4 Correlation Matrix of Residuals

The VAR analysis has an advantage of studying dynamic response of a system to shocks instead of the simple relationships. To understand how innovations in one market affect another, we now examine the contemporaneous correlations between turbulences rising in each market.

Table 8. Correlation Matrix of Residuals for pre-crisis local currency

M1

	prejar	preusr	precnr
prejar	1	0.245	0.1785
preusr	0.245	1	0.0438
precnr	0.1785	0.0438	1

M2

	prejar	preusr	precnr
prejar	1	0.1514 (p=0)	0.1390 (p=0)
preusr	0.1514	1	0.0065 (p=0.7887)
precnr	0.1390	0.0065	1

Table 9. Correlation Matrix of Residuals for pre-crisis dollar currency

M1

	prejard	preusr	precnrd
prejard	1	0.2269	0.1540

preusr	0.2269	1	0.0426
precnrd	0.1540	0.0426	1

M2

	prejard	preusr	precnrd
prejard	1	0. 1421 (p=0)	0.1138 (p=0)
preusr	0.1421	1	0.0114 (p=0.6394)
precnrd	0.1138	0.0114	1

Table 10. Correlation Matrix of Residuals for post-crisis local currency

M1

	postjar	postusr	postcnr
postjar	1	0.1912	0.1979
postusr	0.1912	1	0.1101
postcnr	0.1979	0.1101	1

M2

	postjar	postusr	postcnr
postjar	1	0.1784 (p=0)	0.1982 (p=0)
postusr	0.1784	1	0.1190 (p=0)
postcnr	0.1982	0.1190	1

Table 11. Correlation Matrix of Residuals for post-crisis dollar currency

M1

	postjar	postusr	postcnr
postjar	1	0.1912	0.1979

postusr	0.1912	1	0.1101
postcnr	0.1979	0.1101	1

M2

	postjar	postusr	postcnr
postjar	1	0.2066 (p=0)	0.1913 (p=0)
postusr	0.2066	1	0.1210 (p=0)
postcnr	0.1913	0.1210	1

Tables 8 – 11 report the contemporaneous correlations of the residual returns between the three national stock markets computed by VAR analysis.

The residuals represent abnormal stock market returns that were not predicted on the basis of all the information reflected in past returns. The contemporaneous correlations of residual returns reflect the level of information of irregular return in one market transmitted to another market in the same calendar day.

In Tables 8 and 9, in method 1, the responses of the Asia markets to the U.S. market in the first period does not show any increase from transforming local currency return of stock indexes into dollar term. This can also be seen in the previous impulse response function section. Both the impulse response function and correlation matrix of residuals imply that the inefficiency of the foreign exchange market in Asian countries due to the government deregulation on exchange rate, blocks the negative correlation between exchange rate and stock price. I think that’s mainly because of the government controlled exchange rate in China. In other words, as the government regulated the exchange rate, the exchange rate could not respond properly from any innovations of economic variable in short term. Therefore, the correlation between stock price and exchange rate was broken by government intervention into the exchange market. This also supports the notion that currency movement is a more significant part of total portfolio return under flexible exchange rates.

In method 2, in both local and dollar currency, only the correlation between US and Japan market and correlation between China and Japan market are significant, the correlation between US and China market is not significant. We take a look only at the significant ones, the correlation between US and Japan market and correlation between China and Japan market are getting smaller after adjusted for exchange rate.

In Tables 10 and 11, in method 1, we can see that the correlations between Asia markets and the US market are getting bigger after being adjusted for exchange rate. The implication of these findings is that the markets now move together to a great extent, and the role of exchange rate in correlation with structure between the stock markets is more important than that of before the break. Also noted Asia markets are playing a more important role. The reasons for this may be that international market imperfection has been reduced during financial crisis period because of more communications and capital mobility among countries, combined with various additions of government authorities.

In method 2, the correlation between US and Japan market and correlation between China and Japan market and the correlation between US and China market are all significant. Comparing these with the results in pre-crisis period, for both local and dollar currency, the correlation between China and US market changes from insignificant to significant, which shows that China is now getting more important. And the numbers of correlation between US and Japan market and correlation between China and Japan market are getting larger after financial, which points to the conclusion that the financial markets are getting more closely linked after financial crisis.

In a word, we can see that after the financial crisis, China now is playing a more important role in world markets. China markets are linked much more with Japan market than that with US market before crisis; China market still links with Japan market, but the leakage from US market is getting more.

During the post-crisis period in method 1 and for both periods in method 2, after adjusted for exchange rate, the correlation became a little bit stronger. The international transmission of asset price movement would be increased by adding the exchange rate on stock prices. The relationship between stock price and exchange rate is not very obvious because China is a developing country; exchange rate is decided not only by the market, but more by the governance.

Chapter 7 Source of Structural Break

7.1 Stock-Watson Test

In Chapter 5, we have detected distinct breaks in volatility for data series of the 3 countries' stock returns. For simplicity, we set the breakpoint to be at 12/31/2008 to separate the data series into two sub-periods: pre-crisis period and post-crisis period as method 1. Or we set sub data from 01/01/2002-06/30/2008 to be pre-crisis period and sub data from 07/01/2009-12/31/2014 to be the post-crisis period as method 2. The main focus of this section is on whether the change of volatility pre and post the break points are associated with the shocks or the structure changes.

Stock and Watson (2002) introduced a model to discriminate changes between the coefficients or the variance in a VAR model. Their method relies on an assumption that changes may exist in the coefficients of the model and/or in the innovation variance. Assume X_t is a time series vector with the first and second sub-sample of i =1 and 2, and *L* as the usual lag operator. We can define

$$X_t = \phi_i(L)X_{t-1} + u_t,\ Var(u) = \Sigma_i \tag{24}$$

If there is no change in the coefficients, then $\phi_1(L) = \phi_2(L)$, while if there is no change in variance $\Sigma_1 = \Sigma_2$. Define $\beta_{i,j}$ as the j^th^ lag of $\beta_i(L) = [I - \phi_i(L)L]^{-1}$ where $\beta_i(L)$ is the moving average representation. The Stock – Watson test statistic is

$$\mathrm{var}(X_{kt}) = \left(\sum_{j=0}^{\infty} \beta_{ij}\Sigma_i\beta_{ij}^{'}\right)_{kk} = \sigma_k(\phi_i, \Sigma_i)^2 \tag{25}$$

Here $\sigma_{kij} = \sigma_k(\phi_i, \Sigma_j)$. $\boldsymbol{\sigma_{k11}}$ **and** $\boldsymbol{\sigma_{k22}}$ devote the variance that are supposed to estimate for the k^{th} series in the 1st and 2nd period, and $\boldsymbol{\sigma_{kij}}$, $\boldsymbol{i \neq j}$, denotes a counterfactual where the coefficients and variance stem from different periods. For example, σ_{k12} represents $\boldsymbol{\sigma}$ of X_k in the 1st period with error covariance matrix from the 2nd period, and vice versa. If $\sigma_{k11} = \sigma_{k12}$, $\sigma_{k21} = \sigma_{k22}$, $\sigma_{k11} \neq \sigma_{k21}$, and $\sigma_{k22} \neq \sigma_{k12}$ then the variances were the same but the coefficients changed. Otherwise, only the variance changed when $\boldsymbol{\sigma_{k11} \neq \sigma_{k12}, \sigma_{k21} \neq \sigma_{k22}}$, $\boldsymbol{\sigma_{k11} = \sigma_{k21}}$, **and** $\boldsymbol{\sigma_{k22} = \sigma_{k12}}$. If $\sigma_{k11} = \sigma_{k12}$, $\sigma_{k21} = \sigma_{k22}$, $\sigma_{k11} = \sigma_{k21}$, and $\sigma_{k22} = \sigma_{k12}$, then both were stable. In order to implement the Stock-Watson (2002) test statistic we must first decide on the lag length in $\phi_i(L)$. Next we must decide how many terms to calculate when we invert $[I - \phi_i(L)L]$ to form the moving average representation $\beta_i(L)$.

The statistic of interest is

$$T_{i,j}\_T_{k,l} = | \sigma_{i,j} - \sigma_{k,l} | \tag{26}$$

where $T_{i,i}\_T_{j,i}$ examines counterfactual structural change, and $T_{i,j}\_T_{i,i}$ assesses counterfactual shock change. A two period mode can be applied in the Stock-Watson procedure. In both modes of operation, we can test the single series AR(k) or VAR models.

In our case, the 3 variables VAR model has been estimated, here $X_t = \begin{pmatrix} USR_t \\ CNR_t \\ JAR_t \end{pmatrix}$ or $\begin{pmatrix} USRd_t \\ CNRd_t \\ JARd_t \end{pmatrix}$ detailed discussions of VAR models has been discussed in Chapter 6.

<u>7.2 Stock-Watson Test Results</u>

The lag used for local and dollar currency for method 1 is 2. Lag used for local currency for method 2 is 2, lag used for dollar currency for method 2 is 3. The results of Stock-Watson test are summarized below in Tables 12 and 13.

Table 12. Factual and Counter Factual Data for Stock-Watson Test in local currency

M1

	Factual		**Counter Factual**		**Difference by shock**		**Difference by structure**		**Difference by factual**
	σ_{11}	σ_{22}	σ_{12}	σ_{21}	$\|\sigma_{11}-\sigma_{12}\|$	$\|\sigma_{21}-\sigma_{22}\|$	$\|\sigma_{11}-\sigma_{21}\|$	$\|\sigma_{12}-\sigma_{22}\|$	$\|\sigma_{11}-\sigma_{22}\|$
USr	1.75E-4	1.27E-4	1.29E-4	1.72E-4	4.62E-5***	4.54E-5***	3.12E-6**	2.26E-6	4.85E-5***
CNr	2.97E-4	1.65E-4	1.63E-4	3.01E-4	1.35E-4***	1.35E-4***	3.57E-6	2.68E-6	1.32E-4***
JAr	2.31E-4	1.88E-4	1.80E-4	2.41E-4	5.06E-5***	5.32E-5***	1.06E-5	8.03E-6	4.25E-5**

M2

	Factual		**Counter Factual**		**Difference by shock**		**Difference by structure**		**Difference by factual**
	σ_{11}	σ_{22}	σ_{12}	σ_{21}	$\|\sigma_{11}-\sigma_{12}\|$	$\|\sigma_{21}-\sigma_{22}\|$	$\|\sigma_{11}-\sigma_{21}\|$	$\|\sigma_{12}-\sigma_{22}\|$	$\|\sigma_{11}-\sigma_{22}\|$
USr	1.024E-4	0.977E-4	0.97E-4	1.03E-4	0.50E-5	0.52E-5	0.43E-6	0.22E-6	0.47E-5
CNr	2.608E-4	1.526E-4	1.49E-4	2.65E-4	1.12E-4***	1.13E-4***	4.47E-6**	4.12E-6*	1.08E-4***
JAr	1.619E-4	1.723E-4	1.58E-4	1.79E-4	0.44E-5	0.62E-5	1.66E-5***	1.48E-5***	1.04E-5

*p<0.1; **p<0.05;***p<0.01

Table 13. Factual and Counter Factual Data for Stock-Watson Test in dollar currency

M1

	Factual		**Counter Factual**		**Difference by shock**		**Difference by structure**		**Difference by factual**
	σ_{11}	σ_{22}	σ_{12}	σ_{21}	$\lvert\sigma_{11}$-$\sigma_{12}\rvert$	$\lvert\sigma_{21}$-$\sigma_{22}\rvert$	$\lvert\sigma_{11}$-$\sigma_{21}\rvert$	$\lvert\sigma_{12}$-$\sigma_{22}\rvert$	$\lvert\sigma_{11}$-$\sigma_{22}\rvert$
USr	1.752E-4	1.268E-4	1.290E-4	1.721E-4	4.621E-5***	4.538E-5***	3.103E-6**	2.274E-6	4.849E-5***
CNrd	2.985E-4	1.673E-4	1.637E-4	3.033E-4	1.348E-4***	1.360E-4***	4.835E-6	3.625E-6	1.311E-4***
JArd	2.031E-4	1.514E-4	1.413E-4	2.169E-4	6.180E-5***	6.555E-5***	1.384E-5**	1.009E-5	5.171E-5***

M2

	Factual		**Counter Factual**		**Difference by shock**		**Difference by structure**		**Difference by factual**
	σ_{11}	σ_{22}	σ_{12}	σ_{21}	$\lvert\sigma_{11}$-$\sigma_{12}\rvert$	$\lvert\sigma_{21}$-$\sigma_{22}\rvert$	$\lvert\sigma_{11}$-$\sigma_{21}\rvert$	$\lvert\sigma_{12}$-$\sigma_{22}\rvert$	$\lvert\sigma_{11}$-$\sigma_{22}\rvert$
USr	1.024E-4	0.977E-4	0.965E-4	1.041E-4	0.594E-5	0.638E-5	1.673E-6**	1.228E-6	0.471E-5
CNrd	2.625E-4	1.549E-4	1.502E-4	2.679E-4	1.123E-4***	1.129E-4***	5.389E-6**	4.742E-6**	1.075E-4***
JArd	1.631E-4	1.385E-4	1.277E-4	1.777E-4	3.537E-5**	3.925E-5***	1.467E-5**	1.079E-5**	2.458E-5

*p<0.1; **p<0.05;***p<0.01

Let's discuss results of method 1 first.

In Table 12 M1. Here $X_t = \begin{pmatrix} USR_t \\ CNR_t \\ JAR_t \end{pmatrix}$. Take the USR (US market return) data series as an example, the factual variance for the first period is 1.75*e(-4), for the second period is 1.27*e(-4), and the difference is 4.85*e(-5), which is significant. The counterfactual variance which is the combination of first period dynamics and second period shock σ_{12} is 1.29*e(-4), another counterfactual variance which is the combination of second period dynamics and first period shocks σ_{21} is 1.72*e(-4). The structure change for the first period $|\sigma_{11}$-$\sigma_{21}|$ is 3.12*e(-6) for the first period which is significant at 5% level, and $|\sigma_{12}$-$\sigma_{22}|$ is 2.26*e(-6) for the second period which is not significant. If we now look at the shock change, that in the first period $|\sigma_{11}$-$\sigma_{12}|$ is 4.62*e(-5) and that for the second period $|\sigma_{21}$-$\sigma_{22}|$ is 4.54*e(-5). Both of the shock changes are significant at 1% level. Consequently, we may conclude that the volatility change in series USR (local currency) by the break point is mainly attributable to the shocks or impulses.

This would be clearer when we take a look at the China market return and Japan market return. The difference by factual is of course significant again. The differences by structure change for both periods of both series are not significant. However, the differences by shock change for both periods of both series are significant at 1% level, which implies that the volatility changes in series CNR and JAR (local currency) by the break point are mainly attributed to the shocks or impulses.

If we make a check on Table 13, which is the dollar currency data adjusted for exchange rate in the similar analysis, we would get the same conclusions as above.

Hence, based on the results from tables 12 & 13, it was an innovation change rather than the coefficient change to cause the volatility change for pre-crisis period and post-crisis period by the breakpoint.

The following graphs confirm our prior statements that it was mainly change in the variance in method 1.

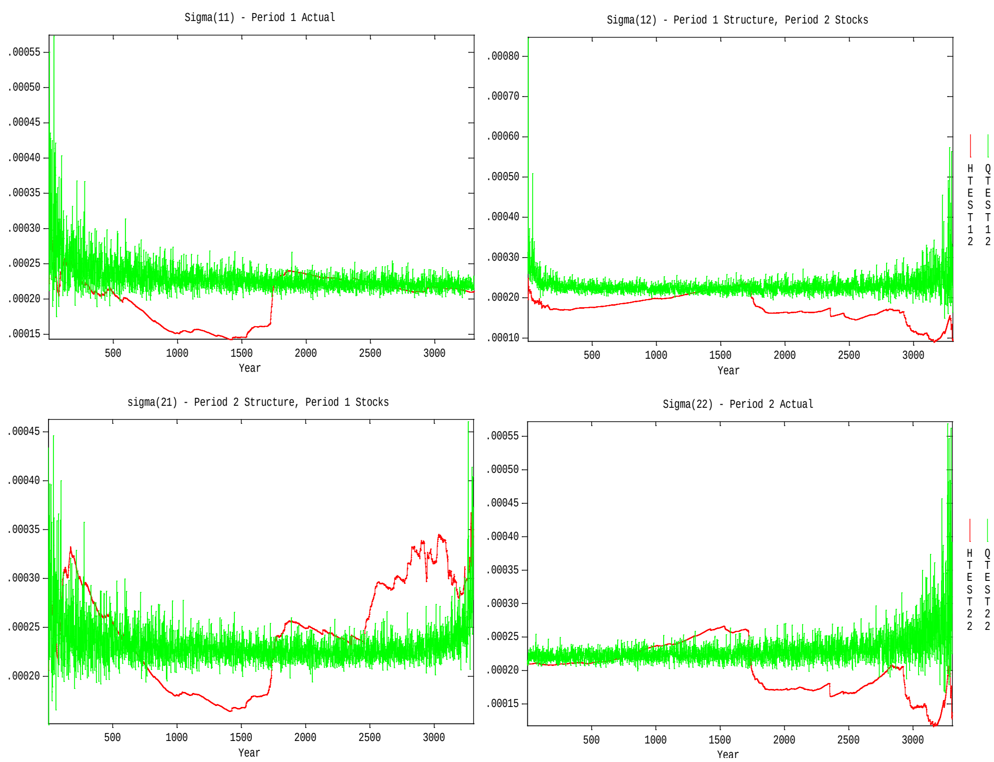


Figure 10. Stock-Watson Values and Critical Values for local currency

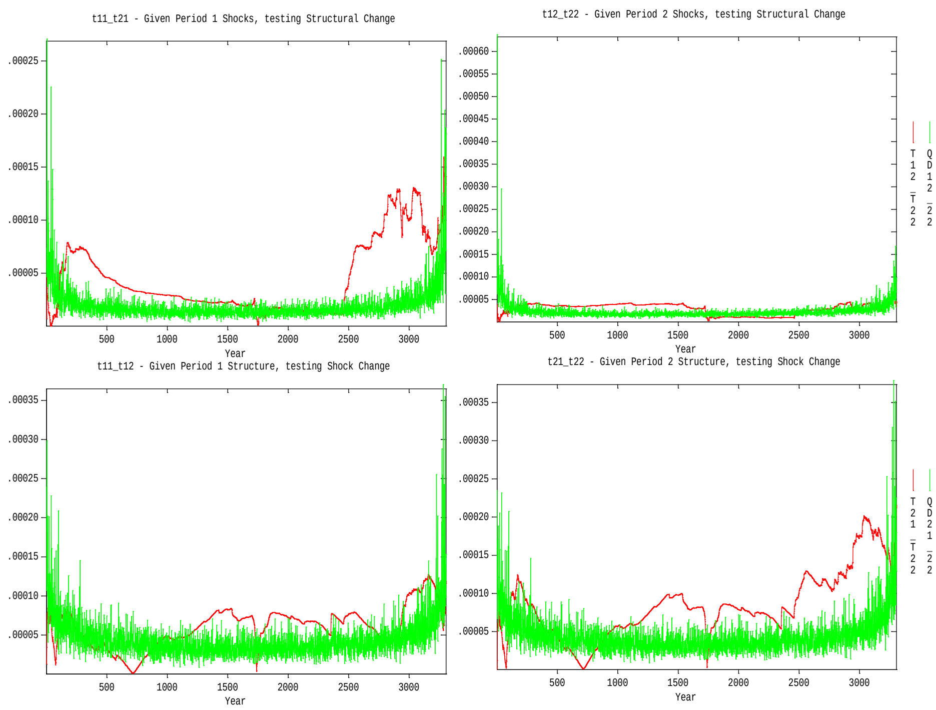


Figure 11. Factual and Counter Factual Data for local currency

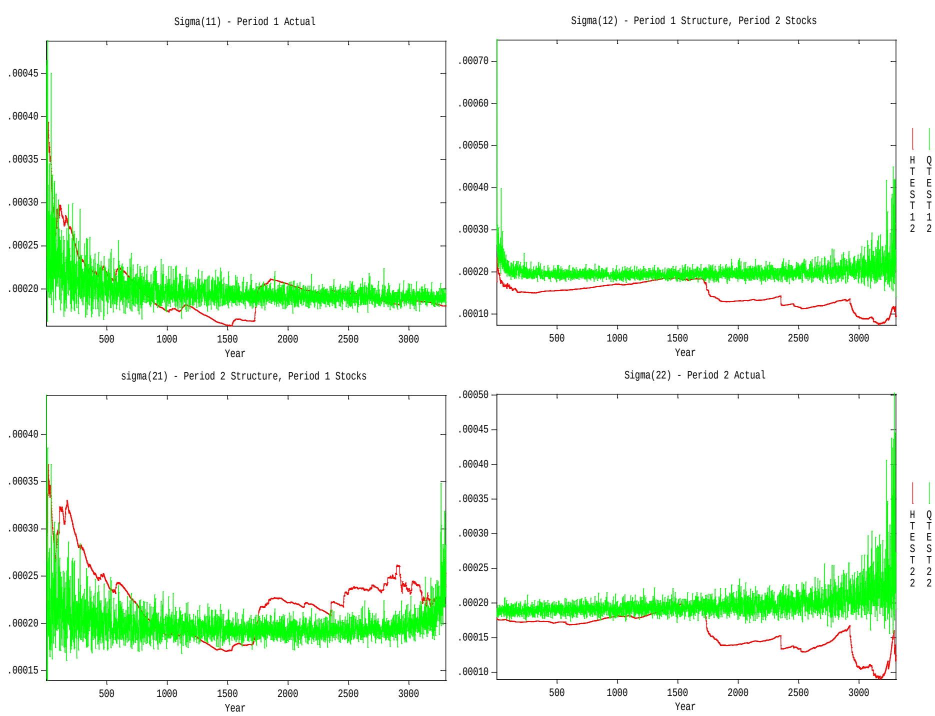


Figure 12. Stock-watson values and critical values for dollar currency

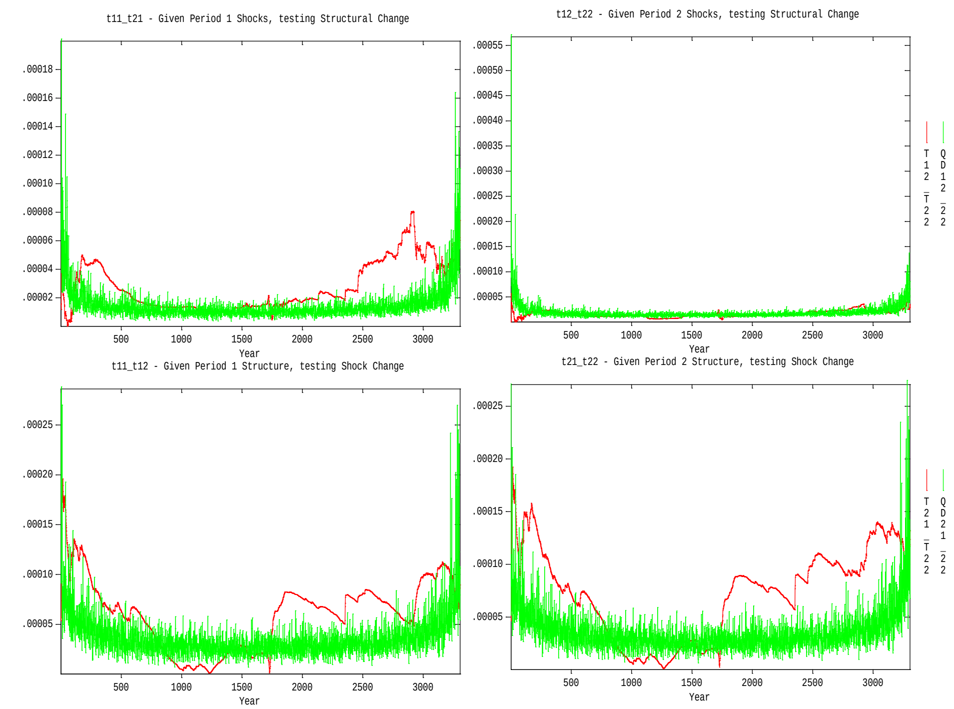


Figure 13. Factual and counter factual data for dollar currency

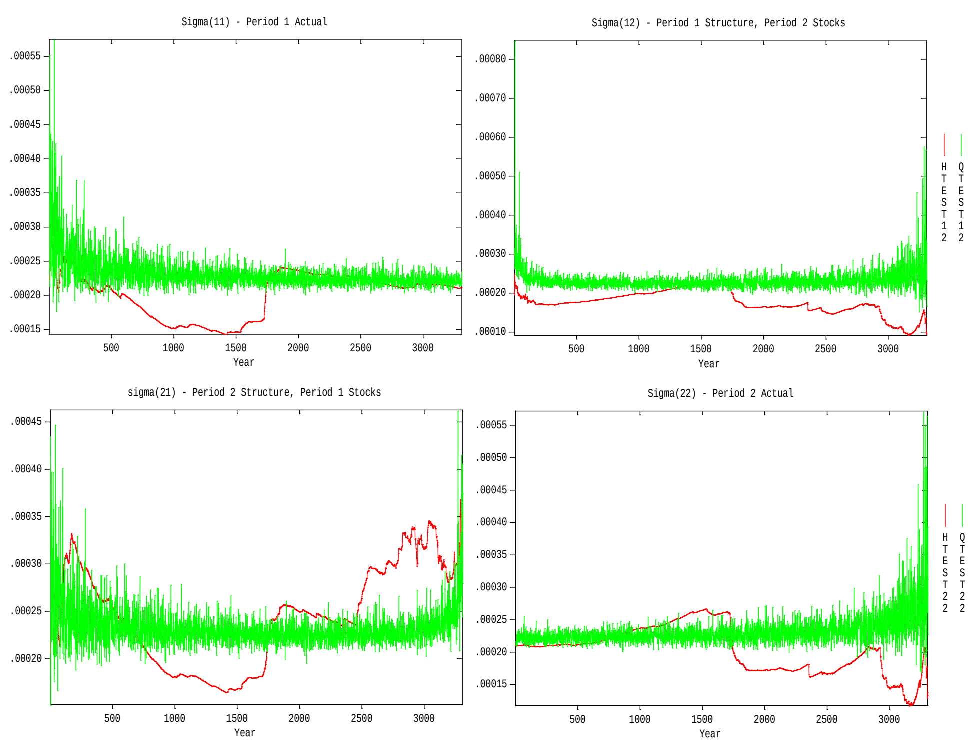


Figure 14. Stock-Watson Values and Critical Values for local currency

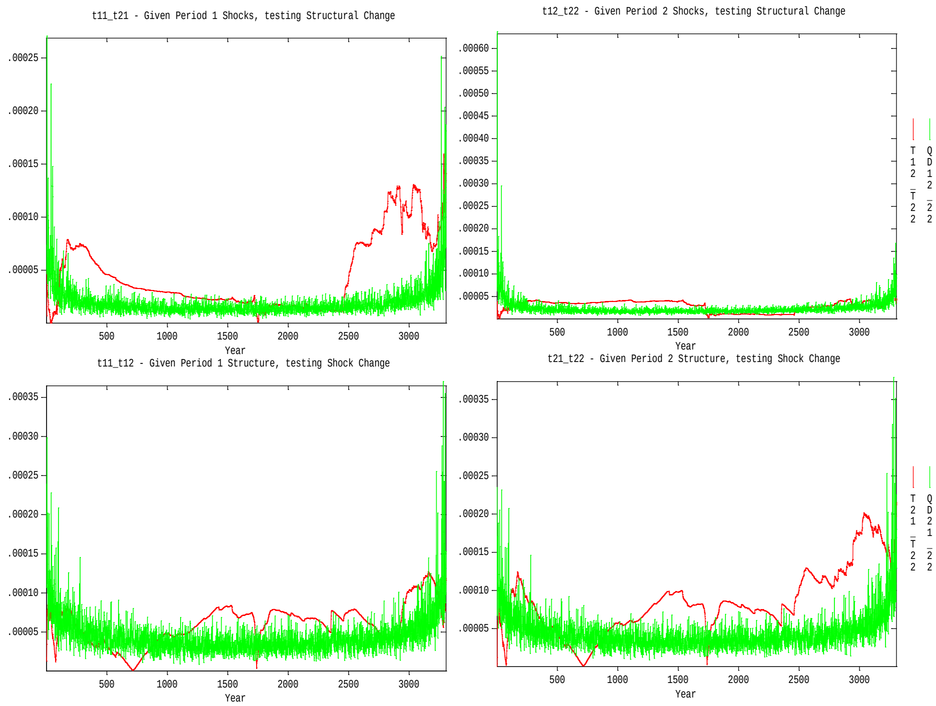


Figure 15. Factual and Counter Factual Data for local currency

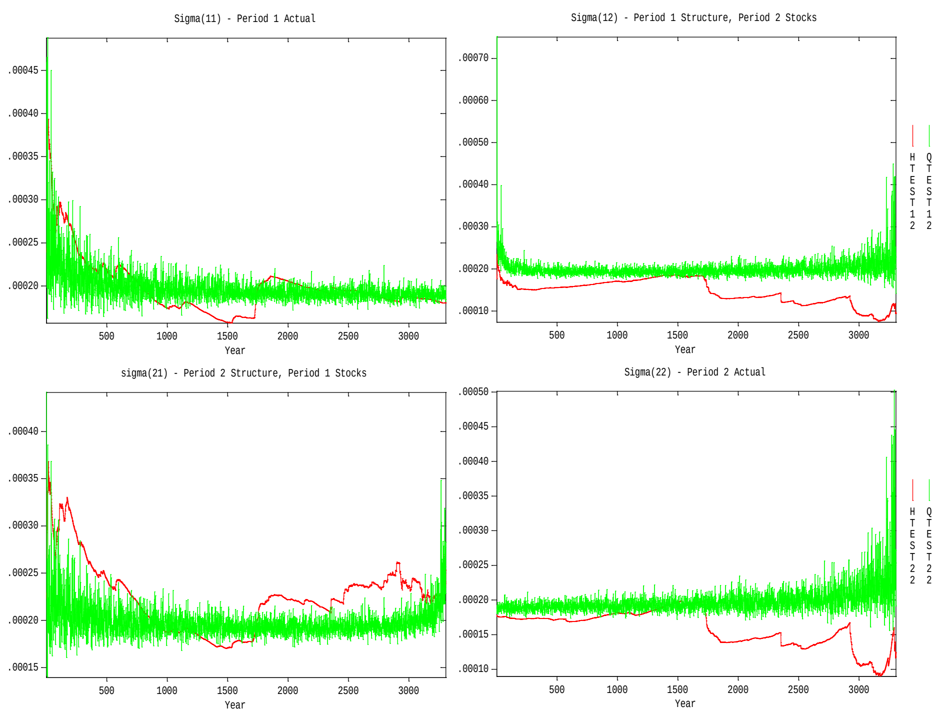


Figure 16. Stock-watson values and critical values for dollar currency

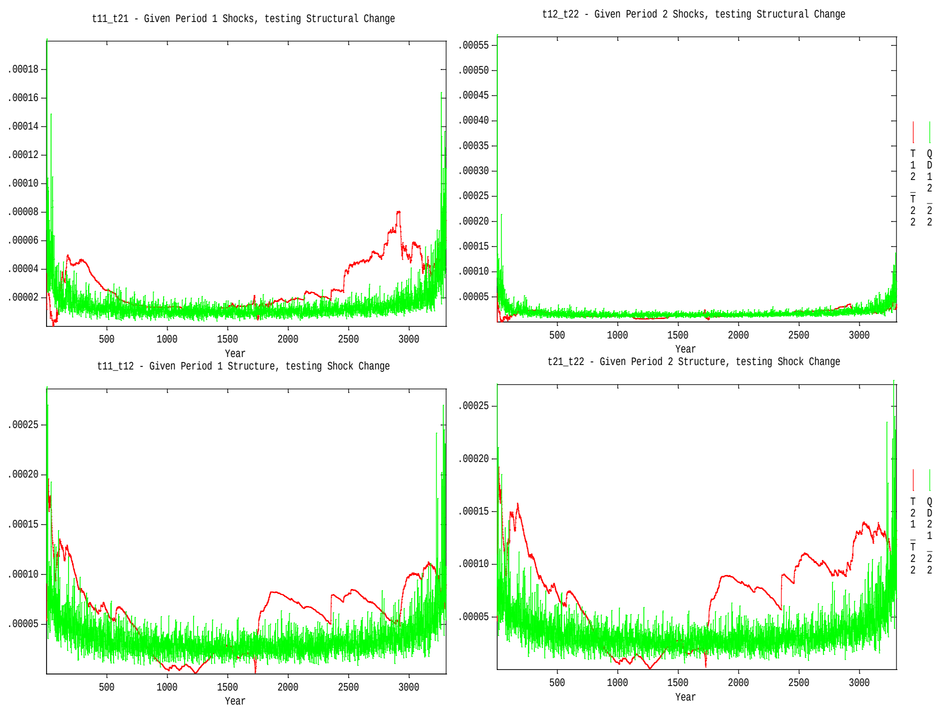


Figure 17. Factual and counter factual data for dollar currency

Then, let's talk about method 2. Actually, from Table 12 & Table 13 method 2, the differences by factual are not significant in both local and dollar currency, except for China market. This may suggest that there is no obvious structure breakpoint in the data series if we take out the unstable period from 07/01/2008-06/30/2009. So it may not make too much sense to talk about whether the differences of variances are by shock or by structure. This can also be supported by Figure 5. You can see from the plot that without considering the take out period, the plots look like a whole period now. The only exception is China.

In 1999, China introduced the Security Law and announced financial and structural reforms. In December 2001, China was admitted to the World Trade Organization (WTO). The country made some major commitments to open its financial markets. Two important ones are: (1) China would allow qualified domestic institutions to invest in foreign stock markets. (2) China would also list its state-owned large companies on foreign stock markets and also list foreign companies on its stock markets. These policies took into action at the end of 2006. Following these reforms, Li (2007) and Lin, Menkveld et al. (2009), and Moon and Yu (2010) found a structural break in the return series of stock market of China in 2005. They also revealed volatility spillovers, both symmetric and asymmetric, between USA and China stock markets after that break point.

CHAPTER 8. COINTEGRATION ANALYSIS

Granger (1981) first introduced the concept of cointegration. Originally, it was to solve the issue of so-called "spurious regression". In macroeconomics, it has been a common practice to estimate a model involving non-stationary variables by linear regression process for a long time. The problem is that even if the result suggests there be a statistically significant relationship between variables, there could be none existed due to the non-stationary of series. So the relationship indicated by the result might be well spurious. Granger's solution to this problem is to develop the concept of co-integration. Cointegration therefore describes whether or not two (or more) non-stationary series follow the same long-run trends by an equilibrium relationship. Equilibrium theories with non-stationary variables rely on a combination process of stationary variables (Watson (1994)). When a linear combination of non-stationary time series becomes stationary and invertible, it generally means cointegration. One of the most commonly employed procedures to test the existence of a co-integration relationship is the Engle and Granger two-step methodology.

Generally, long run equilibrium between series $x_{1t}, \cdots, x_{kt}$ implies

$$\beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_k x_{kt} = 0 \tag{27}$$

where $\beta = (\beta_1, \cdots, \beta_k)$ is the cointegrating vector. $X_t = (x_{1\,t}+, \cdots, +x_{k\,t})$. For long run equilibrium, the error $e_t = \beta X_t$ should be stationary. Cointegration indicates a linear combination of nonstationary series. Stock and Watson (1988) observed that cointegreated variables share common stochastic trends. The parameters of cointegrating vector must eliminate the trend from the linear combination. If they are cointegrated, the degree of variation from equilibrium will affect their time paths. That is, long run and short run interest rates should ultimately have associated trends of movement if they are cointegrated.

The analysis in this chapter is based on the separation of dataset using method 1.

8.1 Linear Cointegration Analysis

8.1.1 Johansen Cointegration Test

For our data series, we perform the ADF test; the results are shown in Table 14.

Table 14. ADF test results for both pre- and post-crisis.

	Pre-Crisis		**Post-Crisis**	
	ADF	p-value	ADF	p-value
US	0.2021	0.99	-2.6139	0.3184
USr	-11.8617	<0.01	-12.217	<0.01
CN	-0.9825	0.9416	-2.2302	0.4809
CNr	-11.0098	<0.01	-10.6412	<0.01
JA	-0.0937	0.99	-1.4302	0.8195
JAr	-11.3964	<0.01	-11.923	<0.01
CNd	-1.0139	0.9365	-2.1337	0.5217
CNrd	-11.0736	<0.001	-10.6868	<0.01
JAd	-0.6128	0.9767	-2.6936	0.2847
JArd	-11.6732	<0.01	-12.059	<0.01

Based on the above table, we can see that for both pre- and post-crisis, the stock price (whether adjusted for exchange rate or not) has a unit root, and the return (whether adjusted for exchange rate or not) does not have a unit root. So stock price series (both local currency or dollar currency) are I(1) series.

So we need cointegration analysis to test whether there is a long run equilibrium among those stock series.

One of the commonly used cointegration tests is the Engle-Granger two step test. But Enders (2004) mentioned that although the Engle-Granger procedure is convenient, there are two important defects. First, the procedure requires placing one variable on the left-hand side and using the others as regressors on the right-hand side. If three or more variables are used since any of the variables can be selected as the left-hand side variable, the result of the test will be different. Second, the coefficient is got by assessing a regression using the residuals from another one, so any error raised in step 1 is transmitted into step 2.

Johansen (1991) proposed a systems approach that is substantially more complex than the Engle-Granger two-step test.

Assume the vector of *M* variables in the VAR are contained in y_t and that the lag length has be set as ρ using the appropriate test. The first step is to estimate the level equation

$$y_t = \sum_{i=1}^{p} \Gamma_i y_{t-i} + u_t \tag{28}$$

Define

$$z_t = [\Delta y_{t-1}, \Delta y_{t-2}, ..., \Delta y_{t-p-1}] \tag{29}$$

For the *M* variables in *y* define

D= the residuals in the regression of Δy_t on z_t

E= the residuals in the regression of y_{t-p} on z_t

The M^2 squared canonical correlations between the columns in *D* and those in *E* can be shown to be the ordered characteristic roots (eigenvalues) of the symmetric matrix

$$R^{*} = R_{DD}^{-.5}\, R_{DE}\, R_{EE}^{-1}\, R_{ED}\, R_{DD}^{-.5} \tag{30}$$

where $R_{i,j}$ is the cross-correlation matrix between the variables in set i and set j.

The null hypothesis that there are *r* or fewer cointegrating vectors is tested using

$$\lambda(\text{trace}) = -N \sum_{i=r+1}^{M} \ln[1-(r_i^{*})^{2}] \tag{31}$$

where r_i^{*} is the ordered eigenvalue or squared canonical correlation. The statistic $\lambda(\text{maximum})$ can be used to test if there are any cointegrating vectors (*r=0)* against the hypothesis that there are indeed at least one cointegrating vector. Inspection of $\lambda(\text{trace})$ can be used to test how many cointegrating vectors.

A specific test was proposed by Davidson and MacKinnon (2004) who define

$$A \equiv \psi_{DD}^{'} \hat{\Sigma}_{DE} \hat{\Sigma}_{EE}^{-1} \hat{\Sigma}_{ED} \hat{\psi}_{DD} \tag{32}$$

where $\hat{\psi}_{DD}\hat{\psi}_{DD}^{'} = \Sigma_{DD}^{-1}$. Although $A \neq R^{*}$, the eigenvalues are the same. If these eigenvalues and their corresponding eigenvectors Ξ are reordered, then the first *r* columns of

$$Z = \hat{\psi}_{DD}\Xi \tag{33}$$

are the maximum likelihood estimates of $\hat{\eta}$ where from

$$\Delta y_t = x_t B + y_{t-1}\pi + \sum_{i=1}^{p} \Delta y_{t-i}\Gamma_i + u_t \tag{34}$$

$$\pi = \eta\alpha' \tag{35}$$

Note that y_t is a *N* by *k* matrix of data and x_t is a constant and or trend term that may or may not be in the model. Equation (21) is in error correction form. It can be reparametrized as

$$y_t = x_t B + \sum_{i=1}^{P+1} y_{t-i}\phi_i + u_t \tag{36}$$

Where $\Gamma_p = -\phi_{p+1}$, $\Gamma_i = \Gamma_{i+1} - \phi_{i+1}$ and $\pi = \sum_{i=1}^{p+1}\phi_i - I_k$

8.1.2 Johansen Cointegration Test Results

First, we need to choose lag orders for the VAR model of the raw index series.

Table 15. VAR Lag Selection Result for index data

Data Sets	AIC	HQ	SC	FPE
Pre-Crisis Local	6	3	2	6
Pre-Crisis Dollar	5	3	3	5
Post-Crisis Local	3	2	2	3
Post-Crisis Dollar	4	3	2	4

From Table 15, we can see different criteria will give different order selection number. Because the stock series itself is not stationary, we would prefer to a longer lag than a shorter lag. So we choose lag order=6 for pre-crisis local currency dataset; lag order=5 for pre-crisis dollar currency dataset; lag order=3 for post-crisis local currency dataset; lag order=4 for post-crisis dollar currency dataset.

For pre-crisis local series, the estimated eigenvalues are 9.623836e-03, 6.825142e-03, 8.714556e-04, and 1.301043e-18. And the test results of eigenvalue test and trace test are reported below:

Table 16. Values of Test Statistics and Critical Values of the Test for pre-crisis local currency

Rank	Test	10pct	5pct	1pct
r<=2	1.58/1.58	7.52/7.52	9.24/9.24	12.97/12.97
r<=1	12.41/13.99	13.75/17.85	15.67/19.96	20.20/24.60
r=0	17.52/31.51	19.77/32.00	22.00/34.91	26.81/41.07

*values on the top are eigenvalue test results, values on the bottom are trace test results
*rank r implies the number of linearly independent cointegration vectors

We can see from Table 16, both the eigenvalue test statistic and trace test statics fall in even 10% critical values, which implies there is no cointegration vectors found in the dataset. Therefore, no linear cointegration relationship is found among pre-crisis stock series SP500, China and Japan in their local currency.

Similar conclusions are also found in the other three datasets. The estimated eigenvalues for pre-crisis dollar currency are 7.496157e-03, 4.589300e-03, 1.223201e-03, and 1.267771e-18. The estimated eigenvalues for post-crisis local currency are 7.725443e-03, 2.528586e-03, 1.177877e-03, -9.953344e-19. The estimated eigenvalues for post-crisis dollar currency are 7.263065e-03, 5.421693e-03, 9.493180e-04, -5.832928e-18.

We can see from Tables 17 - 19, for all the rest three datasets, both the eigenvalue test statistic and trace test statics fall in even 10% critical values, which implies there is no cointegration vectors found in the datasets. Therefore, no linear cointegration relationship is found among pre-crisis stock series SP500, China and Japan in their dollar currency; no linear cointegration relationship is found among post-crisis stock series SP500, China and Japan in local currency; no linear cointegration relationship is found among post-crisis stock series SP500, China and Japan in dollar currency.

Table 17. Values of Test Statistics and Critical Values of the Test for pre-crisis dollar currency

Rank	Test	10pct	5pct	1pct
r<=2	2.22/2.22	7.52/7.52	9.24/9.24	12.97/12.97
r<=1	8.34/10.56	13.75/17.85	15.67/19.96	20.20/24.60
r=0	13.64/24.20	19.77/32.00	22.00/34.91	26.81/41.07

*values on the top are eigenvalue test results, values on the bottom are trace test results
*rank r implies the number of linearly independent cointegration vectors

Table 18. Values of Test Statistics and Critical Values of the Test for post-crisis local currency

Rank	Test	10pct	5pct	1pct
r<=2	1.84/1.84	7.52/7.52	9.24/9.24	12.97/12.97
r<=1	3.96/5.81	13.75/17.85	15.67/19.96	20.20/24.60
r=0	12.14/17.94	19.77/32.00	22.00/34.91	26.81/41.07

*values on the top are eigenvalue test results, values on the bottom are trace test results
*rank r implies the number of linearly independent cointegration vectors

Table 19. Values of Test Statistics and Critical Values of the Test for post-crisis dollar currency

Rank	Test	10pct	5pct	1pct
r<=2	1.49/1.49	7.52/7.52	9.24/9.24	12.97/12.97
r<=1	8.50/9.99	13.75/17.85	15.67/19.96	20.20/24.60
r=0	11.40/21.39	19.77/32.00	22.00/34.91	26.81/41.07

*values on the top are eigenvalue test results, values on the bottom are trace test results
*rank r implies the number of linearly independent cointegration vectors

8.2 Nonlinear Cointegration Analysis

In the previous section, we found out that there is no linear cointegration relationship among the three national stock market index. But does that mean there is no common trend in the three national stock market index data? We will answer this question by looking into the nonlinear cointegration relationship of the data series in this section.

In Johansen methodology we discussed, cointegration refers to a linear combination of non-stationary variables $z_t = x_t - Ay_t$ that is stationary. Actually, in many macroeconomic and financial situations, a linear relationship is not found in non-stationary contexts, but it is possible that a nonlinear long-run equilibrium exists among the integrated variables, even if the variables are not linearly cointegrated. Michael, Nobay et al. (1997) used nonlinear error-correction in the residuals from linear cointegration to capture the deviations from **purchasing power parity** (PPP). The nonlinear adjustment process was characterized in terms of an exponential smooth transition autoregressive (ESTAR) model, and concluded that the failure to get co-integration from a linear model does not necessarily refute long-run PPP.

In the linear case, if x_t, y_t are $I(1)$ and there exists a linear combination $z_t = x_t - Ay_t$ which is I(0), the line $x = Ay$ can be thought of an attractor. In the nonlinear case, if x_t, y_t are not linearly cointegrated, but we have $q_t = g(x_t) - h(y_t) \sim I(0)$, we define $A = (x; y : g(x) = h(y) \text{ or } f(x; y) = 0)$, then A is a nonlinear attractor for x_t and y_t.

Hence, Granger and Hallman (1991) proposed generalizations extended to nonlinear co-integration. X and Y are nonlinearly cointegrated if the linear combination of nonlinearly transformed variables $z_t = g(x) - Ah(y)$ is short memory in mean. Granger and Hallman (1991) also defined the variable that is short memory / long memory in mean. Given information It at time t, if the conditional mean of a variable x at time $t + h$, $E(x_{t+h} \mid I_t)$ converges to a constant, when $h \to \infty$, then we say the variable x is short memory in mean (SMM). If $E(x_{t+h} \mid I_t)$ depends on It for all h, variable x is long memory in mean (LMM). In long memory series, the shocks have persistent effects.

8.2.1 ACE Cointegration Test

Suppose two series have no linear co-integration, but there exists a nonlinear attractor, then it can be considered as a nonlinear co-integration. ACE transformation is widely used in building nonlinear models. ACE algorithm also provides a practical estimation to obtain the nonlinear attractor if there is no existing information on the shape of a possible attractor.

The Alternating Conditional Expectations (ACE) model proposed by Breiman and Friedman (1985) smooths both the left hand side and the right hand sides and is an alternative to the GAM model. The ACE model is written as $\Theta(y) = \alpha_0 + \sum_{j=1}^{k} a_j(x_j)$, where $\alpha_j(.)$ is the unknown smooth function. The ACE algorithm minimizes the squared error $E\{\Theta(y) - \alpha_0 - \sum_{j=1}^{k} \alpha_j(x_j)\}^2$ subject to $\mathrm{var}\{\Theta(y)\} = 1$. The steps of the ACE algorithm are:

(i) Initialize by setting $\Theta(y) = \{y - E(y)\}/\{\mathrm{var}(y)\}^{.5}$

(ii) Fit an additive model to $\Theta(y)$ that will obtain new functions $\alpha_1(x_1),...,\alpha_k(x_k)$.

(iii) Compute $\hat{\Theta}(y) = E\{\sum_j \alpha_j(x_j) \mid y\}$ and update the left hand side by forming $\Theta(y) = \hat{\Theta}(y) / [\mathrm{var}\{\hat{\Theta}(y)\}]^{.5}$.

(iv) Alternate: steps (ii) and (iii) until $E\{\Theta(y) - \alpha_0 - \sum_j \alpha_j(x_j)\}^2$ does not change.

Step (ii) can be thought of as for a fixed θ, the minimizing $\alpha_i(x_i)$ is $\alpha(X) = E\{\theta(y) \mid X\}$ while step (iii) can be thought of as for fixed $\alpha(\,)$, the minimizing θ is $\theta(y) = E\{\alpha(X) \mid y\}$.

In our three national stock market index data series case, according to Granger's generalization of nonlinear co-integration, if the residual of transformed series x, y, z, $q_t = g(x_t) - h(y_t) - t(z_t) \sim I(0)$, then we say x and y are non-linearly cointegrated.

8.2.2 ACE Cointegration Analyses Results

Since we already identified that US leads Asia markets in both pre-crisis and post-crisis period, I am considering US, Japan, China index series in the following 8 models:

Pre-Crisis Period:

Model 1: cn~us+ja; Model 2: ja~us+cn; Model 3: cnd~us+jad; Model 4: jad~us+cnd

Post-Crisis Period:

Model 5: cn~us+ja; Model 6: ja~us+cn; Model 7: cnd~us+jad; Model 8: jad~us+cnd

Figures of the ACE transformation of the 8 models are reported in Appendix D. Those figures clearly show strong evidence of nonlinearity for all the three transformed series in all 8 models, because no plots are even close to straight lines. There will be more discussions on the nonlinearity of the data in Chapter 9.

Table 20 shows the adjusted R square values for the linear model and ACE transformation model for all the 8 models. It can be clearly observed that all the adjusted R-squared of ACE model are superior to the linear model. This suggests that the ACE transformation offers a much better fit than the linear model, which is a strong support for the necessity of the ACE transformation.

Table 20. Comparison of Adjusted R-squared value for liner model and ACE Transformation

	Pre-Crisis				Post-Crisis			
Model	1	2	3	4	5	6	7	8
Linear	0.4652	0.8475	0.4481	0.8685	0.3033	0.7929	0.2173	0.8837
ACE	0.9004	0.9434	0.8619	0.945	0.8877	0.9845	0.7846	0.9759

The residuals of the corresponding 8 models we discussed can be seen as follows:

For pre-crisis period:

$q_{1t} = g(cn_t) - h(us_t) - t(ja_t)$, $\qquad q_{2t} = g(ja_t) - h(us_t) - t(cn_t)$

$q_{3t} = g(cnd_t) - h(us_t) - t(jad_t)$, $\qquad q_{4t} = g(jad_t) - h(us_t) - t(cnd_t)$

For post-crisis period:

$q_{5t} = g(cn_t) - h(us_t) - t(ja_t)$, $\qquad q_{6t} = g(ja_t) - h(us_t) - t(cn_t)$

$q_{7t} = g(cnd_t) - h(us_t) - t(jad_t)$, $\qquad q_{8t} = g(jad_t) - h(us_t) - t(cnd_t)$

Table 21 shows the ADF test statistics of the above 8 residuals series of the models

Table 21. ADF Test Statistics for Transformed Residual Series

	Pre-Crisis				Post-Crisis			
	q_{1t}	q_{2t}	q_{3t}	q_{4t}	q_{5t}	q_{6t}	q_{7t}	q_{8t}
ADF	-5.6072	-5.091	-5.2123	-5.0359	-6.1848	-6.6409	-5.3253	-6.5033
Significance	***	***	***	***	***	***	***	***

*p<0.1; **p<0.05;***p<0.01

All the test statistics are significant at 1% level, which is enough evidence of saying all the residuals, q_{1t} , q_{2t} , q_{3t} , q_{4t} , q_{5t} , q_{6t} , q_{7t} , q_{8t} are I(0). Thus, we can conclude that the nonlinear transformations of all the three national stock series in the 8 models are short memories.

Here we can also define the nonlinear attractors for the series of the 8 models as follows:

For pre-crisis period:

$$A_1 = (cn, us, ja : g(cn) = h(us) = t(ja)), \quad A_2 = (ja, us, cn : g(ja) = h(us) = t(cn))$$

$$A_3 = (cnd, us, jad : g(cnd) = h(us) = t(jad)), \quad A_4 = (jad, us, cnd : g(jad) = h(us) = t(cnd))$$

For post-crisis period:

$$A_5 = (cn, us, ja : g(cn) = h(us) = t(ja)), \quad A_6 = (ja, us, cn : g(ja) = h(us) = t(cn))$$

$$A_7 = (cnd, us, jad : g(cnd) = h(us) = t(jad)), \quad A_8 = (jad, us, cnd : g(jad) = h(us) = t(cnd))$$

Although we found no linear co-integration relationship among stock indices of US, Japan and China markets in previous section, it doesn't mean there is no common trend among those series. After transforming the data series using ACE algorithm, we found out that the residuals of the transformed series are stationary, and the nonlinear attractors were also established.

According to the generalizations of Granger's nonlinear co-integration relationship, we can conclude the data series US stock market index, China stock market index, Japan stock market index are said to be co-integrated nonlinearly, thus have a common nonlinear long term trend for in both pre-crisis and post-crisis period no matter the order of the series.

CHAPTER 9. CONCLUSION AND FUTURE WORK

9.1 Conclusion

Overall, my PhD research focuses on the information transmission and price dynamics among stock markets' movement between US and Asia markets (China and Japan). Especially, I pay attention to the structural change of 2008 financial crisis period. I identify the lead-lag relationship between US stock market and Asia markets. The co-movement is stronger after crisis. In the long run US lead Asian markets, and there is a nonlinear common trend for US and China and Japan markets. But China is getting to play a more important role in the world markets after financial crisis. And the international economy is getting more closely linked after financial crisis. Furthermore, I examine the role of exchange rate and stock indices, the exchange rate can explain part of the dynamic relationship in the data. During my research, I used statistical methods such as Recursive Residuals and Stock-Watson Test, VAR model and Granger-Causality Test and co-integration analysis, etc. The results suggest possible unexploited arbitrage and profit opportunities in international portfolios. In addition, these findings can potentially help predict the 2015 Chinese stock market crash and its relationship with US markets.

9.2 Future Work

(1) Nonlinear Model

Linear modeling methods, e.g., VAR and OLS, require normally distributed values of the error term (Neuburger and Stokes (1991)). It is important for us to check the residuals of these models to see if the residual series violate the assumptions. If residuals of the VAR model of stock returns display nonlinearity, we may use some nonlinear models to decrease the residual sum of squares and the nonlinearity in stock return series. By doing so, we may get a more precise result of our analysis. If the normality assumption is violated, the model specification often has problems. Therefore, after (before) using linear modeling methods like VAR or OLS, it is necessary to verify that the behavior of model residual is linear, or close to linear. The Hinich test is used to find that there is evidence of nonlinearity and non-normality in stock return series. It can reveal whether x_t, x_{t-k}, and x_{t-j} are mutually interrelated for $k \neq j$. In contrast, autocorrelation examines only x_t and x_{t-k}.

The problem arising in our model was whether the expected value of residual (e) of the VAR model in a day (t) is related to the expected value of residual of the model for any previous days.

The Hinich test results for Gaussianity (G) and for linearity (L) are reported below in Table 22. Here we reported an average of G and L. The statistical results are normally distributed; if G or L is ≥ 2, we can discard the hypothesis of linearity at the 95% level, which implies there is persistence in the series.

All the numbers in Table 22 are much greater than 2, which implies that the normality and linearity are all rejected for the 4 different datasets. This suggests that the return rates for the stock indices are not independent and linear and it is possible to improve the model fit by using nonlinear method.

Table 22. Summary of Gaussianity and Linearity Test Results

	M1	
	G	**L**
preUSR	146.22	45.53
preCNR	21.90	7.79
preJAR	76.37	22.91

preUSRd	146.37	45.36
preCNRd	21.37	7.78
preJARd	42.39	12.59
postUSR	46.14	13.32
postCNR	20.11	7.51
postJAR	24.66	8.51
postUSRd	47.17	13.00
postCNRd	19.77	7.32
postJARd	28.89	10.68

	M2	
	G	**L**
preUSR	48.42	14.06
preCNR	20.69	7.28
preJAR	12.88	7.21
preUSRd	47.45	12.81
preCNRd	21.08	8.38
preJARd	9.99	5.86
postUSR	39.14	11.79
postCNR	19.96	8.56
postJAR	27.79	9.21
postUSRd	39.27	12.12
postCNRd	19.45	8.31
postJARd	36.08	11.15

The finding from the Hinich test on residuals of the VAR model suggest that residuals of the international co-movement model are generated by a nonlinear process. Thus, it is very necessary that we try to investigate nonlinear models of international stock returns to refine my results.

Possible methodologies for the nonlinear regression modeling are Multivariate Adaptive Regression Splines (MARS), Generalized Additive Model (GAM), Projection Pursuit (PPreg) and Random Forest, etc.

(2) In addition to that, my thesis topic also has more expansions. Since I already have identified that US lead Asian markets, then how well can lagged US-returns predict excess returns in those

Asian countries, especially comparing to the economic variables of each country, such as dividend yields and lagged nominal interest rates. That’s one part I want to dig into more.

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APPENDIX A. ADF TEST RESULTS

Table A.1 ADF Test Result of Stock Index Price in their local and dollar currency

	ADF	p-value
US	-0.9367	0.949
CN	-1.8097	0.6589
JA	-1.2671	0.8886
CNd	-1.8068	0.6601
JAd	-2.2679	0.4649

Table A.2 ADF Test Result of Stock Returns in their local and dollar currency

	ADF	p-value
USR	-15.1445	<0.01
CNR	-12.9928	<0.01
JAR	-14.5072	<0.01
CNRd	-13.0658	<0.01
JPRd	-14.7884	<0.01

APPENDIX B. TIMELINE OF THE GLOBAL ECONOMIC & FINANCIAL CRISIS*

September 4, 2007 The rate at which banks lend to each other rises to its highest level since December 1998.

December 17, 2007 The central banks continue to make more funding available

March 16, 2008 —March 17, 2008 JP Morgan Agrees To Buy Bear Stearns for $2 a Share

September 7, 2008 The Government Takes Control of Fannie Mae and Freddie Mac

September 14, 2008 Merrill Lynch Sold to Bank of America

September 15, 2008 Lehman Brothers Files for Bankruptcy

September 29, 2008 House Rejects Bailout Plan; Dow Plunges 788 Points

October 3, 2008 Banks Get Bailout: TARP Passed

October 8, 2008 NY Fed Bails Out AIG, Twice

October 12, 2008 Wells Fargo Acquires Wachovia

December 11, 2008 The Federal Government Declares the Economy is in a Recession

February 17, 2009 President Obama Signs American Recovery and Reinvestment Act of 2009

February 18, 2009 Obama Announces Homeowner Affordability and Stability Plan

June 9, 2009 Big Banks Repay Bailout Funds

December 11, 2009 Citigroup and Wells Fargo Put Plans in Place for Repayment

April 16, 2010 SEC Sues Goldman Sachs

July 21, 2010 Obama Signs Overhaul of Financial System

August 5, 2011 S&P Downgrades US Credit Rating to AA-Plus

January 2, 2013 Bill Passed by Congress to Avert US ‘Fiscal Cliff’

March 1, 2013 AIG Makes Final Repayment to Government for Bailout

*For the detailed timeline, see: Guillén, Mauro. "The global economic & financial crisis: A timeline." *The Lauder Institute, University of Pennsylvania* (2009).

APPENDIX C. VAR LAG SELECTION INFORMATION CRITERIA

Table C.1 Information Criteria for Pre-Crisis Local Currency

M1

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-25.5494	-25.5722	-25.5781	-25.5827	-25.5867	-25.5897
HQ(n)	-25.5359	**-25.5486***	-25.5444	-25.5389	-25.5328	-25.5256
SC(n)	**-25.5129***	-25.5083	-25.4868	-25.464	-25.4406	-25.4161
FPE(n)	8.02E-12	7.84E-12	7.79E-12	7.75E-12	7.72E-12	7.70E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-25.5871	**-25.5946***	-25.5908	-25.5858	-25.5855	-25.5832
HQ(n)	-25.5130	-25.5103	-25.4964	-25.4813	-25.4709	-25.4584
SC(n)	-25.3862	-25.3663	-25.335	-25.3026	-25.2749	-25.2452
FPE(n)	7.72E-12	**7.66E-12***	7.69E-12	7.73E-12	7.73E-12	7.75E-12

M2

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	**-26.4231***	-26.4216	-26.4176	-26.4212	-26.4187	-26.4163
HQ(n)	**-26.4088***	-26.3965	-26.3817	-26.3745	-26.3613	-26.3481
SC(n)	**-26.3842***	-26.3538	-26.3207	-26.2952	-26.2636	-26.2322
FPE(n)	**3.34E-12***	3.35E-12	3.36E-12	3.35E-12	3.36E-12	3.36E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-26.4089	-26.4096	-26.4072	-26.4002	-26.4000	-26.3925
HQ(n)	-26.3299	-26.3199	-26.3067	-26.2889	-26.2780	-26.2597
SC(n)	-26.1957	-26.1674	-26.1359	-26.0998	-26.0706	-26.0340
FPE(n)	3.39E-12	3.39E-12	3.39E-12	3.42E-12	3.42E-12	3.45E-12

*indicates the smallest number in the series

Table C.2 Information Criteria for Pre-Crisis Dollar Currency

M1

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-25.5308	-25.5628	-25.5654	-25.57	-25.5717	-25.572
HQ(n)	-25.5173	**-25.5392***	-25.5317	-25.5262	-25.5178	-25.5079
SC(n)	-25.4942	**-25.4988***	-25.4741	-25.4513	-25.4256	-25.3984
FPE(n)	8.17E-12	7.91E-12	7.89E-12	7.85E-12	7.84E-12	7.84E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-25.5693	**-25.5766***	-25.571	-25.5673	-25.5661	-25.56
HQ(n)	-25.4952	-25.4923	-25.4766	-25.4628	-25.4515	-25.4353
SC(n)	-25.3684	-25.3482	-25.3153	-25.2841	-25.2556	-25.2221
FPE(n)	7.86E-12	**7.80E-12***	7.85E-12	7.88E-12	7.88E-12	7.93E-12

M2

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-26.3249	-26.3256	-26.3220	**-26.3262***	-26.3220	-26.3178
HQ(n)	**-26.3105***	-26.3005	-26.2861	-26.2796	-26.2646	-26.2496
SC(n)	**-26.2861***	-26.2578	-26.2251	-26.2003	-26.1670	-26.1336
FPE(n)	3.69E-12	3.68E-12	3.70E-12	**3.68E-12***	3.70E-12	3.71E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-26.3116	-26.3107	-26.3050	-26.2988	-26.2983	-26.2899
HQ(n)	-26.2326	-26.2210	-26.2045	-26.1875	-26.1763	-26.1571
SC(n)	-26.0984	-26.0685	-26.0336	-25.9984	-25.9688	-25.9314
FPE(n)	3.74E-12	3.74E-12	3.76E-12	3.78E-12	3.79E-12	3.82E-12

*indicates the smallest number in the series

Table C.3 Information Criteria for Post-Crisis Local Currency

M1

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-26.71772	**-26.72288***	-26.7201	-26.71482	-26.70911	-26.70577
HQ(n)	**-26.70237***	-26.69601	-26.68172	-26.66493	-26.64771	-26.63285
SC(n)	**-26.67644***	-26.65064	-26.6169	-26.58065	-26.54399	-26.50969
FPE(n)	2.49254E-12	**2.47972E-12***	2.48662E-12	2.49979E-12	2.5141E-12	2.52251E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-26.70529	-26.70182	-26.69954	-26.69961	-26.70595	-26.69937
HQ(n)	-26.62086	-26.60588	-26.59209	-26.58064	-26.57547	-26.55737
SC(n)	-26.47825	-26.44382	-26.41058	-26.37969	-26.35507	-26.31753
FPE(n)	2.52373E-12	2.53251E-12	2.53829E-12	2.53813E-12	2.5221E-12	2.53877E-12

M2

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-27.08835	-27.09574	**-27.09891***	-27.08938	-27.08486	-27.07875
HQ(n)	**-27.07176***	-27.0667	-27.05744	-27.03546	-27.0185	-26.99995
SC(n)	**-27.04394***	-27.01801	-26.98788	-26.94504	-26.90722	-26.86779
FPE(n)	1.72059E-12	1.70794E-12	**1.70252E-12***	1.71883E-12	1.72661E-12	1.7372E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-27.07388	-27.07331	-27.07312	-27.07265	-27.07814	-27.06952
HQ(n)	-26.98263	-26.96963	-26.95699	-26.94408	-26.93713	-26.91606
SC(n)	-26.82961	-26.79574	-26.76224	-26.72846	-26.70064	-26.65871
FPE(n)	1.74569E-12	1.74669E-12	1.74702E-12	1.74786E-12	1.7383E-12	1.75336E-12

*indicates the smallest number in the series

Table C.4 Information Criteria for Post-Crisis Dollar Currency

M1

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-26.85592	-26.87464	**-26.88124***	-26.88046	-26.8756	-26.87182
HQ(n)	-26.84057	**-26.84778***	-26.84286	-26.83057	-26.81419	-26.79891
SC(n)	**-26.81464***	-26.8024	-26.77804	-26.7463	-26.71047	-26.67574
FPE(n)	2.17081E-12	2.13055E-12	**2.11654E-12***	2.11819E-12	2.12852E-12	2.13657E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-26.87737	-26.87558	-26.87269	-26.87379	-26.87752	-26.87187
HQ(n)	-26.79294	-26.77964	-26.76524	-26.75482	-26.74704	-26.72988
SC(n)	-26.65033	-26.61758	-26.58373	-26.55387	-26.52664	-26.49003
FPE(n)	2.12475E-12	2.12857E-12	2.13473E-12	2.13239E-12	2.12447E-12	2.13651E-12

M2

	1	**2**	**3**	**4**	**5**	**6**
AIC(n)	-27.24152	-27.2611	**-27.26872***	-27.26405	-27.26027	-27.25368
HQ(n)	-27.22493	**-27.23207***	-27.22724	-27.21014	-27.19391	-27.17488
SC(n)	**-27.19711***	-27.18338	-27.15769	-27.11971	-27.08262	-27.04272
FPE(n)	1.47624E-12	1.44762E-12	**1.43664E-12***	1.44336E-12	1.44883E-12	1.45841E-12
	7	**8**	**9**	**10**	**11**	**12**
AIC(n)	-27.25196	-27.25236	-27.25187	-27.25183	-27.25596	-27.24993
HQ(n)	-27.16072	-27.14867	-27.13574	-27.12326	-27.11495	-27.09647
SC(n)	-27.0077	-26.97479	-26.94098	-26.90763	-26.87846	-26.83912
FPE(n)	1.46092E-12	1.46034E-12	1.46107E-12	1.46114E-12	1.45512E-12	1.46394E-12

*indicates the smallest number in the series

APPENDIX D. VMA COEFFICIENTS FOR IMPULSE RESPONSE FUNCTION

Table D.1 For pre-crisis local currency: M1

$preusr

Lag	prejar	precnr
[1]	0	1.00617E-6
[2]	0.00779	0.00214
[3]	-2.19667E-4	1.91205E-4
[4]	-0.00102	-3.8244E-4
[5]	8.0261E-5	8.47895E-6
[6]	9.4974E-5	3.67481E-5
[7]	-5.68E-6	-4.36015E-7
[8]	-9.94159E-6	-3.6928E-6
[9]	3.20119E-7	-7.28885E-8
[10]	1.08287E-6	3.98E-7
[11]	-1.79912E-8	1.44327E-8

$precnr

Lag	prejar	preusr
[1]	0	0
[2]	-6.63319E-4	-1.81773E-4
[3]	2.79126E-4	-3.82395E-4
[4]	-2.76285E-4	6.86343E-5
[5]	2.24396E-5	3.4275E-5
[6]	2.94638E-5	-6.11358E-6
[7]	-3.4265E-6	-3.48625E-6
[8]	-2.71839E-6	4.8878E-7
[9]	2.32527E-7	3.95002E-7
[10]	2.97798E-7	-4.61906E-8
[11]	-1.77654E-8	-4.29561E-8

$prejar

Lag	preusr	precnr
[1]	0.00321	0.00306
[2]	-4.41837E-4	-6.86241E-4
[3]	-5.00389E-4	9.27684E-5
[4]	1.18095E-4	-1.22949E-4
[5]	4.0812E-5	9.43068E-6
[6]	-1.08644E-5	1.52311E-5
[7]	-4.27222E-6	-1.87558E-6
[8]	9.68076E-7	-1.383E-6
[9]	4.92689E-7	1.38767E-7
[10]	-9.65738E-8	1.48729E-7
[11]	-5.40736E-8	-1.06089E-8

M2

$preusr

Lag	prejar	precnr
[1]	0	-2.36836E-4
[2]	0.00556	0.00126
[3]	-5.59392E-4	-8.91651E-5
[4]	-4.6871E-5	-1.42385E-5
[5]	1.51229E-5	3.09436E-6
[6]	-6.55587E-7	-4.77912E-8
[7]	-2.14779E-7	-5.26623E-8
[8]	3.38567E-8	6.20301E-9
[9]	5.72947E-10	3.52275E-10
[10]	-6.86803E-10	-1.50792E-10
[11]	5.86745E-11	8.67488E-12

$precnr

Lag	prejar	preusr
[1]	0	0
[2]	-3.63061E-4	7.36363E-5
[3]	5.52104E-5	6.52058E-6
[4]	1.26391E-6	-1.95739E-6
[5]	-1.15279E-6	7.67593E-8
[6]	9.28721E-8	2.8618E-8
[7]	1.20426E-8	-4.31439E-9
[8]	-2.94079E-9	-9.62063E-11
[9]	7.3089E-11	8.9861E-11
[10]	4.72561E-11	-7.28232E-12
[11]	-6.12734E-12	-9.34404E-13

$prejar

Lag	preusr	precnr
[1]	0.00153	0.00224
[2]	-4.14963E-4	1.57229E-4
[3]	1.36504E-5	-5.35197E-5
[4]	6.3322E-6	2.50037E-6
[5]	-8.9269E-7	7.42004E-7
[6]	-2.75385E-8	-1.2134E-7
[7]	1.93635E-8	-1.53788E-9
[8]	-1.44274E-9	2.40943E-9
[9]	-2.14113E-10	-2.14612E-10
[10]	4.84129E-11	-2.31009E-11
[11]	-9.08576E-13	6.31852E-12

Table D.2 For pre-crisis dollar currency: M1

$preusr

Lag	prejard	precnrd
[1]	0	1.35489E-4
[2]	0.00592	0.00211
[3]	5.21445E-4	2.43825E-4
[4]	-9.21159E-4	-3.48148E-4
[5]	-1.68462E-5	3.86678E-6
[6]	8.27002E-5	2.8044E-5
[7]	7.37753E-6	1.81814E-6
[8]	-8.22587E-6	-2.77085E-6
[9]	-1.3558E-6	-4.12833E-7
[10]	8.44143E-7	2.93865E-7
[11]	1.8428E-7	5.66264E-8

$precnrd

Lag	prejard	preusr
[1]	0	0
[2]	-4.96098E-4	-1.5861E-4
[3]	4.61261E-4	-3.75084E-4
[4]	-2.43789E-4	5.55E-5
[5]	-8.7612E-6	3.20258E-5
[6]	2.50733E-5	-2.01172E-6
[7]	9.12473E-7	-3.57465E-6
[8]	-2.21711E-6	-7.26028E-8
[9]	-3.10816E-7	4.08388E-7
[10]	2.3497E-7f	2.41235E-8
[11]	4.57134E-8	-4.20337E-8

$prejard

Lag	preusr	precnrd
[1]	0.00297	0.00264
[2]	-6.46203E-4	-6.77432E-4
[3]	-4.91685E-4	2.15763E-4
[4]	1.37411E-4	-1.37084E-4
[5]	3.62698E-5	1.50206E-5
[6]	-9.50761E-6	1.19801E-5
[7]	-4.47582E-6	-1.65922E-6
[8]	6.78924E-7	-1.03409E-6
[9]	5.54355E-7	3.98082E-8
[10]	-5.21874E-8	1.26247E-7
[11]	-6.11374E-8	1.69419E-9

M2

$preusr

Lag	prejard	precnrd
[1]	0	-7.75693E-5
[2]	0.00469	0.0014
[3]	6.35251E-4	5.83892E-4
[4]	4.12065E-4	1.25119E-4
[5]	8.24922E-5	8.43209E-4
[6]	-1.64868E-4	2.40959E-4
[7]	-6.93246E-5	5.76954E-6
[8]	-3.52687E-5	4.75055E-5
[9]	4.68366E-6	1.29969E-5
[10]	-2.20789E-6	-2.29246E-6
[11]	-4.28867E-6	-4.74515E-6

$precnrd

Lag	prejard	preusr
[1]	0	0
[2]	-2.83288E-4	8.22211E-5
[3]	-1.99805E-4	-1.59897E-4
[4]	6.41709E-6	-1.3769E-4
[5]	3.46925E-4	-4.17722E-4
[6]	-2.84634E-4	1.6932E-5
[7]	-6.43555E-5	1.30143E-5
[8]	7.09943E-6	-2.68932E-5
[9]	1.21192E-5	-2.00741E-6
[10]	-1.37703E-5	6.15081E-6
[11]	-6.69645E-7	9.17655E-7

$prejard

Lag	preusr	precnrd
[1]	0.00144	0.00183
[2]	-4.76553E-4	-1.72873E-4
[3]	2.64086E-4	-1.46471E-4
[4]	-2.45508E-4	-9.75055E-5
[5]	-2.14216E-4	9.57818E-4
[6]	4.63292E-5	-1.2824E-4
[7]	-5.60829E-6	-3.76596E-5
[8]	-4.49915E-7	1.82834E-5
[9]	-1.54797E-5	4.34078E-5
[10]	4.05818E-6	-1.75306E-5
[11]	1.99035E-6	-4.87572E-6

Table D.3 For post-crisis local currency: M1

$postusr

Lag	postjar	postcnr
[1]	0	9.28697E-4
[2]	0.00732	0.00255
[3]	-1.87022E-4	8.95247E-5
[4]	3.27642E-4	-4.17801E-5
[5]	-1.49143E-4	-4.22953E-5
[6]	2.45712E-5	-4.00874E-6
[7]	-1.53801E-5	-1.84622E-6
[8]	4.36003E-6	5.48618E-7
[9]	-1.42886E-6	-4.54981E-8
[10]	5.60582E-7	6.81808E-8
[11]	-1.71895E-7	-1.33993E-8

$postcnr

Lag	postjar	postusr
[1]	0	0
[2]	-6.35104E-4	1.59324E-5
[3]	-8.51923E-5	2.65441E-4
[4]	1.71704E-4	6.56384E-6
[5]	6.77483E-6	1.80629E-5
[6]	1.21909E-5	-4.88747E-6
[7]	-2.77175E-6	1.08944E-6
[8]	6.37837E-7	-6.51564E-7
[9]	-3.96865E-7	1.63636E-7
[10]	9.25895E-8	-6.16824E-8
[11]	-3.67122E-8	2.25406E-8

$postjar

Lag	postusr	postcnr
[1]	0.00215	0.00249
[2]	1.38754E-4	-5.5417E-4
[3]	-3.14911E-4	2.16032E-5
[4]	3.6222E-5	-1.12116E-4
[5]	-3.59903E-5	-4.68864E-6
[6]	1.08885E-5	-4.13977E-6
[7]	-3.46637E-6	1.15641E-6
[8]	1.4528E-6	-5.40159E-8
[9]	-4.42294E-7	1.23564E-7
[10]	1.59767E-7	-2.08121E-8
[11]	-5.56979E-8	7.85436E-9

M2

$postusr

Lag	postjar	postcnr
[1]	0	0.00103
[2]	0.0066	0.00238
[3]	2.86725E-4	1.03763E-4
[4]	4.96927E-4	-2.96336E-5
[5]	-4.69273E-4	-3.27179E-4
[6]	1.08631E-5	-2.05787E-5
[7]	-6.80068E-5	-2.35835E-5
[8]	2.94108E-5	1.93029E-5
[9]	-7.99892E-6	-9.9379E-7
[10]	6.14148E-6	2.59228E-6
[11]	-3.35017E-6	-1.45837E-6

$postcnr

Lag	postjar	postusr
[1]	0	0
[2]	-6.06483E-4	4.61315E-4
[3]	2.43604E-5	6.75114E-5
[4]	7.07853E-4	3.61073E-4
[5]	1.47252E-4	-3.77042E-5
[6]	2.79883E-5	3.76328E-5
[7]	3.64615E-5	-3.73094E-5
[8]	-2.30353E-5	6.1973E-6
[9]	4.08058E-6	-5.27336E-6
[10]	-4.72128E-6	2.64767E-6
[11]	1.42342E-6	-9.05941E-7

$postjar

Lag	postusr	postcnr
[1]	0.00175	0.00241
[2]	-2.11817E-5	-5.36463E-4
[3]	3.26366E-4	2.1954E-4
[4]	-3.20442E-4	-2.61956E-4
[5]	2.47838E-5	-6.99252E-5
[6]	-4.71422E-5	-1.65215E-5
[7]	1.78047E-5	-2.12067E-5
[8]	-4.12076E-6	9.02199E-6
[9]	3.79799E-6	-1.2162E-6
[10]	-1.59816E-6	1.76311E-6
[11]	6.86539E-7	-3.2689E-7

Table D.4 For post-crisis dollar currency: M1

$postusr

Lag	postjard	postcnrd
[1]	0	9.40697E-4
[2]	0.00586	0.00266
[3]	1.01891E-4	-2.68106E-5
[4]	4.00062E-4	-1.77622E-4
[5]	-5.69688E-4	-1.41284E-4
[6]	2.85322E-5	1.22368E-6
[7]	-6.10854E-5	-3.24512E-6
[8]	2.81885E-5	5.83248E-6
[9]	1.76256E-6	3.18848E-6
[10]	4.83567E-6	7.17708E-7
[11]	-2.35625E-7	-1.71413E-7

$postcnrd

Lag	postjard	postusr
[1]	0	0
[2]	-5.54844E-4	8.47473E-6
[3]	-2.24724E-4	2.258E-4
[4]	3.12259E-4	4.01808E-4
[5]	1.95916E-4	1.03229E-5
[6]	2.6812E-5	1.81015E-5
[7]	1.46357E-5	-3.08083E-5
[8]	-2.12965E-5	-1.10146E-6
[9]	-1.01774E-6	-3.15066E-6
[10]	-2.66662E-6	1.43206E-6
[11]	1.23125E-6	3.44753E-7

$postjard

Lag	postusr	postcnrd
[1]	0.00236	0.00242
[2]	5.65963E-4	-4.23275E-4
[3]	2.20223E-4	3.64103E-4
[4]	-5.8032E-4	5.11205E-5
[5]	6.8001E-5	-1.61438E-4
[6]	-3.47722E-5	4.78057E-6
[7]	3.53778E-5	8.39109E-6
[8]	-5.22976E-6	6.01844E-6
[9]	4.74039E-6	-7.58847E-7
[10]	-1.31407E-6	4.92066E-7
[11]	-2.45726E-7	-1.84159E-7

M2

$postusr

Lag	postjard	postcnrd
[1]	0	0.00102
[2]	0.00529	0.00255
[3]	3.84827E-4	3.88344E-5
[4]	2.68918E-4	-8.18657E-5
[5]	-5.09185E-4	-2.47984E-4
[6]	-3.96083E-5	-3.25713E-5
[7]	-6.47073E-5	-1.91242E-5
[8]	2.9205E-5	1.81872E-5
[9]	6.3296E-6	4.95348E-6
[10]	7.44886E-6	3.08902E-6
[11]	-6.84055E-7	-7.38524E-7

$postcnrd

Lag	postjard	postusr
[1]	0	0
[2]	-4.14597E-4	4.37339E-4
[3]	-2.06094E-4	5.03132E-5
[4]	3.70251E-4	4.22569E-4
[5]	1.80963E-4	-3.20302E-5
[6]	2.15464E-6	4.41669E-5
[7]	2.43995E-5	-4.54394E-5
[8]	-2.71868E-5	1.87582E-6
[9]	-9.32827E-8	-5.69039E-6
[10]	-3.88153E-6	2.70299E-6
[11]	1.8385E-6	1.7384E-7

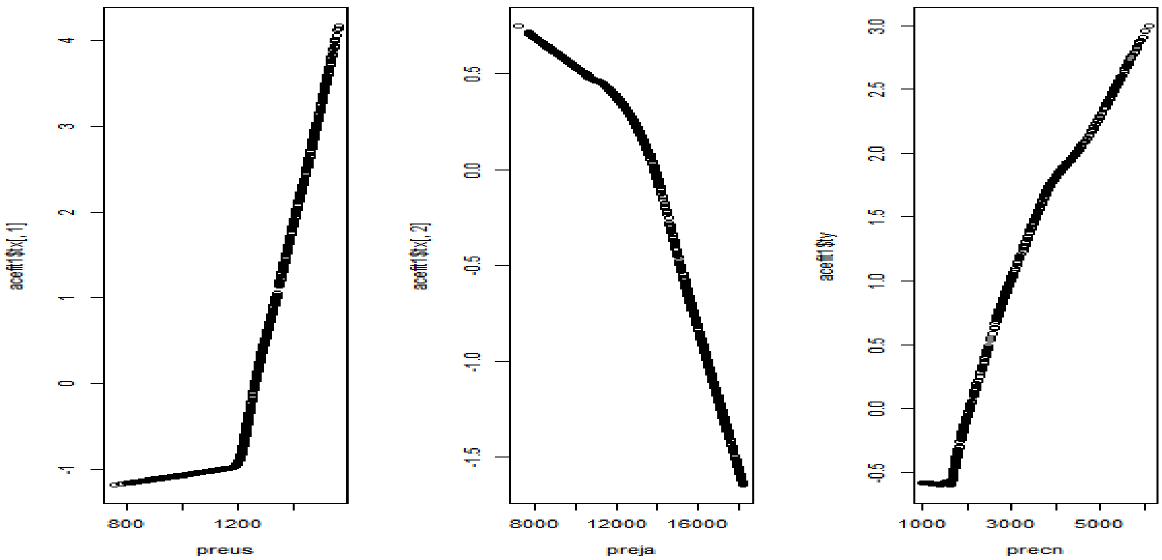
$postjard

Lag	postusr	postcnrd
[1]	0.00203	0.00233
[2]	1.48263E-4	-4.16823E-4
[3]	2.69419E-4	3.57515E-4
[4]	-6.14384E-4	-1.59511E-4
[5]	9.00004E-5	-1.35176E-4
[6]	-5.19969E-5	7.37955E-6
[7]	4.13904E-5	-4.44113E-6
[8]	-3.14785E-6	1.29499E-5
[9]	6.22261E-6	5.37214E-8
[10]	-2.23316E-6	1.51072E-6
[11]	-2.04357E-7	-8.87986E-7

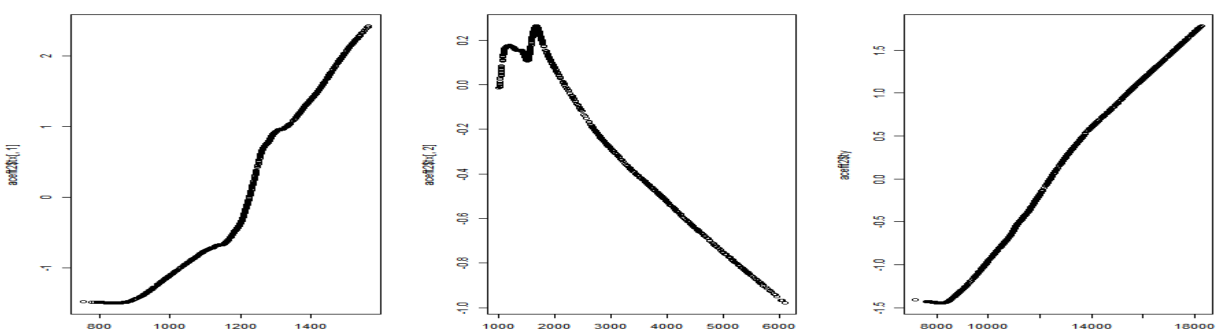
APPENDIX E. ACE TRANSFORMATION

ACE Transformation for data series in the 8 models specified in Section 8.4

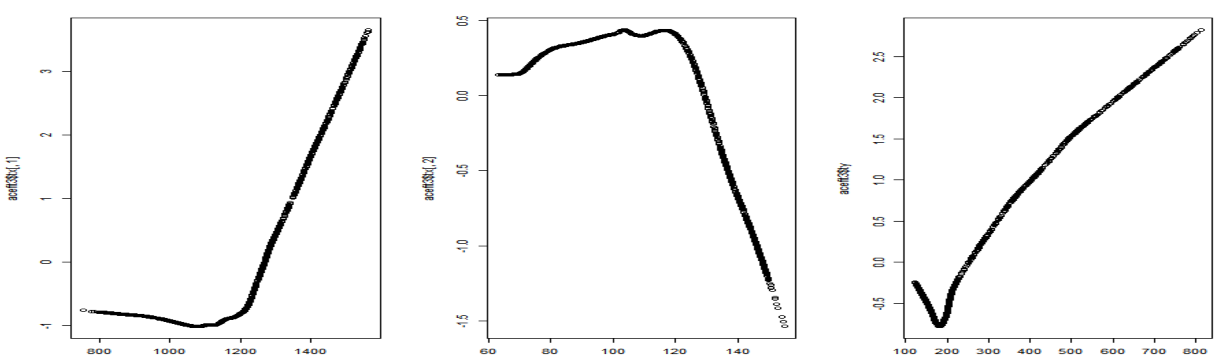
For model 1:



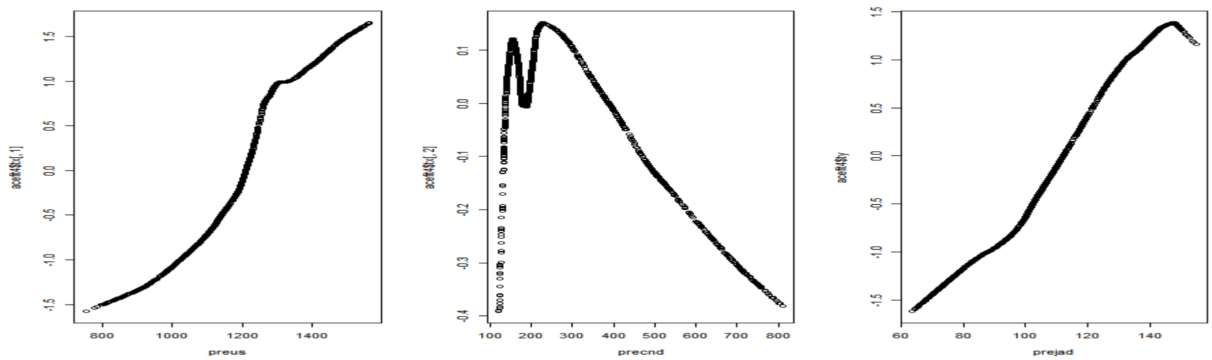
For model 2:



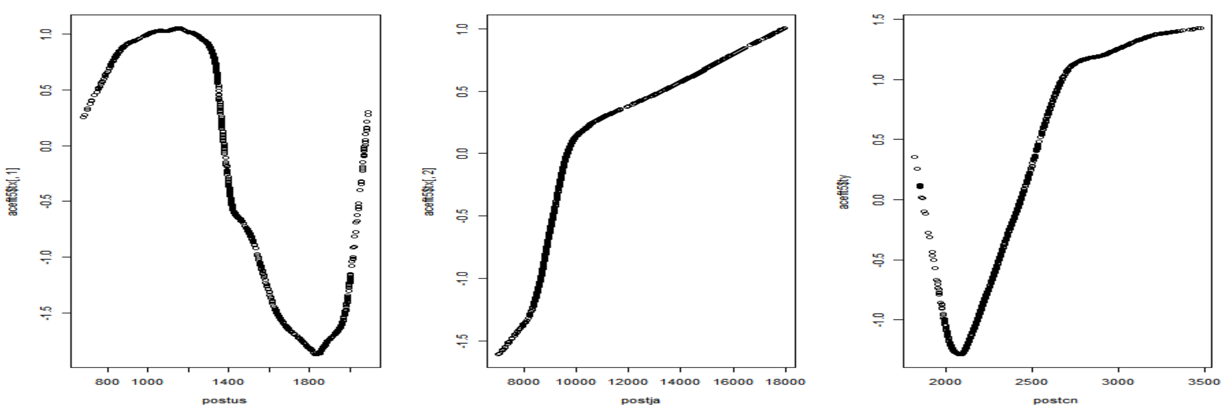
For model 3:



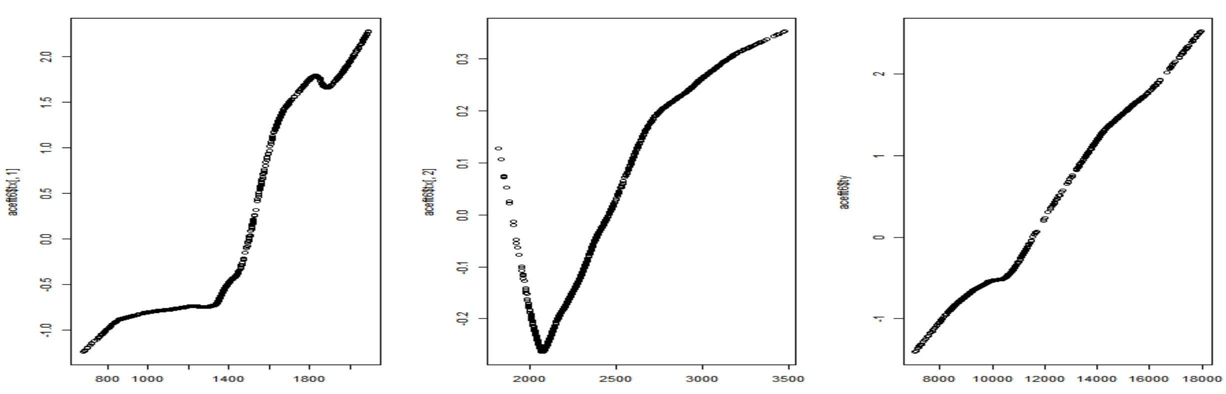
For model 4:



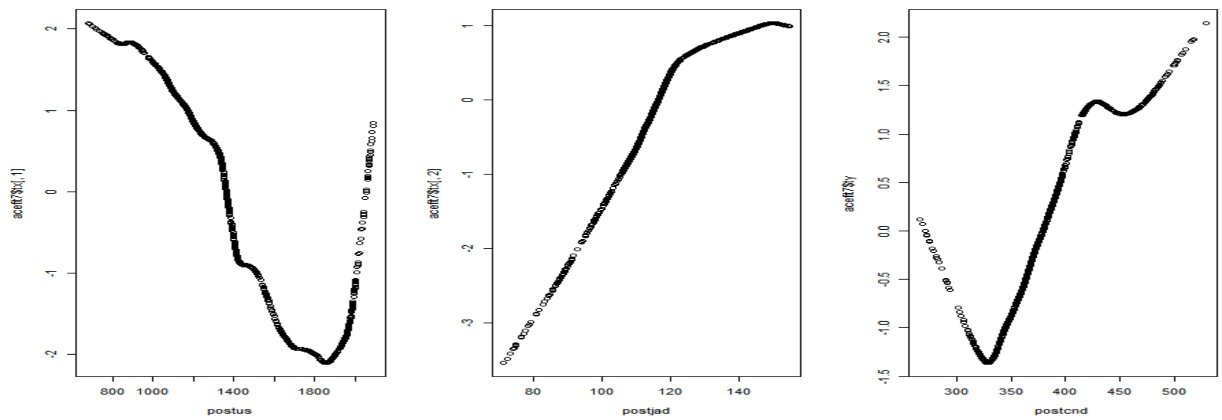
For model 5:



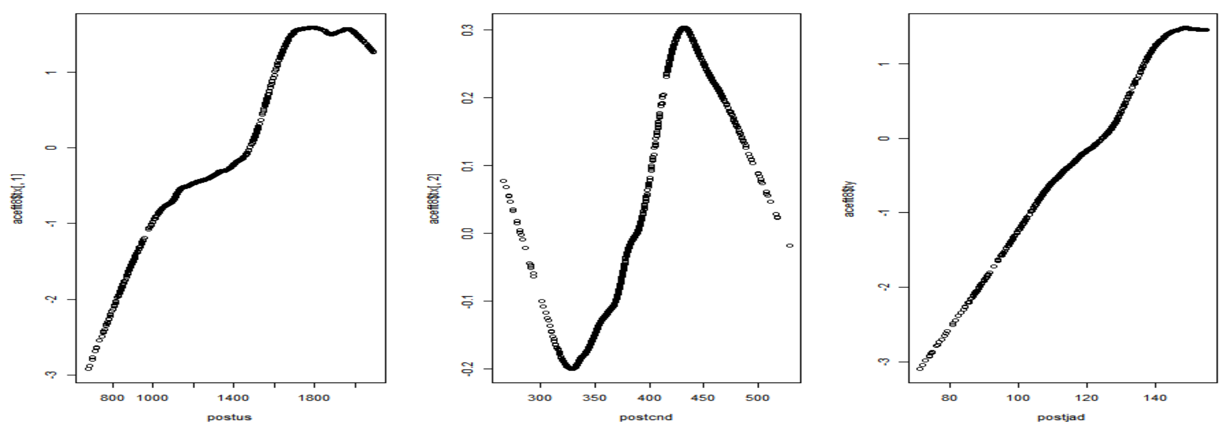
For model 6:



For model 7:



For model 8:



VITA

Name **Shuting Wang**

Education

Ph.D., Business Administration **Aug. 2016**

University of Illinois at Chicago, Chicago, IL

M.S., Finance **May 2016**

University of Illinois at Chicago, Chicago, IL

M.S., Statistics **May 2011**

University of Toledo, Toledo, OH

B.S., Statistics (Special Class for the Gifted Young)* **July 2009**

University of Science and Technology of China, Hefei, China

Teaching Experience

- "Business Statistics"(undergraduate), University of Illinois at Chicago, 2011-2015

  -- received very good teaching evaluations and positive feedbacks from the students

  -- prepared course materials, set up new classroom techniques, led discussion sessions, held office hours, and taught recitation classes

  -- assisted the instructor to adjust the class schedule based on the students' mastery of knowledge

  -- trained and organized work of new TAs since it had been a big class with over 250 students and more than 3 TAs every year

- "Introduction to Operations Management" (MBA,2012) and "Statistics for

* A program aiming to select gifted young students under 16 to enter the university based on national exams and interview, only top 1% applicants are selected.

Management“(MBA,2011), University of Illinois at Chicago, online courses

-- assisted the instructor to prepare website materials and class videos for these online courses

-- graded their online reports and provided prompt, patient and elaborated explanations regarding students’ concerns and confusions

- “Calculus I” and “Calculus II” (undergraduate), University of Toledo, 2009-2011
- “Statistical Software for Business Applications” (MBA,2011,2015) and “Data Visualization” (MBA,2011,2015), University of Illinois at Chicago

Professional Membership

American Finance Association Membership

Fellowship

Liautaud School of Business Fellowship, 2011-2015

Services

- Served as the Head of Publicity Department at Chinese Students & Scholars Association, University of Illinois at Chicago, 2011-2012
- Served as Chief Erhu Instrumentalist in Chinese Classical Orchestra, University of Science and Technology of China, 2005-2007

Skills

- Computer Skills: R, SAS, B34S, Java, Python, Matlab, Tableau
- Language Skills: Chinese(Native), English(Fluent), Japanese(Knowledge Of)