UNIVERSITAS INDONESIA

FINANCIAL CONTAGION BETWEEN SEVERAL FINANCIAL SECTOR INDICES OF STOCK PRICES IN THIS DECADE

SKRIPSI

FIRHAT NAWFAN HILMANDA
0806464772

FAKULTAS EKONOMI
PROGRAM SARJANA REGULER
KEKHUSUSAN KEUANGAN
DEPOK
July, 2015

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Diajukan sebagai salah satu syarat untuk memperoleh gelar sarjana

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NPM	: 0806464772
Program Studi	: Manajemen
Judul Skripsi	: Financial Contagion between Several Financial Sector Indices of Stock Prices in this Decade

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1. Bapak Buddi Wibowo, selaku dosen pembimbing yang telah menyediakan waktu, tenaga, dan pikiran untuk mengarahkan saya dalam penyusunan skripsi ini;
2. orang tua dan keluarga saya yang telah memberikan bantuan dukungan material dan moral; dan
3. sahabat yang telah banyak membantu saya dalam menyelesaikan skripsi ini.

Akhir kata, saya berharap Tuhan Yang Maha Esa berkenan membalas segala kebaikan semua pihak yang telah membantu. Semoga skripsi ini membawa manfaat bagi pengembangan ilmu.

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Firhat NH

(Firhat Nawfan H)

ABSTRAK

Nama : Firhat Nawfan Hilmanda
Program Studi : Manajemen
Judul : Financial Contagion Antar Beberapa Indeks Sektor Keuangan dari Harga Saham pada Dekade ini

Skripsi ini menguji pola transmisi volatilitas indeks sektoral dengan menggunakan model DCC MGARCH yang diusulkan oleh (Engle, 2002) untuk meneliti pola transmisi volatilitas. Data yang digunakan adalah data harian dari 2003 hingga 2013 dengan menggunakan indeks sektor keuangan untuk menganalisis contagion antara Indonesia dan Negara-negara yang menjadi partner dagang utama dengan Indonesia. Dari hasil output ditemukan bahwa investor cenderung untuk bereaksi terhadap "bad news". Saya juga menemukan bahwa efek contagion yang diakibatkan oleh Eurozone Sovereign Debt Crisis lebih terasa dibandingkan dengan efek contagion yang diakibatkan US Subprime Mortgage Crisis

Kata kunci:
DCC MGARCH, Krisis Finansial, Indeks Sektoral, Transmisi Volatilitas

ABSTRACT

Name : Firhat Nawfan Hilmanda
Major : Management
Title : Financial Contagion between Several Financial Sector Indices of Stock Prices in this Decade

This thesis tested the pattern of volatility transmission of sectoral indices by using DCC MGARCH model proposed by (Engle, 2002) to assess volatility transmission. I used daily data from 2003 to 2013 to analyze contagion between financial sector of Indonesia and its major trading partner. We found that investors overreacts to bad news, and that the contagion effect following Eurozone Sovereign Debt Crisis is more pronounced than the one following US Subprime Mortgage Crisis

Keyword:
DCC MGARCH, Financial Crisis, Sectoral Indices, Volatility Transmission,

JEL Codes:
G01, G15,

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CHAPTER 1
INTRODUCTION

1.1 Background

Every investor wishes to achieve return, however in every investment there also are risks. Risks can be categorized into systematic risk, risks that affected an entire financial market and unsystematic risk, risks that affected particular company or industry. An international investors should be concerned for international risk because although it is true to some extent that decision making on a financial market should be based on that particular market peculiarity, for example industry maturity, financial regime, economic policy . However, recent financial globalization and both global and regional financial crisis in this decade suggest that investors should also look into relationship between financial markets. Financial globalization should be the keyword for this phenomenon, investors may now internationally buy an asset, invest, bought sovereign CDS on different countries, although there are several exception to the availability of international investing, this trend is inevitable. The advancement of information technology virtually makes the entire earth a single financial market; a financial institution can reap benefits of simultaneously trading globally for 24 hour a day by exploiting different trading windows in USA and Asia, and Europe

Amidst today's financial market trend of globalization, knowledge of interdependence between financial markets particularly on the topic of transmission volatility will become even more important for policy maker and business decision maker. For investors this trend pose serious problem as existing diversification strategies can be disturbed by changes in correlation between assets, leaving portfolios exposed to international shocks, particularly in the case of a Financial Crisis.

Financial crisis itself is defined as a disruption to financial markets in which adverse selection and moral hazard problems become much worse, so that financial markets are unable to efficiently channel finds to those who have the most productive investment opportunities. Thus, a financial crisis results in the inability of financial markets to function efficiently, which leads to a sharp contraction in economic activity (Mishkin, 1992).

One of the most prominent financial crisis affecting Indonesia was the the 1997's Asian Financial Crisis, this crisis is a watershed moment in financial studies as it had reaffirmed the long held suspicion on the role of shocks transmission on explaining why country-specific crises could spread internationally. The crises of 1990s decade had shown that crises spread internationally even to countries with strong fundamental as evidenced by the direction South Korea took in the 1997 Asian financial crisis.

The crisis of 1997 underline the inadequacy of standard economic theories such as balance of payment models which underline country's weak fundamental, and multiple equilibria models which incorporate investor's expectation and government policy objectives to explain and predict crises (Claessens & Forbes, 2001).

To explain the spread of market disturbance as one commonly found in a case of financial crisis, scholar coined the term "contagion" (Dornbusch, Park, & Claessens, 2000). The study on contagion was extremely difficult; of the many difficulties, there were: econometric issues; interaction between various propagation mechanism hindering the effort to isolate certain transmission channel to be meaningful; and data availability particularly about financial linkage (Claessens & Forbes, 2001). This difficulty was further exacerbated with the fact there isn't yet any consensus on how exactly to define contagion (Dornbusch, Park, & Claessens, 2000).

Forbes and Rigobon (2001) proposed shift contagion, an increase in cross-market linkage after a shock to an individual country, as the more proper definition of contagion. They underline three concerns when choosing more proper definition of contagion. First, it had to address investor's motive for international diversification. One of investors motive to internationally diversify their portfolio is to hedge for a specific country disturbance, which in the event of financial contagion can be rendered useless.

Second, whether such definition is useful in evaluating the role and potential effectiveness of international institution and bailout funds. This definition would have to be able to justify an intervention and the sums of resources used in the process. Two countries closely linked in term of their economic fundamentals should expect impact if shocks were to occur to once of them, intervention will reduce initial negative impact, but it will also serve to lengthen the time for the economy to adjust.

Third, the definition should be able to provide useful method of distinguishing between explanations of how shocks are transmitted across markets. the shift contagion definition provide useful method to distinguish whether volatility which entails certain shocks are either a change in the transmission mechanism after a shock, or continuation of existing mechanism. A significant increase in the correlation between two markets may indicate which transmission mechanism are most important. These arguments elaborate on the merit of using shift contagion as the chosen definition of financial contagion discussed in this paper.

That brings us to the next question: how does shocks transmitted in a way that they exhibit contagion? There were plethora theorethical literatures on how shocks are transmitted internationally. Forbes and Rigobon (2001) divided those broad set of theories into two groups. First, crisis-contingent theories are theories which explain why transmission mechanism chage during a crisis and therefore why cross-market linkage increase after a shocks. Second, non-crisis-contingent are theories which assume that transmission mechanism are the same during a crisis and during more stable periods.

Chiang, Jeon, and Li (2007) argued that previous literatures had several limitations and drawbacks. Some of the points raised by them are: First, heteroskedasticity problem arisen when measuring correlations, caused by volatility increases during the crisis. Second, consistent and compatible financial data in Asian Markets are lacking in availibility. Third, since contagion is defined as significant increases in cross-market comovements, while any continued market correlation at high levels is considered to be interdependence, the existence of contagion must involve evidence of dynamic increament in correlations. Fourth, studies in the field of financial contagion had shown that virtually all tests are affected by identifying the source of crisis and the choice of window length (Billio & Pelizzon, 2003). Fifth, it is generally understood that indicators of sovereign credit worthiness represented by sovereign credit ratings ratings announced by international credit-rating agencies and publications are based on economic fundamentals, which reflect an external assessment of the risk associated with changes in economic fundamentals or political risk, which should have an impact on stock returns and, in turn, the correlation coefficients.

To address these problems, they used cross-country multivariate DCC-GARCH [1] model. In their reasoning they pointed three advantages of this estimation method. First, it estimates correlation coefficients of the standardized residuals and this accounts for heteroskedasticity directly. Second, it allows to include additional explanatory variables in the mean equation to measure a common factor. Third, it can be used to examine multiple asset returns without adding too many parameters

Cho and Parhizgari (2008) went along similar reasoning when they recognized the necessity to employ the time varying dynamic aspect of correlation proposed by Engle (2002), the DCC-GARCH estimation method. They also added that despite stark differences among instances of contagion, they share similar features. Initialy volatility tend to concentrate within a certain country with lack of observed cross-border effect. However, as time progressed accompanied with the spread of the news such contained volatility may escape to global market. Therefore, they argued that shocks transmission resembles gradual evolutionary process receveiving feedback from every other ends, than a sudden one-time transmission. They also noted that DCC is capable to address problem which had long plagued financial studies, that is the nature of financial data to exhibit heteroskedasticity.

Although Cho and Parhizgari (2008); and Chiang, Jeon, and Li (2007) came to the same conclusion of using DCC MGARCH[2] model proposed by Engle (2002) as an adequate model to capture for this phenomenon, they differed in their approach on detecting the evidence the evidence in the increament in correlation needed to detect the presence of contagion. The former employed difference t-

[1] Stands for Dynamic Conditional Correlation – General Autoregregressive Conditional Heteroskedastic, see chapter 2 for further explanation

[2] A generalization of DCC GARCH Model vor multivariate model, the “M” stand for “Multivariate”, see chapter 2 for further explanation

tests and median difference z-tests, while the latter employed regression method. The focal point which underline their difference was that the latter reluctance to divide the timeframe into “stable” and “crisis” periods, which was influenced, by Billio and Pelizzon (2003) which shown that virtually all tests are affected by identifying the source of crisis and the choice of window length. However, we need to understand that the Billio and Pelizzon (2003) study was built under the premise that contagion conveys the idea that international propagation mechanism are discontinuous, whereas a contrasting view of contagion as evolutionary process advocated by the former.

Kenourgios, Samitas, and Paltalidis (2011) extended the research on financial contagion by applying the Asymmetric DCC model by Cappiello, Engle, and Sheppard (2006) to asses the presence of contagion effect. They argued that ADCC[3] can better explain asymmetries in conditional variances and correlation dynamics

1.2 Problem Formulation

Bekaert, Ehrmann, Fratzscher, and Mehl (2011) analyzed transmission of crises to country-industry equity portfolios in 55 countries. They examined six channels of contagion, categorized into:

1. International banking sector linkage;
2. Firm-Specific characteristics; role of financial policies introduced during the crisis;
3. “Globalization Hypothesis” which implies that crisis will hit more severely in economies that are highly integrated globally, through trade and financial linkages;
4. Information Asymmetries where investors become subject of widely spread public news;
5. “Wake Up Call Hypothesis” which states that a crisis which initially restricted to one market segments or country provides new information that may prompt investors to reassess the vulnerability of other market segments or countries which carry similar trait;

[3] A variant of DCC GARCH model which take account asymmetries phenomenon, see chapter 2 for further explanation

6. Herding Behavior or investors risk appetite which goes beyond what the fundamentals suggest.

They found weak evidence of contagion from US markets to global equity market during crisis. Surprisingly, they found that in the 2007-2009 financial crisis, fundamental factor such as banking, trade, or financial linkages played no meaningful role for the global equity market transmission. However, they found that countries with weak economic fundamentals, poor sovereign ratings, and high fiscal and current account deficits experienced more contagion and overall more severely affected by the global financial crisis. It was as if investors focused primarily on country-specific characteristics and punished markets with poor macoeconomic fundamentals, policies and institution. The presence of policies to protect domestic banks during the crisis in the form of debt and deposits guarantees was instrumental in shielding domestic equity portfolios from the 2007-2009 crisis. This result implies that the first line of defense from financial contagion is by addressing on the very cause of the shock: investors. A market may seem healthy and well regulated, but once it exhibit symptom of weakness, investors will punish that market by reexamining that market and we can expect them will apply their newly found tacit knowledge toward other market.

These findings forewarned that several factors may expose Indonesian market to global financial market risks as several aspect of our recent economy resemble Indonesia in the years prior to the Asian Financial Crisis where Indonesia and the ASEAN at that time had received large influx of foreign capital prior to the crisis (Radelet & Sachs, 1998)

It is well known that in the post 2000’s many of Indonesian bank had been acquired entirely or partly by overseas institutions, this raises a possibility of contagion through financial institution linkage. Second, Indonesia today faced a greater exposure to foreign capital, with the slowdown of US and European economies, Indonesia had been the destination of flight to liquidity by investors. However there were some possibilities of reversal, as most of these capitals do not enter real economy but instead invested in Treasury bond (Koeberle, 2011). It is also important to note that Indonesian stock market is dominated by foreign investors reaching up to 60% (Indonesian Central Securities Depository, 2011).

These facts pointed out that the stability of Indonesian financial market is predominantly at the mercy of foreign investors. Had these investors at a certain point reconsider their capital in Indonesia, e.g.: for reason of flight to liquidity, flight to quality, margin call, panic due to investors-induced contagion, or reassessment of their portfolio; then a great portion of capital is at risk of flowing out of our economy.

Past studies on 1997's Asian Financial Contagion in the past decade, underline that much of the contagion itself was driven purely by "pure contagion", one that had little to do with the fundamentals but rather the market panics and sentiment. Therefore, we see merit on addressing the question on how investors react to information. In this thesis we will not discuss about the policy taken by financial and fiscal policy to mitigate such crisis, but rather on how does investors perceive market. We are interested on examining how the market reacts to recent events such as US subprime mortgage crisis, and European sovereign debt crisis.

First, when speaking about investors and financial market, there exist phenomenon known as asymmetric or leverage effect, where good news and bad news may have affect volatility predictability differently[4]. If investors had a tendency to overreact on certain market, then we can suspect that a bad news from that certain market will cause it to plummet even further (Lin, Engle, & Ito, 1994).

To address this leverage effect phenomenon, Engle and Ng (1993) devised news impact curve, as a means to provide a measure on how new information is incorporated into volatility estimates. They found that GJR GARCH[5] and EGARCH[6] are the best model which can capture asymmetry. A study by Kroner and Ng (1998) extends by generalizing this news impact curve into news impact surface for multivariate GARCH model. Cappiello, Engle, and Sheppard (2006) extended this model on the issues of asymmetry on multivariate GARCH Model

To provide a statistical meaning to the news impact curve, Engle and Ng (1993) also devised diagnostic tests for volatility models to examine the extant of leverage effect. These tests are Sign Bias Test, Negative Sign Bias Test and

[4] It is important to note that what we called "bad news" and "good news" are not in literal sense, see chapter 2 for further explanation
[5] Glosten-Jagannathan-Runkle GARCH
[6] Exponential GARCH

Positive Sign Bias Test. Sign Bias Test, to test the impact of positive and negative return shocks on volatility not predicted by the model under consideration, while the negative and positive sign bias test focuses on the effect of negative and postive return shocks, respectively.

It is also important to note that previous studies on asymmetric effect on Asian countries are rather scarce. The 1997 financial crisis had only been brought up a decade latter by Leeves (2007). He studied asymmetric volatility return on Indonesian market by using the daily stock-price index on Jakarta Stock Exchange. They found that initially, from the 1990-1999 period no asymmetric effect observed, however the data from 1997-1999 did show asymmetric effect.

In addressing this problem we will examine the leverage effect exhibited several selected countries through their daily financial sector stock price indices, consumer goods sector stock price indices, and industrial sector stock price indices data by constructing news impact curve and news impact surface of bivariate conditional correlation between sectoral indices. As far as I know there was not yet another study covering the more recent financial crises on Indonesian Market, hence the motives to analyze asymmetric effect.

Second, we are interested on whether there was continuity in volatility pattern over time (i.e contagion effect) between certain sector indices. This is important because we wanted to know whether the financial crisis in this decade left a long lasting effect on Indonsia.

Following Forbes and Rigobon (2001) reasoning, we will use Pericoli and Sbracia (2003) 3rd definition of contagion to define contagion as significant increase in co-movements of prices and quantities across markets, conditional on a crisis occurring in one market or group of markets.

Several studies had explored the issue on explaining the cross market contagion phenomenon. King and Wadhwani (1990) assert that shocks may spread to other markets as a result of rational agent using information on particular market to infer information about another market. There are two key in this statement: rational agent; and information usage[7]

[7] Further explanation regarding information channel is available in chapter 2

Regarding on how this rational agent acted, Perry and Lederman (1998) found that investor may prefer to liquidate investments in assets that have no yet been affected by financial crisis, but seem vulnerable thus reducing portfolio risk. Thus, they underline two issue: information asymmetries; and portfolio rebalancing, both are factors that were found to be exacerbating factor on the previous 1997 Asian Financial Crisis as found by study of Corsetti, Pessenti, & Roubini (1999) and Dornbusch, Park, & Claessens (2000).

Fleming, Kirby, and Ostdiek (1998) explained on how information can create market linkage. The first is information that simultaneously alters expectations in more than one market (i.e.: common information), this source generates trading activity and volatility in each market through changes in speculative demand. The second is information that alters expectations in one market and impacts trading and volatility in other markets through changes in hedging demand (i.e information spillover).

The important role of information asymmetry as a channel of contagion was shown by Horta, Mendes, and Vieira (2010), where they found that contagion was present between several selected European financial sector indices and between several selected European industrial sector indices. They also noted that contagion sign was equally intense across financial sector indices and across industrial sector indices, which indicate that investors had expected that the financial crisis will eventually spread to industrial sector long before it was observable in real economy

Baur (2012) studied the transmission of shocks from financial sector stock market indices across countries, he underlined that strong contagion effect was observed between between financial sector indices which underline the importance of this sector in crisis. He inquired whether investors sell stocks of specific sector and countries or do they sell stocks across all sectors and countries. This question was important since it affect diversification strategies; latter scenarios would render diversification effectiveness while the former support the argument for diversification. Another argument raised on the importance of the study was that a better assessment of contagion can better assist government to discern sectors more prone to contagion and design stimulus package. He showed that contagion between financial sectors is strong, and this implies that financial sector is important in crisis

In his conclusion, he also shows that while contagion between non-financial sectors indices shows mixed results and this may be affected by the behavior of globally lending and borrowing by firm in that sectors . An important result of this study is that when domestic financial sector is infected by crisis (i.e. contagion) it will spread to other domestic non-financial sectors, he also noted that Indonesia is one of the countries which experiences highest level of contagion between financial sector and non-financial sector. Hence we see the merit to examine relationship between financial sector indices

It is very reasonable for financial sector indices to first show sign of contagion between two different markets. In a case of financial crisis, firms dealing with transaction in foreign exchange be under pressure[8] since they had to deal with potential fluctuation in exchange rate; in a case of a depreciating local currency against currency of the country where imported goods originated; firm will be forced to borrow to bank to make up for the discrepancy of their expected payment with real payment in foreign currency; this, will inturn put pressure on bank liquidity; because of it nature bank is a very potent institutional investors, therefore a portfolio rebalancing act will impact stock market. Investors as a rational agent are also very perceptive to the financial sector, a sign of distress in financial sector can possibly lead to drastic action by investors.

Therefore, in this study, we suspected that US Subprime Mortgage Crisis and later European Sovereign Debt Crisis present a certain message to investors, and we wish to capture on how investors reacted following those events by examining contagion between financial sector indices and between financial sector indices and non-financial sector indices

In choosing the model to answer our question, I would like to remind that in the previous part of this chapter we had agreed on adopting the definition by Forbes and Rigobon (2001) where shift contagion, an increase in cross-market linkage after a shock to an individual country is the more proper definition of contagion

[8] See chapter 2 on how does volatility transmitted between money market and stock market

Empirically, scholar had used model such as DCC MGARCH model to model this “increase in cross-market linkage”, they presented conditional correlation as the “linkage” and subjected this “linkage” to test whether there’s an “increase” in this “linkage”. In the previous part of this chapter we elaborated on the reasoning of why we will use DCC MGARCH and ADCC MGARCH as our tools to arrive on bivariate conditional correlation of return of stock price indices data that we used in this study.

In orther to test for the presence of contagion we will use the method by Cho and Parhizgari (2008) where they studied the Asian Financial market by using mean difference t-tests and median difference z-tests to test conditional correlation result to test for the presence of contagion in our data.

We will extends previous studies by comparing the relatively stable pre US subprime mortgage crisis periods, US subprime mortgage crisis periods, and Eurozone Sovereign Debt Crisis periods. However, due to to computational capability limitation I will limit this study to address only on how the various market sectors from other countries affect Indonesian market (i.e Indonesia as receiver of shocks).

The choosing of the countries was based several considerations. First, the rank of the most prominent financial market which was published on Long Finance’s Global Financial Centers Index 2011 and Xinhua-Dow Jones’s International Financial Centers Development Index 2011. The second consideration is the importance that particular country in the recent financial crises in this decade (i.e Greece as the main source of shocks related to Eurozone Sovereign Debt Crisis). The third consideration is geographical proximity to Indonesia, the main reason why this study conducted. The fourth consideration is the scale of trade linkage between Indonesia and said country[9]

Hence these are countries (and it’s code) that we used in this study: PR China (CHN), Germany (GER), Greece (GRE), Indonesia (ID), Japan (JP), Malaysia (MY), Singapore (SING), USA (US)

[9] (Badan Pusat Statistik, 2014a) for export data and (Badan Pusat Statistik, 2014b) for import data

The scarcity of studies that comprehensively address the question of how investors reacts on Indonesian market, and how does recent global financial crisis affected Indonesian market prompted me write this paper

1.3 Hypothesis

In this study, we intend to test two hypotheses:

1. Does asymmetry effect observed in the volatility of return of financial sector indices of PR China (CHN), Germany (GER), Greece (GRE), Indonesia (ID), Japan (JP), Malaysia (MY), Singapore (SING), USA (US)[10]
2. Does volatility transmission in the form of contagion observed between financial sector indices of PR China (CHN), Germany (GER), Greece (GRE), Japan (JP), Malaysia (MY), Singapore (SING), USA (US); with Indonesian financial sector index

1.4 Purposes of This study

This study intends to give a zoomed out picture for investors and policy makers, of how market may react on volatility shocks transmission. However, this isn't intended to be exhaustive study, nor intended as an investing guide. Rather the result of this study hopefully can be used to construct a big picture and instead of directly used in asset allocation calculation, is to be treated as an insight.

Specifically, the purpose is:

1. Analyzing on how investors tends to react to a particular market, and whether there is some different treatment to different market, this will underline the effectiveness of diversification strategy under a case of financial contagion
2. Analyzing on how does the recent financial crises spread internationally and domestically

1.5 Benefit of this study

I hope that the output of this study may shed another light on the corpus of financial studies and gives insight to business people, policymaker, investors, and scholar

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[10] See sign bias test on chapter 3

With this study, I hope that business people and investors will be able to allocate their capital wisely, and responds to recent trends no overreactively nor underestimating it

To policy makers, I hope this study may give another perspective on how investors will react on Indonesian markets, in the light of information from another market and trends

To scholar, this study can be another addition on the growing corpus of studies on financial contagion and hopefully will add another perspective to which future scholar can pick and expands

1.6 Data Sampling

The choosing of the countries was based several considerations. First, the rank of the most prominent financial market which was published on Long Finance's Global Financial Centers Index 2011 and Xinhua-Dow Jones's International Financial Centers Development Index 2011. The second consideration is the importance that particular country in the recent financial crises in this decade (i.e Greece as the main source of shocks related to Eurozone Sovereign Debt Crisis). The third consideration is geographical proximity to Indonesia, the main reason why this study conducted. The fourth consideration is the scale of trade linkage between Indonesia and said country[11]

Hence these are countries (and it's code) that we used in this study: PR China (CHN), Germany (GER), Greece (GRE), Indonesia (ID), Japan (JP), Malaysia (MY), Singapore (SING), USA (US)

The type of data used in this thesis are Financial Sector Indices, Non-Financial Sector Indices (Consumer Good Sector Indices and Industrial Sector Indices), all in daily frequency

The classification of sector index on point are based on Thomson Reuter Business Classification (TRBC), while the data is provided through Thomson Reuter DataStream

1.7 Structure of this paper

This paper structured as below

[11] (Badan Pusat Statistik, 2014a) for export data and (Badan Pusat Statistik, 2014b) for import data

- Chapter 1: Introduction

  This chapter contain the background story on why does the theme needs to be studied, problem formulation, purposes of study and hypotheses being tested, benefits of this study, shot intro on determination of data sampling, and a general overview of the structure of this paper
- Chapter 2: Literature Review

  This chapter discuss about a deeper understanding of theme raised in this paper, the historical context of the theme, seminal paper on this field of study, the development of this theme in financial studies, and theoretical background
- Chapter 3: Methodology

  This chapter explains methodology used in this paper, including further explanation on data sampling, and method used in data analysis
- Chapter 4: Analysis

  This chapter shows the result of data analysis and interpreted those result
- Chapter 5: Conclusion

  This chapter summarizes the conclusion of this study, and explains limitation and further improvement may be done in this study

CHAPTER 2
LITERATURE REVIEW

2.1 A Review on Studies of Contagion: History and Regionality and Why Trade Linkage Matter

The occurrence of financial crises is unexpected, and the losses resulting from them are very costly, yet through the course of history we had seen that every now and then financial crisis had occurred in one and other form again and again. These historical facts raises a question, that why is it despite the damage; it seems that we can not prevent another occurrence of such thing. And why despite advances in information technology we had not been able to effectively predict the coming of such event.

From the previous paragraphs it is tempting to say that financial crisis occurs simply out of the blue, however studies had proved otherwise. Goodhart and Delargy (1998) found that the onset of Asian Financial Crisis bear striking resemblance to previous crises, and that the background of the crisis reenact similar situation to the pre 1914 crisis. They argued that the pattern is probably an inherent feature of development, and therefore similar event will happen again, and again. This development occurred on a backdrop known as Financial Globalization, which is generally defined as gradually evolving interaction and integration of economies and societies around the world (Das, 2006). This term is not to be confused with Financial Integration, which refers to an individual country linkage to international capital market. Financial globalization is also often mistaken as Financial Liberalization because integration to international financial market require that government liberalize the domestic financial sector and the capital account (Schmukler, 2004). Financial liberalization itself is defined as integration of a country’s local financial system with the international financial markets and institutions through reduction of restriction on financial flows, achieved by deregulation on domestic financial market and liberalization of the capital account.

Financial Globalization is hardly a new thing as it had been around at least since 1870-1914 period (Das, 2006) and may had been occurring in two waves:

the 1870-1914 period and the period of 1960-ongoing (Baldwin & Martin, 1999), while the period between these wave is known as Great Reversal. The first wave of globalization was driven by advances in information and communication technologies, particularly transatlantic communication, industrial revolution and growth of trade attributed to trade liberalization and expansion of lending. The second wave was characterized with the rapid progress of information and communication technology and computer technologies.

These waves of financial globalization had brought so much improvement to global economies. The first wave of globalization saw international trade rising 4% rate annually, and international flows of capital grew annually at 4.8%. The second wave saw even higher figure, international trade grew 11% annualy, while flow of capital rising from 5% to 21% of world GDP (Mishkin, 2007). Bekaert, Harvey, and Lundblad (2001) shows that financial liberalization is related with real economic growth, they found that on average, real economic growth at the rate 1% to 2% annualy after financial liberalization. However, it is observed that the occurrence of financial crisis had become more frequent following the trend of financial liberalization

Eichengreen and Bordo (2002) tried to explore on the notion that the more often reccurence of financial crisis in the last several decade may be attributed to the recent proliferation of financial globalization in the form of financial liberalization. In it's conclusion this paper refute the notion presented in Goodhart and Delargy (1998) that pre 1914 international financial system with it's very hard currency peg in gold standard was more resilient to crisis. In their conclusion they found that the previous era was more stabil, because the banking sector had little impact to destabilize the currency market, which prevent financial crisis to spillover to currency market and producing twin crisis

Mishkin (2007) defended financial globalization by asserting that financial globalization encourages development of institutions so that financial markets can effectively perform a crucial function of getting capital to finance growth and reduce poverty. He rejects the notion that financial globalization leads to harmful financial crises. Instead, he argued that it is the mismanagement in financial globalization that may often lead to a crisis. The increased likelihood of financial crisis following for a countries embracing financial globalization comes from the lessening of restrictions which may encourage financial institution to take risks more than it can take. These moral hazard incentives are more likely to be the source of bad loans rather than lack of expertise. Another study (Mendoza & Quadrini, 2010) found that cross country difference in enforcement of financial market is found lead to sharp rise in net credit in developed countries (i.e. USA) and relatively small shock to equity of one country's financial intermediaries may incite large responses in equilibrium asset price world wide. Both study shed some light in USA sub prime mortgage crisis, where large increase in debt and leverage from foreign lending led tu surplus money supply, coupled with lack of enforcement, in how financial institution may lend money make financial institution to take bold policy of pushing loan to less financial literate borrower.

Today, financial globalization had became an acceptable fact, and it is fair to expect that hardly anyone with a sane mind would objected to financial globalization let alone to reverse the state of current financial globalization, that is unless a major conflict like a world war were to happen and triggering another great reversal. Hence, regardless of whether financial globalization induces financial crises, or financial crises merely resulted from mismanagement, we can expect to see more occurrence of financial crises in the future.

Eichengreen, Rose, and Wyplosz (1996) conducted very thorough study on contagion which covered a great length of channel that may transmit volatility, and other recent studies are rarely as comprehensive as this study. They tried to compare which channel of contagion is more significant in currency crisis, is it trade linkage or economic and political commonalities. This study include data from 1959 through 1993 across 20 industrial countries, with variables that covered these aspects: presence of capital control; electoral victory of defeat of the government; the growth of domestic credit; inflation; output growth; employment growth; unemployment rate; and government budget surplus or deficit as percentage of GDP. They found that contagion does exist and that international trade linkages matter more than economic or political commonalities on explaining the volatility transmission. Speculative attack on a region will increase the odds of an attack on another region currency. However, they also noted that their result may not offer the best explanation to real word crisis since commonalities are more difficult to capture in a weighting scheme, and that the result of preferring trade linkage channel may had been reflection of better proxying trade linkage. At the end of the paper they also recognize the increasing importance of emerging market in Latin America and Asia.

Another study by Glick and Rose (1998) confirm the conclusion of Eichengreen, Rose, and Wyplosz (1996). This study tried to examine why currency crises tend to be regional by contrasting macroeconomic and financial influences. They also found that patterns of international trade are important in understanding how currency crises spread, by showing that trade linkages help explain cross-country correlations in exchange market pressure during crisis episode, even after controlling for macroeconomic factor

It is interesting to note that, trade linkage influenced how contagion spread, therefore to asses Indonesian market, we need take a special note on Indonesian trade balance and which market are it’s major partner. The data for was taken from Export – Import report from National Statistical Bureau (BPS).

Hence these are countries (and it’s code) that we used in this study: PR China (CHN), Germany (GER), Greece (GRE), Indonesia (ID), Japan (JP), Malaysia (MY), Singapore (SING), USA (US). Note that the inclusion of Greece was due to it role on the European Sovereign Debt Crisis. Although Netherland was higher than Germany in Export value, I choosed Germany since it’s total Export-Import value was higher.

Negara Tujuan *Country of Destination*	2009	2010	2011	2012	2013
(1)	(2)	(3)	(4)	(5)	(6)
ASIA					
ASEAN	**24 624,0**	**33 347,5**	**42 098,9**	**41 829,1**	**40 630,0**
Thailand	3 233,8	4 566,6	5 896,7	6 635,1	6 061,9
Singapura/*Singapore*	10 262,7	13 723,3	18 443,9	17 135,0	16 686,3
Filipina/*Philippines*	2 405,9	3 180,7	3 699,0	3 707,6	3 817,0
Malaysia	6 811,8	9 362,3	10 995,8	11 278,3	10 666,6
Myanmar	174,8	284,2	359,5	401,6	556,4
Kamboja/*Cambodia*	201,2	217,7	259,5	292,2	312,4
Brunei Darussalam	74,9	61,0	81,7	81,8	122,7
Laos/*Lao People's Dem. Rep.*	4,7	5,5	8,6	23,8	5,8
Vietnam	1 454,2	1 946,2	2 354,2	2 273,7	2 400,9
Asia Lainnya/*Rest of Asia*					
Jepang/*Japan*	18 574,7	25 781,8	33 714,7	30 135,1	27 086,3
Hongkong	2 111,8	2 501,4	3 215,5	2 631,9	2 693,3
Korea Selatan/*Korea, Republic of*	8 145,2	12 574,6	16 388,8	15 049,9	11 422,5
Taiwan	3 382,1	4 837,6	6 584,9	6 242,5	5 862,4
Cina/*China*	11 499,3	15 692,6	22 941,0	21 659,5	22 601,5
Lainnya/*Others*	13 498,0	17 416,6	22 902,8	22 059,7	22 630,6
AFRIKA/*AFRICA*	**2 802,9**	**3 657,0**	**5 675,3**	**5 713,7**	**5 615,5**
AUSTRALIA & OCEANIA					
Australia	3 264,2	4 244,4	5 582,5	4 905,4	4 370,5
Selandia Baru/*New Zealand*	349,5	396,2	371,7	441,0	469,5
Oceania Lainnya/*Rest of Oceania*	243,0	249,8	348,9	336,4	367,5
AMERIKA/*AMERICA*					
NAFTA	**11 746,5**	**15 761,2**	**18 077,8**	**16 316,7**	**17 161,3**
Amerika Serikat/*USA*	10 850,0	14 266,6	16 459,1	14 874,4	15 691,7
Kanada/*Canada*	512,5	731,9	960,3	792,4	782,3
Meksiko/*Mexico*	384,0	762,7	658,4	649,9	687,3
Amerika Lainnya/*Rest of America*	**1 717,2**	**2 740,3**	**3 295,2**	**2 975,2**	**3 018,5**
EROPA/*EUROPE*					
Uni Eropa/*European Union*	**13 568,1**	**17 127,4**	**20 508,9**	**18 027,3[r]**	**16 763,7**
Inggris/*United Kingdom*	1 459,3	1 693,2	1 719,7	1 696,8	1 634,8
Belanda/*Netherlands*	2 909,1	3 722,5	5 132,5	4 664,3	4 106,0
Perancis/*France*	870,2	1 122,8	1 284,6	1 128,2[r]	1 062,7
Jerman/*Germany*	2 326,7	2 984,7	3 304,7	3 075,0	2 883,4
Belgia/*Belgium*	1 048,3	1 190,1	1 374,7	1 297,7	1 259,3
Denmark	168,8	180,2	250,2	229,4	224,5
Swedia/*Sweden*	144,3	156,5	170,4	166,3	162,4
Finlandia/*Finland*	61,2	122,7	219,0	197,8	149,1
Italia/*Italy*	1 651,1	2 370,0	3 168,3	2 277,0	2 128,6
Spanyol/*Spain*	1 830,5	2 328,7	2 427,9	2 069,3[r]	1 810,4
Yunani/*Greece*	165,7	155,4	157,5	139,9	149,2
Polandia/*Poland*	259,7	313,3	379,5	340,0	365,4
Uni Eropa Lainnya *Rest of European Union*	673,2	787,3	919,9	745,6[r]	827,9
Eropa Lainnya/*Rest of Europe*	**983,5**	**1 450,7**	**1 789,7**	**1 696,9[r]**	**1 858,7**
Jumlah/*Total*	**116 510,0**	**157 779,1**	**203 496,6**	**190 020,3**	**182 551,8**

Figure 1: Export Value, by Country of Destination 2009-2013, (Badan Pusat Statistik, 2014b)

The major export destinations for Indonesia are: Singapore, Malaysia, Japan, China, USA and Netherland

Negara Asal *Country of Origin*	2009	2010	2011	2012	2013
(1)	(2)	(3)	(4)	(5)	(6)
ASIA					
ASEAN	**27 722,0**	**38 912,2**	**51 108,9**	**53 662,2**	**53 851,4**
Thailand	4 612,9	7 470,7	10 405,1	11 438,5	10 703,1
Singapura/*Singapore*	15 550,4	20 240,8	25 964,7	26 087,3	25 581,8
Filipina/*Philippines*	544,0	706,3	852,4	799,7	777,4
Malaysia	5 688,4	8 648,7	10 404,9	12 243,5	13 322,5
Myanmar	29,1	31,9	71,3	63,5	73,2
Kamboja/*Cambodia*	3,4	4,7	7,9	11,6	17,8
Brunei Darussalam	639,6	666,2	1 018,4	419,8	645,4
Laos/*Lao People's D Rep*	0,4	0,6	1,3	3,3	7,6
Vietnam	653,8	1 142,3	2 382,9	2 595,0	2 722,6
Asia Lainnya/*Rest of Asia*					
Jepang/*Japan*	9 843,7	16 965,8	19 436,6	22 767,8	19 284,3
Cina/*China*	14 002,2	20 424,2	26 212,2	29 385,8	29 849,5
Korea Selatan/*Korea Republic of*	4 742,3	7 703,0	12 999,7	11 970,4	11 592,6
Lainnya/Others	12 932,6	17 016,9	22 505,3	24 086,7	24 471,9
AFRIKA/*AFRICA*	**2 047,4**	**2 455,4**	**4 029,9**	**5 703,4**	**5 549,6**
AUSTRALIA & OCEANIA					
Australia	3 436,0	4 099,0	5 177,1	5 297,6	5 038,2
Selandia Baru/*New Zealand*	556,8	726,9	729,2	696,3	806,0
Oceania lainnya/*Rest of Oceania*	154,0	54,3	37,6	62,4	23,4
AMERIKA/*AMERICA*					
NAFTA	**8 216,2**	**10 720,5**	**13 241,7**	**13 981,8**	**11 648,9**
Amerika Serikat/*United States*	7 083,9	9 399,2	10 813,2	11 602,6	9 065,7
Kanada/*Canada*	992,5	1 108,4	2 015,8	1 810,8	2 067,4
Meksiko/*Mexico*	139,8	212,9	412,7	568,4	515,8
Amerika Lainnya/*Rest of America*	**2 282,0**	**3 212,9**	**4 231,1**	**4 457,0**	**4 768,4**
EROPA/*EUROPE*					
Uni Eropa/*European Union* [1]	**8 679,9**	**9 862,5**	**12 499,7**	**14 132,2**	**13 708,1**
Inggris/*United Kingdom*	844,6	937,9	1 173,9	1 366,3	1 081,9
Belanda/*Netherlands*	554,1	681,9	808,5	880,2	1 033,8
Perancis/*France*	1 633,1	1 340,5	2 004,6	1 924,2	1 590,7
Jerman/*Germany*	2 373,5	3 006,7	3 393,8	4 188,6	4 426,3
Austria	259,3	292,0	396,4	324,5	383,6
Belgia/*Belgium*	434,3	555,4	593,6	628,1	642,5
Denmark	116,6	168,4	176,2	173,5	199,3
Swedia/*Sweden*	712,3	725,6	886,2	1 298,7	825,6
Finlandia/*Finland*	227,0	358,7	500,1	448,8	442,5
Irlandia/*Ireland*	185,6	102,0	107,9	109,9	115,8
Italia/*Italy*	726,1	909,7	1 222,8	1 523,8	1 695,6
Spanyol/*Spain*	254,0	309,3	379,6	459,1	545,2
Uni Eropa Lainnya/ *Others of European Union*	359,4	474,4	856,1	806,5	725,3
Eropa Lainnya/*Rest of Europe*	**2 214,1**	**3 509,7**	**5 226,6**	**5 485,9**	**6 036,4**
Jumlah/*Total*	**96 829,2**	**135 663,3**	**177 435,6**	**191 689,5**	**186 628,7**

Figure 2: Import Value, by Country of Destination 2009-2013, (Badan Pusat Statistik, 2014c)

While the major import origin are also: Singapore, Malaysia, Japan, China, USA, and Germany

2.1.1 Studies on Asia Pacific Region

The years 1997-1998 was a time of turmoil for Indonesian and left a deep scar on our collective psyche as nation. The Asian Financial Crisis had caused a long lasting and devastating effect to Indonesian economy and political stability. The crisis had penetrated into social fabric of Indonesian society as shown by the toppling of the old political establishment, violence directed into certain ethnic minority, deadly conflict over several region on the archipelago, and the loss of East Timor province

The crisis had caused the value of Indonesian rupiah to plummet into one sixth of the pre-crisis level, capital flow to Indonesia turn from a net inflow of over $ 10 billion in 1996 to a net outflow of $1.1 billion in 1997 this trend continued to widen, reaching a total outflow $ 8.0 billion in 2000 (Athukorala, 2003). By the end of the year 1998 the economy had already contracted by almost 14 per cent, way higher than in historical low, 3.0 per cent in 1963

Table 2.1: Real GDP growth at 1993 constant prices by industrial sector, 1995-1999

	Sector	1995	1996	1997	1998	1999
1	Agriculture, livestock, forestry, and fishery	4.4	3.1	0.7	0.2	0.7
2	Mining and quarrying	6.7	6.3	1.7	-4.2	-0.1
3	Manufacturing	10.9	11.6	6.4	-12.9	2.2
4	Electricity, gas, and water supply	15.9	13.6	12.8	3.7	7.3
5	Construction	12.9	12.8	6.4	-39.7	1.2
6	Trade, hotels, and restaurants	7.9	8.2	5.8	-18.9	-1.1
7	Transports and communication	8.5	8.7	8.3	-12.8	-0.7
8	Financial ownership, and business	11.0	6.0	6.5	-26.7	-8.7
9	Services	3.3	3.4	2.8	-4.7	-2.8
	GDP	8.2	7.8	4.9	-13.7	0.2
	Non-oil and gas GDP	9.2	8.2	5.5	-14.8	0.4

(Athukorala, 2003)

Here we can see that consistently across all industries, real GDP had plummeted drastically even reaching a negative value in the heyday of the crisis especially the manufacturing, construction, and financial industries.

Table 2.2: Stock Markets, 30 June 1997 to 8 May 1998

	6/30/97	12/31/97	Percentage change 6/30/97-12/31/97	5/8/98	Percentage change 1/1/98-5/8/98	Cumulative percentage changed 6/30/97-5/8/1998
Thailand	527.3	372.7	-29.3	386.4	3.7	-26.7
Malaysia	1077.3	594.4	-44.8	580.1	-2.4	-46.2
Indonesia	725.0	401.7	-44.6	434.7	8.2	-40.0
Philippines	2809.0	1869.2	-33.5	2210.0	18.2	-21.3
Hong Kong	15197.0	10772.8	-29.4	1060.4	-6.2	-33.8
Korea, South	745.4	376.3	-49.5	373.0	-0.9	-50.0
Taiwan	9030.0	8187.3	-9.3	8210.8	0.3	-9.1
Singapore	1988.0	1529.8	-23.0	1420.8	-7.1	-28.5

(Goldstein, 1998)

This Crisis had also affected stock market severely, as most ASEAN countries saw their stock market plummeted

It is sobering to remember that thiss 1998 Asian Crisis, was not the only one in its time. Within the 1990's decade alone, there were also several other financial crisis affecting the other part of the world: the crisis on European Monetary System of 1992-1993, the Mexican peso crisis of 1994-1995, Russia's default of 1998, and the 1997 Asian Financial Crisis (Calvo & Mendoza, 2000).

In the post 2000's, the world had seen again other two major financial crisis: the US Subprime Mortgage crisis, and Eurozone Sovereign Debt crisis. These crisis are unlike the crises in the previous decade which impact had been largely contained within some region, their impact were felt in global scale. The reverberation of these crises had sent shock internationally and in the hey day of US Subprime Crisis back in the 2008, the Asia-Pacific economies had felt quite significant shocks on their equity prices and exchange rate (Filardo, 2010)

The occurrence of these historical event which was known as financial contagion, begs for explanation, that how exactly such a devastating event happened, and how did authority failed to notice prior to these crisis.

There were a various explanation on on how and why 1998 Asian flu happened. Corsetti, Pessenti, and Roubini (1999) explored through the notion that the crisis reflected structural and policy distortions in the countries in the region. They show that initially it is financial imbalance that triggered currency and financial crisis, but over time, market overreaction and herding increase the severity of the crisis beyond what it should be through herding and flight to quality.

Similarly, Dornbusch, Park, and Claessens (2000) asserted that the 1998 Asian Financial Crisis was mainly exacerbated by liquidity and incentive problems, which drives investors action which eventually leads to sharp currency depreciation and equity prices in the various country in the region.

Ito and Hashimoto (2005) used high frequency analysis methodology, and found that Indonesia and Korea are the two main shocks origin countries, affecting exchange rates and stock prices of other countries. Surprisingly, they found the evidence that bilateral trade linkage explains shocks transmission in currency market.

Kuper and Lestano (2007) showed that as the crisis intensified, exchange rate and interest rate show higher correlation over time. This implies that investors action are powerful factor affecting the landscape of financial market having the capability to amplify the effect expected from fundamental linkage

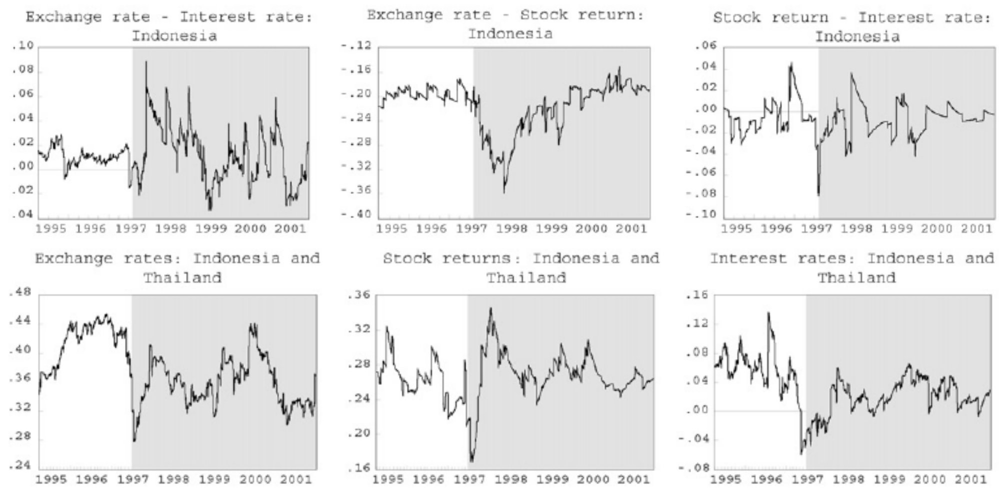


Figure 3: Dynamic conditional correlation within Indonesia and across financial market, and across Indonesia and Thailand (Kuper & Lestano, 2007)

Abeysinghe (2001) also came into similar conclusion, they found that despite fundamental linkage plays important role in transmitting shocks, the bulks of the transmission was created by “pure contagion” which has very little to do with fundamental linkages

This findings built a certain narratives where although the primary driver of financial contagion was “pure contagion” which has very little to do with fundamental linkages, this “pure contagion” can also surprisingly took shape in a way that it can be explained by trade linkages

These studies also pointed that despite sound fundamental policy makers cant stay content and needs to acknowledged the risk of sudden change in market behavior

2.2 “Contagion”: a review on the definition of jargon on volatility transmission literatures

Scholars had yet to agree on the definition of Contagion. Some of the few literature that focusing on defining those term are Pericoli and Sbracia (2003); and Masson (1998)

Masson (1998) differentiates between monsoonal effect, spillover, and contagion. He stated, there are several reasons for expecting crises to be contemporaneous in time.

1. First, they may be due to a common cause, for instance policies undertaken by industrial countries that have similar effects on emerging markets, this kind of crisis is termed as *monsoonal effect.*
2. Second, a crisis in one emerging market may affect the macroeconomic fundamentals in other emerging markets, for instance because devaluation reduces the price competitiveness of other countries, this kind of crisis is termed as *spillovers*.
3. Third, a crisis in one country may conceivably trigger a crisis elsewhere for reasons unexplained by macroeconomic fundamentals (jump between equilibrium), perhaps because it leads to shifts in market sentiment or changes the interpretation given to existing information, this kind of crisis is termed as *contagion*.

Pericoli and Sbracia (2003) further admitted that there is a considerable amount of ambiguity concerning the precise definition of contagion and how it should be measured, and there exist no theoretical or empirical definition on which author agreed. On their paper they listed several definition of contagion commonly adopted in literatures:

1. Contagion is a significant increase in the probability of crisis in one country, conditional on a crisis occurring in another country
2. Contagion occurs when volatility spills over from the crisis country to the financial markets of other countries
3. Contagion is a significant increase in co-movements of prices and quantities across markets, conditional on a crisis occurring in one market or group of markets
4. (Shift-) contagion occurs when the transmission channel is different after a shock in one market
5. Contagion occurs when co-movements cannot be explained by fundamental

This thesis follows the thirds definition of contagion by Pericoli and Sbracia, (2003) where contagion is defined as significant increase in comovement of prices

2.3 How does Volatility Transmitted between Money Market and Stock Market

In the previous part of this chapter we had learned that trade linkage is the factor that strongly influences contagion. However, we had also learned that investor's behavior also play important role particularly in the recent 2007-2009 crisis.

Since we will only discuss about stock market in this paper, then we will naturally arrive at the question of how our study will also explain the financial contagion on another market, if we only examined the asset price of certain market. To answer this question, we need to look for a model explained by Mishkin (1995)

In their paper they shows two model on how monetary policy transmitted through stock price market: through valuation of equities, and through wealth effects on consumption

The first model is modeled $M \downarrow \Rightarrow P_e \downarrow \Rightarrow q \downarrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$, where contractionary monetary policy($M \downarrow$) leads to lower equity prices $P_e \downarrow$which will lead to a lower ratio between a physical asset's market value and its replacement value, also known as Tobin's q(q↓), thus lower investment spending ($I \downarrow$) and leading to lower output

The second model is modeled: $\downarrow \Rightarrow P_e \downarrow \Rightarrow wealth \downarrow \Rightarrow consumption \downarrow \Rightarrow Y \downarrow$. The rationale of the second model is sonce a major component in financial wealth is common stock, when stock prices fall, the value of financial wealth decreases, which will also decrease the resource of consumer leading to lower consumption, and in the end also lower output

2.4 How Information Channel May Explain Financial Contagion

Regarding the question of how information channel itself may explain the phenomenon known as financial contagion. We will need to understand of why information channel is important in the study of financial contagion, and how this may influence the market

Dornbusch, Park, and Claessens (2000) argued that investors behaviors irrespective of whether it is rational or not is an important vector of contagion from one country to another may exarcebate the effect caused by fundamental causes. They identified that this channel termed as investor's practices are: liquidity and incentives problem, information assymetries and coordination problems, multiple equilibrium, and changes in the rule of the game

Kodres and Pritsker (2002) proposes a rational expectation model which may explain how contagion generally spread through information shocks and liquidity shocks. The model of the change in asset price due to information shocks is

$$\frac{\partial P}{\partial \theta} = M_1 \frac{\partial E(v|P)}{\partial \theta} + M_2$$

θ represents information shocks, information learned by informed investors. P stands for asset price. $M_1 \frac{\partial E(v|P)}{\partial \theta}$ is the "expectations component" of the price change which was driven by shocks change $\partial E(v|P)$. M_2 is the the "portfolio balance component" which measures how prices would respond to the shift in the excess demand curve for asset caused by shocks if the uninformed investors believed that the shocks contained no information

2.5 Development in the Studies of Transmission Channel

Volatility transmission and market interdependence play crucial role on the study of propagation of financial crisis. However, the problem on researching volatility transmission is closely related to the fact that there appear several channel that may transmit volatility in which scholars also had differing view on how to explain its mechanism. Complexities of international financial market is also another factor of why there were differing views of how and why a crisis may occurs

On addressing these problem, several paper had proposed these channel of transmission: information shocks, liquidity shocks, financial institution linkages, national and international factors in pricing risk in asset markets, and portfolio rebalancing resulting from information shocks

Calvo and Mendoza (2000) suspected that financial globalization may also promote contagion by weakening incentives for gathering information and by strengthening incentives for arbitration to occur

King and Wadhwani (1990) studied the stock market crash of 1987 and noticed investor produces lots of reports and commentaries on that event, they raised theory that although the phenomenon where stock market in various countries is correlated following the event can be explained by ICAPM[12], perhaps it can also be explained by rational expextation model. In their conclusion they assert that it is possible that a shock may spread to other markets as a result of rational agent using information on particular market to infer information about another market

Allen and Gale (2000) proposed a model where liquidity preference shock can spread contagion, they theorized that contagion may be transmitted by overlapping claims that different regions or sector of the banking system have on one another

Perry and Lederman (1998) stated that institutional investor may had been among channels of transmission. They suspect that investor may prefer to liquidate investments in assets that have no yet been affected by financial crisis, but seem vulnerable thus reducing portfolio risk. This may explain why Indonesia which was seems very healthy at the onset of the crisis eventually fallen

Bekaert and Hodrick (1992) found that a variable like dividend yield have predictive power for excess return in the foreign exchange market, and this also in effect for variables such as forward premiums

Fleming, Kirby, and Ostdiek (1998) proposed that cross market hedging may create volatility linkages between markets. They suspected that when information alter expectation in one market, investors adjust their investment across market producing a spillover. The result found that not only volatility linkage changed over time, it actually have become much stronger since the 1987 stock market crash

Empirically there were also various approach used by scholar to study volatility transmission, most literature on contagion used aggregate stock market indices Forbes and Rigobon (2002); Bae, Karolyi, and Stulz (2003); and Baig and Goldfajn (1999), while paper that test for contagion based on non aggregate data are rare. Previous studies tends to focus on a single asset classess, research are

[12] International Capital Asset Pricing Model

usually between same class of asset market (Dungey & Martin, 2007). Several market which usually addressed on are: currency market, equity market, and bond market

There were many theoretical models and motives proposed to explain financial crisis, however empirical analysis are rare. Forbes and Rigobon (2002) found that stock market comovements shows no increase in unconditional correlational coefficients, however there is a high level of market comovement in all periods. This, shows that when contagion is defined as significant increase in market comovemant after a shock to one country, stock market comovement shows no contagion but only interdependence. However, their conclusion was debated by Corsetti, Pericoli, and Sbracia (2005), which point out that contagion does exist and that the result which shows 'no contagion only interdependence' is due to arbitrary and unrealistic restrictions on the variance of country-specific shocks. By using data of daily returns of emerging markets during the 1990s; Bae, Karolyi, and Stulz (2003) found that contagion is predictable and depends on regional interest rates, exchange rate changes, and conditional stock return volatility

Dungey M. , Fry, González-Hermosillo, and Martin (2006) tried to asses crisis associated with Russian bond default in August 1998 and the LTCM [13] recapitalization announcement in September 1998. They used latent factor model to decompose the premia of 12 bond market into components associated with a common world factor, country-specific factors, regional factors, and contagion effects. Their result show evidence of contagion effects from Russia to both emerging and developed countris, while the effect from LTCM recapitalization announcement tended to be smaller, and that contagion was greater in emerging markets. The effect of contagion was also not only confined in bond market, but may also spred to international equity market (Dungey M. , Fry, Gonzalez-Hermosillo, & Martin, 2007). In this paper they found that in equity market the majoriy of the transmission of the shocks across border is attributable to contagion effects, whereas in bond market contagion effects are relatively small, although in both cases contagion effects are significants.

[13] Long-Term Capital Management L.P. was a prominent hedge fund management firm

Contagion also found to occurs not only within the same type of asset market, it can also occur between different markets. Granger, Huang, and Yang (2000) studied about bivariate causality between stock prices and exchange rate. In their study they noted that previous study using monthly data have found that few of the relation can be established between the two markets or exchange rate market leads stock market, therefore they used daily data on this paper. They found that most markets exhibit either changes in stock prices lead that in exchange rates or either market can take the lead (i.e feedback interaction). Dungey and Martin (2007) developed latent factor framework to model linkages between currency and equity market during Asian financial crisis of 1997-1998, and found that volatility are more affected by spillover than by contagion, although both are statistically significant

2.6 Development of Empirical Technique to Measure Financial Interdependence and Volatility Transmission

Pericoli & Sbracia (2003) tried to provide a unified framework to highlight possible channels for the international transmission of financial shocks by reviewing different definitions and measures of contagion used in the literature. They exhaustively reviewed empirical literature on the international transmission of shocks, and distinguishes two main kinds of study: empirical analyses that attempt to measure the effect of a shock in one country on other countries, and empirical analyses in which contagion is defined in terms of discontinuities in the data generating process

2.6.1 Empirical Analyses that Attempt to Measure the Effect of a Shock in One Country on Other Countries

There were several model which belongs to this category, they were Probit and Logit, Leading Indicator Approach, and GARCH model.

In Probit and Logit model the initial shock is an extreme value of indicator of speculative pressures. Eichengreen, Rose, and Wyplosz (1996) made a seminal approach to the empirical analysis of contagion by constructing an index of exchange rate market pressure (ERP) as weighted average of changes in the exchange rate, short term interest rates, and international reserves. As a dependent variable, they define a “crisis dummy” that takes a unit value for extreme values of ERP (and zero otherwise) and estimate a probit model with a set of macroeconomicand political fundamentals among the independent variables.

Leading Indicator Approach builds on probit and logit models in an attempt to select a parsimonious set of indexes of vulnerability to external and internal shocks. Kaminsky, Lizondo, and Reinhart (1998) evaluate the ability of a set of macroeconomic and financial indicators to forecast the occurrence of a currency crisis correctly

The GARCH model proposed by Bollerslev (1986) dealt with transmission of volatility shocks. This model generalized upon previous model proposed by Engle (1982). Hamao, Masulis, and Ng, (1990) proposed empirical studies of the transmission of shocks across financial markets with ARCH.

Papers that used this model are: Engle, Ito, Lin (1991) which answers the question of yen/dollar intra-day volatility. They study whether such volatility has only country-specific autocorrelation (heat wave) or is affected by spillovers from other countries (meteor showers); and study by Fleming, Kirby, and Ostdiek, (1998) which analyze the co-movements of volatility in US, UK and Japanese Bonds, and show that volatility in Tokyo and London is characterized by *meteor showers*, whilst in New York it is due only to *heat waves*

2.6.2 Empirical analyses in which contagion is defined in terms of discontinuities in the data generating process

Studies on correlation breakdown include tests on structural breaks in correlation. The traditional tests of breakdowns in correlation coefficients, typically find excessive transmission of shocks and discontinuities in the data generating process

In general, correlation coefficients in specific subsamples tend to be biased in the presence of heteroskedasticity and endogeneity or if some variables are omitted. Therefore, when comparing correlation coefficients over a specific subsample, one needs to correct the bias in the coefficients generated by the different variances assumed by the variables in that subsample. For instance, during the crisis periods, economic variables generally show an increase in volatility. Hence, empirical tests that do not correct for the bias, typically tend to favor the hypothesis of excessive transmission

Estimation of Markov switching models directly tests the presence of multiple equilibria. This model is based on the Markov switching model developed by Hamilton (1989).This framework has the advantage that discontinuities can be directly attributed to jumps between multiple equilibria.

2.7 Analyzing the Data: Peculiarity of Financial Data

On choosing what kind of empirical analysis will be used, we need to take into account that financial data had been observed to exhibit some peculiarity which render classical linear regression to be less useful, termed as *stylized facts*. In this part we will try to underline some of those stylized facts before proceeding further

Brooks (2010) mentioned that financial data had some peculiarity that unique to them, he stated that linear structural and time series models are unable to explain several important features common to financial data :

1. Leptokurtosis (Fat Tailed Distribution): tendency for financial asset returns to have distribution that exhibit fat tails and excess peak at the mean

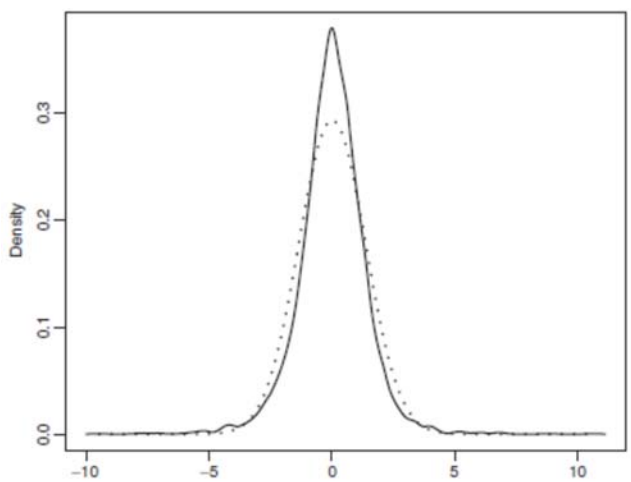


Figure 4: Leptokurtosis; (Brooks, 2010)

2. Volatility Clustering: tendency for volatility in financial market to appear in bunches, or tendency of large changes in asset prices (of either sign) to follow large changes and small changes (also of either sign). In other words, the current level of volatility tends to be positively correlated with its level during the immediately proceedings periods

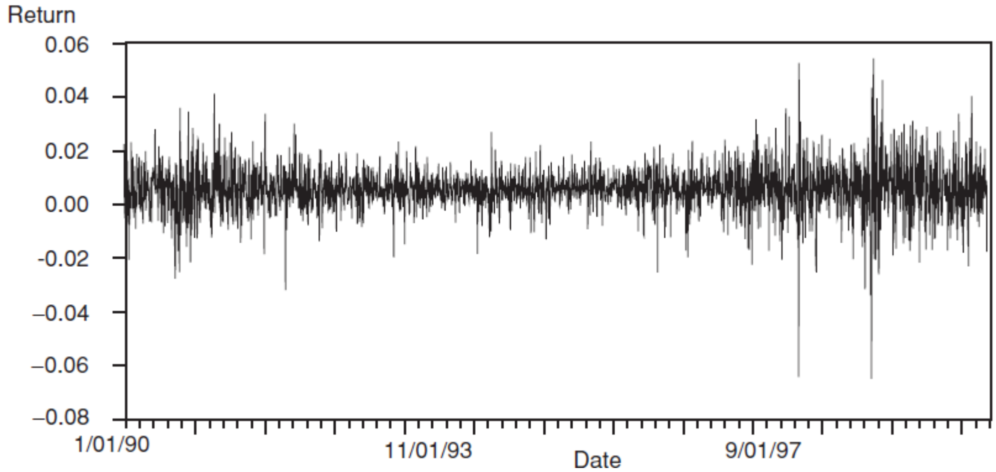


Figure 5: Volatility Clustering; (Brooks, 2010)

3. Leverage Effects: the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude

Enders (1995) mentioned that many economic time series exhibit stylized facts

1. Most of the series contain a clear trend
2. Some series seem to meander
3. Any shock to a series displays a high degree of persistence
4. The volatility of many series is not constant over time
5. Some series share co-movements with other series

Francq and Zakoian (2010) mention the complexities on modeling financial time series is attributed to the variety of the series in use, frequency of observation, and availability of very large data sets. Aside from features mentioned above they also mention these features

1. Nonstationarity of price series

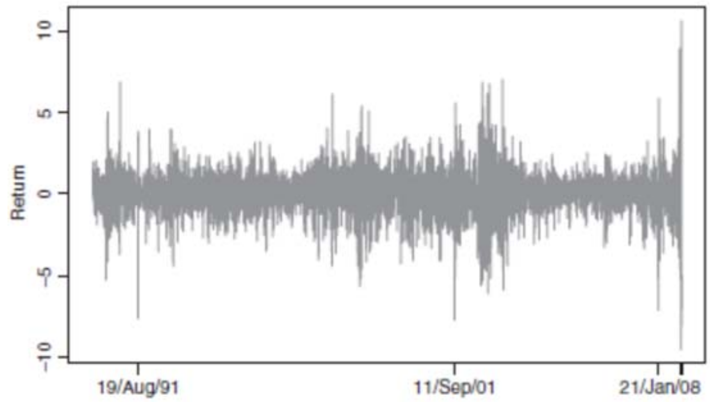


Figure 6: CAC 40 returns (March 2, 1990 to October 15, 2008). August 19, 1991, Soviet Putsch attempt; September 11, 2001, fall of the Twin Towers; January 21, 2008, effect of the subprime mortgage crisis; October 6, 2008, effect of the financial crisis. (Francq & Zakoian, 2010)

2. Absence of autocorrelation for the price variations.

   The series of price variations generally displays small autocorrelations, making it close to a white noise

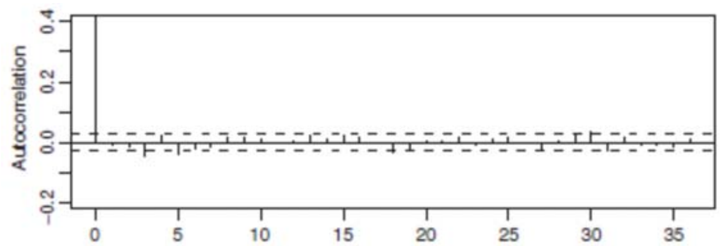


Figure 7: Sample autocorrelations of returns of the CAC 40 (January 2, 2008 to October 15, 2008). (Francq & Zakoian, 2010)

3. Autocorrelations of the squared price returns

   While the squared price return shows autocorrelation, implying that the white noise is not strong.

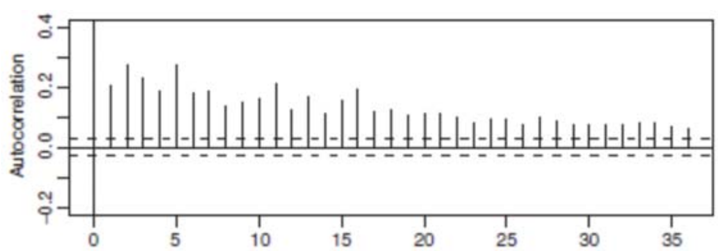


Figure 8: Sample autocorrelations of squared returns of the CAC 40 (January 2, 2008 to October 15, 2008). (Francq & Zakoian, 2010)

4. Seasonality

It was observed that certain calendar effect such as proximity of holiday, may have significant effect on returns

These peculiarity makes Classical Linear Regression Model (CLRM) not suitable, as it's assume that data are homoscedastic. These peculiarity, was in part of the motivations of the propagation of ARCH/GARCH related model by past scholar, as mentioned in chapter 1.

2.8 Development of GARCH-related Technique

The technique to Measure Financial Interdependence and Volatility Transmission used in this thesis is related or derived from GARCH technique, which as mentioned in the previous part, belongs to the kind of empirical analyses that attempt to measure the effect of a shock in one country on other countries

The uses of GARCH technique to analyse relation between financial markets was pioneered by Hamao, Masulis, and Ng (1990) which analyze volatility transmission between New York, London, and Tokyo.

General Autoregressive Conditional Heteroscedasticity (GARCH) itself is a development of ARCH, it addressed important features common to many series of financial assets returns known as volatility clustering. It generalized ARCH by allowing the conditional variance to be dependent upon previous own lags

This GARCH model was a development of ARCH model which was proposed by Engle (1982) that allows variance to be conditional, ARCH model was conceived as an answer to the peculiarity of financial time series; the tendencies of the data to exhibit heteroskedasticity. This peculiarity makes Classical Linear Regression Model (CLRM) not suitable, as it does assume that data are homoskedastic. If the errors are heteroskedastic but assumed homoscedastic, standard errors estimates could be wrong

Conditional variance is defined as

$$\sigma_t^2 = var(u_t|u_{t-1}, u_{t-2}, \dots) = E[\left(u_t - E(u_t)\right)^2|u_{t-1}, u_{t-2}, \dots] \qquad (2.1)$$

Equation 1: Conditional Variance

The ARCH model is then defined as

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \dots + \beta_q x_{qt} \qquad u_t \sim N(0, h_t) \qquad (2.2)$$

$$h_t = {\sigma_t}^2 = \alpha_0 + \alpha_1 {\mu_{t-1}}^2 + \dots + \alpha_q {\mu_{t-q}}^2$$

Equation 2: ARCH (p, q) model

Contrary to ARCH, GARCH model generalizes upon ARCH by allowing conditional variance to be dependent upon previous lags. GARCH (p,q) model let the current conditional variance is parameterized to depend upon q lags of the squared error and p lags of the conditional variance, this model was proposed by (Bollerslev, 1986)

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \sigma_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 \qquad (2.3)$$

Equation 3: Conditional Variance allowed to depend upon lags of squared error

The parameter estimation of GARCH model cannot use OLS method since the model in not a linear form; therefore parameter estimation uses Maximum Likelihood Estimation by constructing Likelihood Function (LF). LF will be a multiplicative function of the actual data, which will consequently be difficult to maximize with respect to the parameters. Therefore, its logarithm is taken in order to turn LF into an additive function of the sample data, i.e. the LLF. The LLF is then maximized

2.8.1 Asymmetric GARCH

Bae and Karolyi (1994) noticed that Financial Studies that left out the possibility of Asymmetric GARCH Model, may reach incorrect conclusion, hence the reason of why it is necessary to consider such model.

Kroner and Ng (1998) explained that GARCH model had left out the issue known in financial studies as Leverage effect, a phenomenon where negative and positive issues may lead to different subsequent volatility.

In their review, Pilar and Diranzo (2006) found that two of the Asymmetric GARCH model, which is EGARCH, and GJR GARCH, was the most widely used model. Hence the reasoning of the use of EGARCH and GJR GARCH to address for leverage effect in this thesis, should the need to asymmetric model arise

2.8.2 Multivariate GARCH

Multivariate GARCH models are very similar to their univariate counterparts, except that MGARCH also specify equations for how the covariances move over time. There are several paper or book which devote to the review of Multivariate GARCH model such as (Bauwens, Rombouts, & Laurent, 2006), (Terasvirta, 2009), and (Francq & Zakoian, 2010)

2.8.2.1 VECH

Bollerslev, Engle, and Wooldridge (1988) proposed a direct generalization of the univariate GARCH model to multivariate GARCH (MGARCH) model. In the general vectorized representation model, which is known as VEC model, each element of $\mathrm{H_t}$ is a linear combination of the lagg $\varepsilon_{i,t-1}{}^{2}$ ²or cross-products of residuals $\varepsilon_{i,t-1}\varepsilon_{j,t-1}$and the lagged elements of $\mathrm{H_{t-1}}$, which can be written as

$$vech(\mathrm{H_t}) = C + A\, vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B\, vech(\mathrm{H_{t-1}}) \qquad (2.4)$$

Equation 4: vech model

Where $vech(\cdot)$ denotes the column stacking operator of the lower portion of a symmetric matrix as a $\frac{1}{2}\mathrm{K}(\mathrm{K}+1)\times 1$ vector, C is $\frac{1}{2}\mathrm{K}(\mathrm{K}+1)\times 1$, A and B are $\frac{1}{2}K(K+1)\times 1 \times \frac{1}{2}K(K+1)\times 1$

The number of parameters involved in $\mathrm{H_t}$ is $\frac{1}{2}\mathrm{K}(\mathrm{K}+1) + 2\left[\frac{1}{4}\mathrm{K}^2(\mathrm{K}+1)^2\right]$. For example, there are 21 parameters when K = 2 and 78 parameters when K = 3.. The large number of parameters in VEC model and the requirement that $\mathrm{H_t}$ is a positive definite matrix for all t motivate some simplifying assumptions. Bollerslev, Engle, and Wooldridge (1988) suggested the diagonal VEC model in which A and B in (1.1) are assumed to be diagonal matrices such that each element (i, j) of $\mathrm{H_t}$ is simply a linear combination of element (i, j) from $\varepsilon_{t-1}\varepsilon'_{t-1}$ and $\mathrm{H_{t-1}}$. The diagonal VEC model is defined as

$$\mathrm{h_{ijt}} = \mathrm{c_{ij}} + \mathrm{a_{ij}}\varepsilon_{\mathrm{i,t-1}}\varepsilon_{\mathrm{j,t-1}} + \mathrm{b_{ij}}\mathrm{h_{ijt-1}} \qquad \mathrm{i,j} = 1, \dots, \mathrm{K} \qquad (2.5)$$

Equation 5: diagonal VEC

Where subscript ij refers to the (i; j)th element of the corresponding matrix. The diagonal VEC model defined above is equivalent to the following representation:

$$\mathrm{H_t} = \mathrm{C} + \mathrm{A}^\circ\varepsilon_{\mathrm{t-1}}\varepsilon'_{\mathrm{t-1}} + \mathrm{B}^\circ\mathrm{H_{t-1}} \qquad (2.6)$$

Equation 6: Alternative representation of VEC

Where ° denotes the Hadamard product of two matrices, that is, the element wise products of two matrices. This specification reduces the number of covariance parameters, $\mathrm{H_t}$ to $\frac{3}{2}\mathrm{K}(\mathrm{K}+1)$. One difficulty n modeling Ht is to ensure that the estimated conditional covariance matrix is positive definite

2.8.2.2 BEKK Model

Since it is hard to guarantee the positivity of the conditional covariance matrix Ht in the VEC model without imposing strong restrictions on the parameters, Engle and Kroner (1995) proposed another specification of the time-varying covariance matrix, which is called Baba-Engle-Kraft-Kroner model (known as BEKK model).

The BEKK(1,1,L) model is defined as

$$H_t = C^{*\prime} C^* + \sum_{l=1}^{L} A_l^{*\prime} \varepsilon_{t-1} \varepsilon'_{t-1} A_l^* + \sum_{l=1}^{L} G_l^{*\prime} \varepsilon_{t-1} \varepsilon'_{t-1} G_l^* \qquad (2.7)$$

Equation 7: BEKK model

Where C^*, A_l^*, G_l^* are $K \times K$ matrices with $C^*$is triangular matrix. The BEKK model can incorporate exogenous influences in covariances, however, it isnot shown in above for simplicity. The summation limit L determines the generality of the process. In the BEKK parameterization, it can overcome the difficulty associated with the VEC parameterization that does not ensure a positive semi-definite Ht, which is necessary for the estimated conditional variance of linear combinations of $y_{1t}, \ldots\ y_{Kt}$ to be greater than or equal to zero. For the VEC parameterization to yield estimates which produce a positive semi-definite Ht matrix, the restriction that all elements in the matrices are greater than or equal to zero has to be imposed.

In BEKK parameterization, positive definite covariance matrix, Ht is generated by essentially unrestricted parameterizations. Also,the number of parameters in BEKK(1,1,1) model is $\frac{1}{2}K(5K + 1)$. In terms of parameter reduction, one can impose a diagonal restriction as in the VEC model, which is called diagonal BEKK model, that is A_l^*, G_l^* 1 in above are diagonal matrices. Thus, the diagonal BEKK model contains only 7 parameters while the diagonal VEC model contains 9 parameters in a bivariate model. Although BEKK model can reduce the number of parameters comparing with the VEC model, the implication or explanation of those parameters cannot be directly interpreted. More details on the relationship between VEC and BEKK models can be found in (Engle & Kroner, 1995).

2.8.2.3 DCC MGARCH

DCC MGARCH model is a development of CCC MGARCH model by (Bollerslev, 1990) which itself was a generalization of MGARCH which further allows for time varying conditional variance and covariance, but constant conditional correlation. DCC MGARCH in contrast to CCC MGARCH also allows for dynamic conditional correlation

This modal was proposed by (Tse & Tsui, 2002) and by (Engle, 2002). In DCC GARCH the conditional matrix H_t can be expressed as $H_t \equiv D_t R D_t$. Where D_t is $k \times k$diagonal matrix of time varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the i^{th} diagonal, and R_t is the time varying correlation matrix. The log-likelihood of this estimator can be written

$$L = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}(k\log(2\pi) + \log(|H_t| + r_t'\, {H_t}^{-1} r_t$$

$$L = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|D_t R_t D_t| + r_t' {D_t}^{-1}\, {R_t}^{-1}\, {D_t}^{-1} r_t)$$

$$L = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t|) + \log(|r_t'|) + \epsilon_t'\, {R_t}^{-1}\epsilon_t \qquad (2.8)$$

Equation 8: Log likelihood of DCC MGARCH estimator

Where $\epsilon_t \sim N(0, R_t)$ are the residuals standardized by their conditional standard deviation. They propose to write the elements of D_t as univariate GARCH models, so that

$$h_{it} = w_i + \textstyle\sum_{p=1}^{P_i}\alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i}\beta_{iq} h_{it-q} \text{for } i = 1,2,\dots,k \qquad (2.9)$$

Equation 9: Conditional variance represented as univariate GARCH model

With GARCH(p,q) restrictions for non-negativity and stationarity being imposed, such as non-negativity of variances and $\sum_{p=1}^{P_i}\alpha_{ip} + \sum_{q=1}^{Q_i}\beta_{iq} < 1$ the subscripts p and q indicate that lag length need not be the same. The specification of the univariate GARCH models is not limited to the standard GARCH (p,q), but can include any GARCH process with normally distributed errors that satisfies appropriate stationarity conditions and non-negativity constraints. The proposed dynamic correlation structure is:

$$Q_t = \left(1 - \sum_{m=1}^{M}\alpha_m - \sum_{n=1}^{N}\beta_n\right)\bar{Q} +$$
$$\textstyle\sum_{m=1}^{M}\alpha_m(\,\epsilon_{t-m}\epsilon_{t-m}') + \sum_{n=1}^{N}\beta_n Q_{t-n} \qquad (2.10)$$

Equation 10: Dynamic Correlation Structure

Where $\bar{Q}$ is the unconditional covariance of the standardized residuals resulting from the first stage estimation, and

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 & \dots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & \sqrt{q_{kk}} \end{bmatrix}$$

So that $Q_t^*$is a diagonal matrix composed of the square root of the diagonal elements of Q_t. The typical element of R_t will be of the form

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit}q_{jjt}}} \qquad (2.11)$$

Equation 11: Conditional correlation

2.8.2.4 ADCC MGARCH

The Asymmetric DCC MGARCH by (Cappiello, Engle, & Sheppard, 2006) extended the DCC MGARCH model to allow for asymmetric dynamics in the correlation in addition to the asymmetric response in variances which was in the original DCC model. The ADCC model extended original DCC Model that assumed that all assets shared the same news impact curves for correlations across distinct assets. They argued that the original DCC estimator is inadequate for higher dimensional models and certain assets. The ADCC estimator was developed to capture heterogeneity present in the data, and allow for asset-specific news and smoothing parameter and asymmetries

2.9 “Good News” and “Bad News”

Engle and Ng (1993) defined news as $\varepsilon_t \equiv y_t - m_t$. Where m_t is the relevant expected return and volatility to the investors are the conditional expected of y_t (rate of return of a particular stock or portfolio from time $t-1$ to time t) given F_{t-1} (past information set containing the realized values of all relevant variables up to time $t-1$) denoted as $m_t \equiv E(y\_t|F_{t-1})$; and h_t is the conditional variance of y_t, given F_{t-1} denoted as h_t in $h_t \equiv \mathrm{Var}(y_t|F_{t-1}$.

ε_t is treated as a collective measure of news at time t. A positive value (an unexpected increase in price) suggest the arrival of good news, while a negative value suggests the arrival of bad news. A large value of $|\varepsilon_t|$ implies that the news is significant in the sense that it produces a large unexpected change in price

CHAPTER 3
METHODOLOGY

3.1 Data Sampling

The choosing of the countries analyzed in this paper was based on several considerations. First, the rank of the most prominent financial market which was published on Long Finance's Global Financial Centers Index 2011 and Xinhua-Dow Jones's International Financial Centers Development Index 2011. The second consideration is the importance that particular country in the recent financial crises in this decade (i.e Greece as the main source of shocks related to Eurozone Sovereign Debt Crisis). The third consideration is geographical proximity to Indonesia, the main reason why this study conducted. The fourth consideration is the scale of trade linkage between Indonesia and said country[14]

Hence these are countries (and it's code) that we used in this study: PR China (CHN), Germany (GER), Greece (GRE), Indonesia (ID), Japan (JP), Malaysia (MY), Singapore (SING), USA (US)

While the type of data used in this thesis are consisted of Financial Sector Index, and Non-Financial Sector Index, which contain Consumer Good Sector Index and Industrial Sector Index

- The date choosing on data sampling was influenced by (Grammatikos & Vermeulen, 2011) which make sure that the data was post 2000s internet bubble crash, therefore their choosing of data from January, 1st 2003
- The data for sector index was taken from Thomson Reuter Data Stream with time frame of January, 1st 2003 – July 16th 2013
  - The DS Mnemonic Code of the financial sector indices data are : FINANCA, FINANBD, FINANGR, FINANID, FINANJP, FINANMY, FINANSG, FINANUS

3.2 Empirical Model

First the data will be log transformed, then the descriptive statistics will be calculated in order to show the general information of the data. Then it will be subjected to stationarity test. Although GARCH models is accommodating to

[14] (Badan Pusat Statistik, 2014a) for export data and (Badan Pusat Statistik, 2014b) for import data

stationary data, for the sake of simplicity in code and parameter estimation we will try to treat for non stationarity by differencing the data if it is found non stationary.

The data will then undergone process to get results of ACF and PACF test to get possible mean equation parameter (i.e AR(p) or MA(q)), than we will find the mean equation (ARIMA model) by choosing the model the most favourable information criteria.

Then the residual will be subjected to ARCH effect test, if the data show conditional heteroskedasticity, then the residual will further modeled in Univariate GARCH model and DCC MGARCH model in order to find persistence, news impact curve, and conditional correlation for our analysis

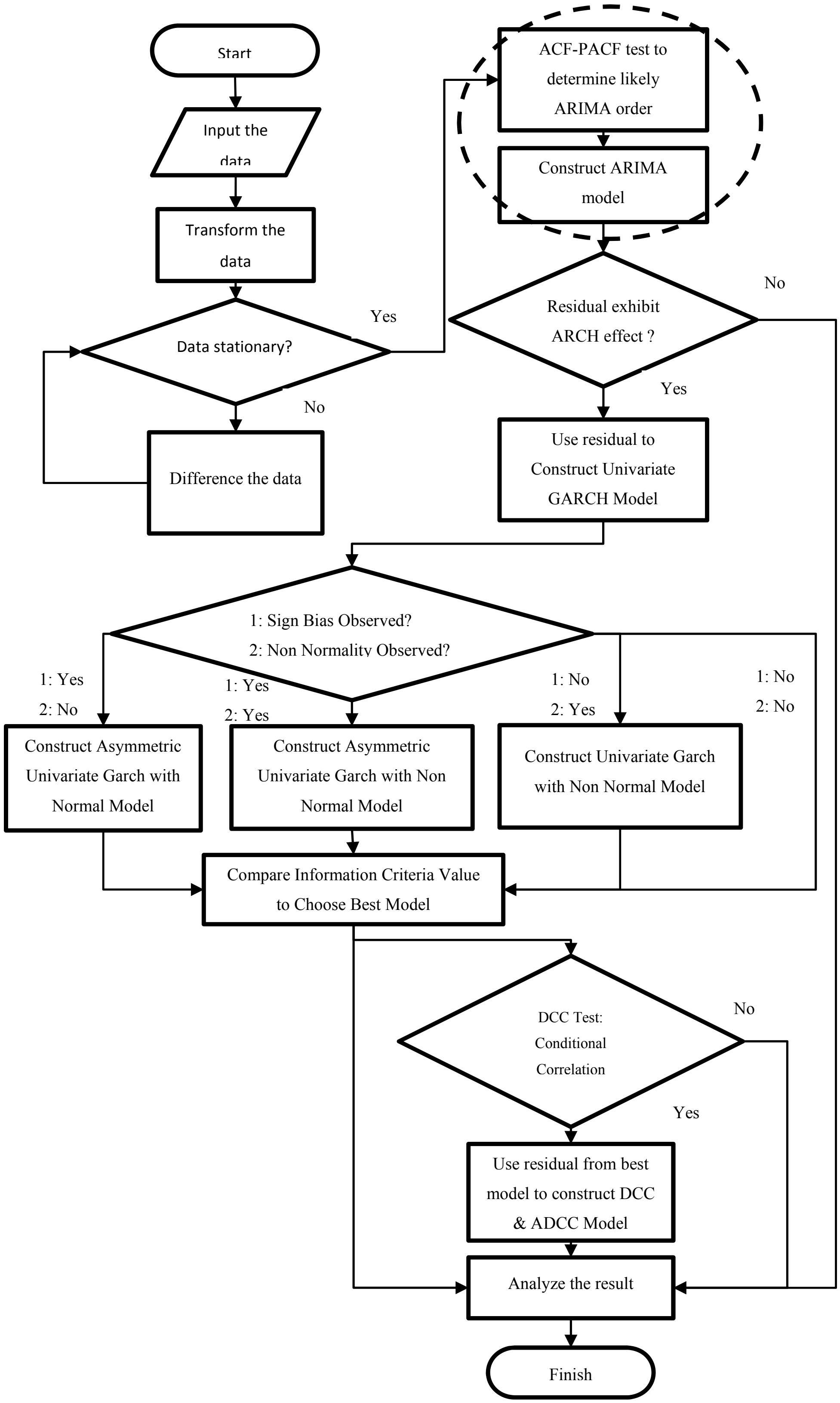


Figure 9: Empirical Model used in this Thesis

3.3 Return Calculation

For the very first step we will transform the data by log difference transformation into return as in the formula below

$$r = \log \frac{P_{t+1}}{P_t} = \log P_{t+1} - \log P_t \tag{3.1}$$

Equation 12: Continuous compounding return

3.4 Descriptive Statistics

Descriptive statistics used in this thesis are histogram, mean, variance, skewness, kurtosis, normality. If kurtosis=3 then the data is normally distributed hence hemoskedastic, if its leptokurtosis then its error may be heteroscedastic, if it's the case then an ARCH-effect test is necessary, if ARCH-effect is significant it implies that the data can be GARCH modeled

3.4.1 Mean

$$\bar{X} = \frac{1}{T}\sum_{t=1}^{T} X_t \tag{3.2}$$

Equation 13: Mean

3.4.2 Variance

$$\sigma^2 = \frac{1}{T}\sum_{t=1}^{T}(X_t - \bar{X})^2 \tag{3.3}$$

Equation 14: Variance

3.4.3 Skewness

a measure of asymmetry of the distribution of the series around its mean

$$S = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{X_t - \bar{X}}{\sigma^3}\right)^3 \tag{3.4}$$

Equation 15: Skewness

$$Z_t = \frac{S}{\sqrt{6/T}} \tag{3.5}$$

Equation 16: Skewness Test

Skewness measures the extent to which a distribution is not symmetric about its mean value. The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail.

3.4.4 Kurtosis

Measures the peakedness or flatness of the distribution of the series

$$S = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{X_t - \bar{X}}{\sigma^4}\right)^4 \tag{3.6}$$

Equation 17: Kurtosis

$$Z_t = \frac{K-3}{\sqrt{24/T}} \tag{3.7}$$

Equation 18: Kurtosis Test

Kurtosis also measures how fat the tails of the distribution are. A normal distribution is not skewed and is defined to have a coefficient of kurtosis of 3. It is possible to define a coefficient of excess kurtosis, equal to the coefficient of kurtosis minus 3; a normal distribution will thus have a coefficient of excess kurtosis of zero. A normal distribution is symmetric and said to be mesokurtic.

3.4.5 Normality

. The Jarque-Bera test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The Null hypothesis for Jarque-Bera Test is that the data follow normal distribution

$$\text{Jarque} - \text{Bera} = \frac{N}{6}\left(+\frac{(K-3)^2}{4}\right) \tag{3.8}$$

Equation 19: Jarque-Bera Test

where N is the skewness, and K is the kurtosis.

3.5 Confirmatory Data Analysis

Confirmatory data analysis is a term for the joint use of stationarity test and unit root test

Data is defined as weakly stationarity data if

$E[X_t] = c$ or $E(y_t) = E(y_{t-l}) = \mu$

$Var[X_t] = \sigma^2$ or $E[(y_t - \mu)^2] = E[(y_{t-l} - \mu)^2] = \sigma_y{}^2$

$Cov[X_t, X_{t-k}] = \sigma_k{}^2$ or

$$E\left[(y_{t_1} - \mu)(y_{t_2} - \mu)\right] = \gamma_{t_2 - t_1} \tag{3.9}$$

Equation 20: Stationarity Condition

A stationary series contains no unit root. The stationarity test becomes necessary because treatment for non-stationary data is different from stationary data for the following reasons

1. The stationarity or otherwise of a series can strongly influence its behavior and properties.
2. The use of non-stationary data can lead to spurious regressions
3. If the variables employed in a regression model are not stationary, then it can be proved that the standard assumptions for asymptotic analysis will not be valid. In other words, the usual 't-ratios' will not follow a t-distribution, and the F-statistic will not follow an F-distribution, and so on.

There were several test for stationarity (also known as test for unit root) some of them are: Augmented Dickey Fuller (ADF) Test, Philips-Perron (PP) Test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. In this paper we used PP Test and KPSS test

Brooks stated that ADF test and PP test suffer from limitation that may reduct the power of the test, hence he combine the ADF test and PP test with KPSS test as below

$$\begin{array}{ll} \text{ADF/PP} & \text{KPSS} \\ H_0: y_t \sim I(1) & H_0: y_t \sim I(0) \\ H_0: y_t \sim I(0) & H_0: y_t \sim I(1) \end{array} \tag{3.10}$$

Equation 21: Hypothesis Testing for ADF/PP and KPSS Test

With four possible outcomes:

1. Reject H_0 and do not reject H_0
2. Do not reject H_0 and reject H_0
3. Reject H_0 and reject H_0
4. Do not reject H_0 and do not reject H_0

Hence for the conclusions to be robust, the results should fall under outcomes 1 where both test concluded that the series tested is stationary and 2 where both test concluded that the series tested is non-stationary

3.6 ARIMA Model Selection

This section exist for the sake of estimating the conditional mean model for the series, which then will be used in the next part

ARIMA model states that the current value of some series y depends linearly on its own previous values (AR) and a combination of current and previous values of a white noise error term (MA). The integration order d are intended to induce stationarity to data , the value of d is the number of how many differencing needed to make a series of data stationary, hence the "I" in the ARIMA, this ARIMA is an extension to ARMA for financial data, since financial data tend to exhibit nonstationarity

$\Phi(L)y_t = \mu + \theta(L)\mu_t$

$\Phi(L) = 1 - \Phi_1 L^1 - \Phi_2 L^2 - \cdots - \Phi_p L^p$

$\theta(L) = 1 + \theta_1 L^1 + \theta_2 L^2 + \cdots + \theta_q L^q$

where

$Ly_t = y_{t-1}$

With

$$Eu_t = 0; E(u_t{}^2) = \sigma^2; E(u_t u_s) = 0, t \neq s \quad (3.11)$$

Equation 222: ARIMA model

To distinguish whether a process is AR(p) or MA(q) or ARIMA (p,d,q) we use both Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

- AR process has:
  1 a geometrically decaying acf
  2 a number of non-zero points of pacf = AR order.
- MA process has:
  1 number of non-zero points of acf = MA order
  2 a geometrically decaying pacf.
- ARMA process has:
  1 a geometrically decaying acf
  2 a geometrically decaying pacf.

The ARIMA modeling follows Box-Jenkins approach

1. Identification

   This phase focused on determining the lag order on data examined by using ACF and PACF

2. Estimation

   In this phase we try to model our data on ARIMA (mean modeling) and GARCH (variance modeling)

3. Diagnostic Checking

   This phase is intended to create a parsimonious model, it could be done by over fitting (see if a model has more parameter than identified in step 1) or residual diagnostic (check residual of the model and examine whether there is significant leg have not been included in the model)

4. Model Selection

   This phase uses AIC, SBIC, and HQIC as information criterion for choosing model, other criterion used is adjusted R^2

$$\mathrm{AIC} = \ln(\hat{\sigma}^2) + \frac{2k}{T} \quad (3.12)$$

Equation 23: SBIC information criterion

$$\mathrm{SBIC} = \ln(\hat{\sigma}^2) + \frac{k}{T}\ln T \quad (3.13)$$

Equation 24: SBIC information criterion

$$\mathrm{HQIC} = \ln(\hat{\sigma}^2) + \frac{2k}{T}\ln(\ln(T)) \quad (3.14)$$

Equation 25: HQIC information criterion

A note on which criterion should be preferred when they suggest different model order is SBIC is strongly consistent (but inefficient) and AIC is not consistent, but is generally more efficient. In other words, SBIC will asymptotically deliver the correct model order, while AIC will deliver on average too large a model, even with an infinite amount of data. On the other hand, the average variation in selected model orders from different samples within a given population will be greater in the context of SBIC than AIC. Overall, then, no criterion is definitely superior to others.

3.7 Test of ARCH Effect

ARCH test was proposed by (Engle, 1982),this test determine whether *ARCH effect* are present in the residual of an estimated model. Implying that ARCH and its related model is suitable for the data

ARCH Testing

Run $y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \cdots + \beta_q x_{qt}$ get residuals $\hat{\mu}_t$

Square the residuals and regress on q own lags to test for ARCH of order q. i.e. run the regression

$$\hat{\mu}_t{}^2 = \gamma_0 + \gamma_1 \hat{\mu}_{t-1}{}^2 + \gamma_2 \hat{\mu}_{t-2}{}^2 + \cdots + \gamma_q \hat{\mu}_{t-q}{}^2 + v_t \quad (3.17)$$

Equation 26: ARCH test

The test statistic is defined as TR^2 (the number of observations multiplied by the coefficient of multiple correlation) from the last regression, and is distributed as $\chi^2(q)$

The null and alternatives hypotheses are

$$\mathrm{H_0}: \gamma_1 = 0 \text{ and } \gamma_2 = 0 \text{ and } \gamma_3 = 0 \text{ and} \ldots \text{and } \gamma_\mathrm{q} = 0$$

$$\mathrm{H_1}: \gamma_1 \neq 0 \text{ and } \gamma_2 =\neq 0 \text{ and } \gamma_3 \neq 0 \text{ and} \ldots \text{and } \gamma_\mathrm{q} \neq 0 \quad (3.18)$$

Equation 27: Hypothesis testing for ARCH test

3.8 Choosing Conditional Variance Model: Estimation of Univariate GARCH

3.8.1 Non Normality Test

Brooks (2010) stated that to estimate a GARCH model, first we need to specify the appropriate equations for the mean and variance then specify Log Likelihood Function (LLF) to maximize for disturbance. The result will be then tested for non normality to and sign bias effect, if normality is observed than we will need to remodel the model to use student-t distribution and skew-t distribution. If sign bias observed, we will also need to remodel the model not only to address on what should be done concerning the result of the non normality test, but also remodel it in Asymmetric Univariate GARCH Model.

The Normality test was adapted from (Vlaar & Palm, 1993), the normality test was necessary in order to pick the more appropriate GARCH estimation method. This test was embedded in the “R” univariate garch estimation function.

3.8.2 Bias Test

In chapter 2, we had learned that GARCH model had not addressed leverage effect, where positive and negative shocks may result in different magnitude of volatility. Engle and Ng (1993) proposed Sign Bias Test, Negative Bias Test, Positive Bias Test, and Joint Test to answer whether an asymmetry is observed. To test for leverage effect, the squared standardized residuals are regressed on a constant and a dummy variable

Sign Bias Test $v_t^2 = a + b.S_t^- + \underline{\beta}' \underline{z}_{ot}^* + e\_t$

Negative Bias Test $v_t^2 = a + b.S_t^- \epsilon_{t-1} + \underline{\beta}' \underline{z}_{ot}^* + e\_t$

Positive Bias Test $v_t^2 = a + b.S_t^+ \epsilon_{t-1} + \underline{\beta}' \underline{z}_{ot}^* + e\_t$

Joint Test $v_t^2 = a + +b_3.S_t^- + b_2.S_t^- \epsilon_{t-1} + b_3.S_t^+ \epsilon_{t-1} + \underline{\beta}' \underline{z}_{ot}^* + e\_t$

With H_0: There is evidence of bias

If Asymmetry Effect is observed in volatility, then we need to construct Asymmetric GARCH Model to address this issue. Among the various Asymmetric Univariate GARCH Model in scholastic corpus, the most commonly used was GJR GARCH and EGARCH (Soriano Felipe & Climent Diranzo, 2006).

3.8.3 Persistence

Francq and Zakoian (2010) stated that in term of persistence of shocks: when $\alpha$is large, sudden volatility variations can be observed in response to shocks; when βapproaches 1 a shock on the volatility has a persistent effect; the sum of $\alpha$and $\beta$is the persistence of shocks that describe how quickly the variance revert to its long run average

3.8.4 News Impact Curve

Financial market, have been known to treat bad news and good news differently, which leads to different predictability to predict future volatility. This effect was known as “leverage” or “asymmetric” effect. Engle and Ng (1993) addressed this problem by devising news impact curve as a measures of how new information is incorporated into volatility estimates.

3.9 Testing for Conditional Correlation Structure

(Engle & Sheppard, 2001) stated that testing whether correlation between asset are not constant through time (testing for constant correlation) is a difficult problem. Testing for dynamic correlation with data that have time-varying volatilities may result in misleading conclusions, which may lead to rejecting constant correlation when it is true (type 1 error).

They propose a test that only requires a consistent estimate of the constant conditional correlation and can be implemented using a vector autoregression

The testing procedure is :

1. Estimate the univariate GARCH processes and standardize the residuals for each series
2. Estimate the correlation of the standardized residuals and jointly standardize the vector of univariate standardized residuals by the symmetric square root decomposition of the R

The null hypothesis for this test is that the series exhibit constant correlation, hence a rejected H_0 implies that conditional correlation is time varying.

3.10 Estimation of Bivariate DCC MGARCH

The estimation on DCC MGARCH in this paper follow Engle & Sheppard (2001). In this paper they used two stage estimation where in the first stage univariate GARCH models are estimated for each residual series, and in the second stage, residuals transformed by their standard deviation estimated during the first stage, are used to estimate the parameters of the dynamic correlation. The likelihood used in the first stage involves replacing $R_t$with I_k, an identity matrix of size k. let the parameters of the model θ , be written in two groups $(\phi_1, \phi_2, \dots, \phi_k, \psi) = (\phi, \psi)$, where the elements of θ_i correspond to the parameters of the univariate GARCH model for the i^{th} asset series, $\theta_i = (\omega, \alpha_{1i}, \dots, \alpha_{P_i i}, \beta_{1i}, \dots, \beta_{Q_i i})$

$$QL_1(\phi|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|I_k| + 2\log(|D_t|)$$

$$+ r_t{}'D_t{}^{-1}\, R_t{}^{-1}\, D_t{}^{-1}r_t)$$

$$QL_1(\phi|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t|) + r_t{}'D_t{}^{-2}r_t)$$

$$QL_1(\phi|r_t) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\left(k\log(2\pi) + \sum_{n=1}^{k}\left((\log(h_{it}) + \frac{r_{it}^2}{h_{it}}\right)\right) QL_1(\phi|r_t) =$$

$$-\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\left(T\log(2\pi) + \sum_{n=1}^{k}\left((\log(h_{it}) + \frac{r_{it}^2}{h_{it}}\right)\right) \qquad (3.19)$$

Equation 28: First part of two step QMLE estimation

Which is simply the sum of log-likelihoods of the individual GARCH equations for the assets. Once the first stage has been estimated, the second stage is estimated using the correctly specified likelihood, conditioning on the parameters estimated in the first likelihood:

$$QL_2(\psi|\hat{\phi}, r_t) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\big(k\log(2\pi) + 2\log(|D_t|) + \log\big(|R_t| + r_t{}'D_t{}^{-1}\,R_t{}^{-1}\,D_t{}^{-1}r_t\big)\big) \quad (3.20)$$

$$QL_2(\psi|\hat{\phi}, r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t|) + \log(|R_t| + \epsilon_t'\,R_t{}^{-1}\epsilon_t)$$

Equation 29: Second part of two step QMLE estimation

Since we are conditioning on $\hat{\phi}$, the only portion of the log-likelihood that will influence the parameter selection is $\log(|R_t| + \epsilon_t'\,R_t{}^{-1}\epsilon_t$, and in estimation of the DCC parameters, it is often easier to exclude the constant terms and simply maximize:

$$QL_2^*(\psi|\hat{\phi}, r_t) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}(\log(|R_t| + \epsilon_t'\,R_t{}^{-1}\epsilon_t) \quad (3.21)$$

Equation 30: Shortened second part of two step QMLE estimation

3.11 Estimation of Bivariate ADCC MGARCH

In the ADCC model the Q_t takes form

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\,\epsilon_{t-1}\epsilon_{t-1}'A + G'\,n_{t-1}n_{t-1}'G + B'Q_{t-1}B \quad (3.22)$$

Equation 31: Estimation of ADCC MGARCH Model

Where A, B, and G are diagonal parameter matrices, $n_t = I[\epsilon_{t-1} < 0] \circ \epsilon\_t$ ($I[\cdot]$ is a $k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise, while $\circ$ indicates the Hadamard product) and $\bar{N} = E[n_t n_t']$

3.12 Analysis of DCC/ADCC MGARCH Conditional Correlation

To test for the presence of contagion, I employed (Cho & Parhizgari, 2008) approach, which used mean difference Student's t-test and median difference z-test to test between stable periods and volatile periods. To determine the periodization on interpreting the data, I used these particular period and date

1. February 2, 2010 : Greek Prime Minister George Papandreou proposes measures to freeze civil service salaries and raise fuel taxes and retirement ages.
2. March 8, 2010: Portugal announces a series of austerity measures intended to cut its nation's budget deficit by 2013.

3. May 27, 2010: Spain's parliament approves roughly $18 billion package in spending cuts, including wage cuts for civil servants, by a one-vote margin.
4. November 16, 2010: Ireland started talks with the EU over a bailout. The move prompted further worry that Greece and Portugal were also in poor fiscal shape. The move follows previous denials that Ireland would need external help to alleviate its debt burden.
5. August 18, 2011: The European stock markets suffered further heavy falls due to persistent fears about the world economic outlook
6. August 24, 2011: The French government unveiled a €12 billion deficit cutting package that raised taxes on the rich and closed some tax loopholes
7. September 21, 2011: S&P have downgraded seven Italian banks after they've dropped Italy's sovereign rating two days ago.
8. October 4, 2011: European shares declined for a second day on fears that Franco-Belgian bank Dexia may need to be rescued due to its exposure to Greek debt. Concern increased that the Eurozone sovereign debt crisis is spreading to the banking sector
9. October 7, 2011: Credit ratings agency Fitch cut Italy's credit rating by one notch to A+ from AA- and cut Spain's rating to AA- from AA+
10. October 13, 2011: S&P cut Spain's long-term credit rating by one notch from AA to AA- with a negative outlook.
11. November 25, 2011: Standard and Poor's downgrades Belgium's long-term sovereign credit rating from AA+ to AA, and 10-year bond yields reach 5.66%
12. December 8, 2011: Fitch cuts Greece's rating to BBB+ from A-, with a negative outlook
13. January 13, 2012: Standard & Poor’s downgrades France and Austria from AAA rating, lowers Spain, Italy and five other euro members further, and maintains the top credit rating for Finland, Germany, Luxembourg, and the Netherlands.

An ongoing timeline of the crisis also provided by ECB on *http://www.ecb.europa.eu/ecb/html/crisis.en.html*

My periodization to analyze the contagion effect is based on the time frame of US subprime mortgage crisis is taken from Grammatikos, and Vermaulen (2011), while the key date of ongoing Eurozone financial crisis which was not discussed on that paper are constructed based on facts above.

1. Pre US Subprime Mortgage Crisis
   January 1, 2003 – February 26, 2007
2. US Subprime Mortgage Crisis
   February 27, 2007 – August 30, 2010
   a. Crisis (pre Lehman Brother bankruptcy)
      February 27, 2007 – September 14, 2008
   b. Crisis (post Lehman Brother bankruptcy)
      September 15, 2008 – August 30, 2010
3. Eurozone Sovereign Debt Crisis
   February 2, 2010 –
   a. February 2, 2010 – August 17, 2011
      Sovereign Debt Crisis
   b. August 18, 2011 – …
      Ongoing EMU Economic Downturn

Therefore we will test the period 1 against 2, 1 against 3, and 2 against 3

I will also present the news impact surface of the bivariate conditional correlation. News impact surface by (Cappiello, Engle, & Sheppard, 2006) is an extension of the earlier news impact curve by (Kroner & Ng, 1998). This surface area describe the effect was known as “leverage” or “asymmetric” effect between the two series analyzed in the bivariate ADCC/DCC MGARCH model

CHAPTER 4
ANALYSIS

4.1 Introduction

The analysis of data used "R" software from cran.r-project.org. R is a free software environment for statistical computing and graphics. It compiles and runs on a wide variety of UNIX platforms, Windows and MacOS

The complete code used in this chapter can be found in appendices. Further description on package used and function built in within package can be found in cran.r-project.org

In this chapter only some graph and output will be shown in this chapter since the series used in this works are plenty. Further detail of the calculation result, graph and code used in this work will be shown in the appendices

For test output below that gives TRUE or FALSE value it should be noted that the output table was transformation of the original output of R which return the value of whether

1. the p value > significance level is true or
2. the test statistics < critical value at chosen significance level is true

A condition that satisfy either point 1 or 2 imply that H_0 can't be rejected. Therefore, a TRUE statement imply that H_0 is not rejected (accepted). For a further inquiry of the original output values and the code to reproduce the output table, look in appendix

To calculate function that experienced convergence failure, I used Return.clean to clean the data before resubmitting into the function

4.2 Descriptive Statistics

First we turn raw data (the sectoral indices) into continuous compounding return by applying diff(log) to each series, there are several reason for applying for this filter, e.g:

1. Removes trends and seasonality
2. To make the series to be stationary

The next two pictures will show how the diff(log) filter address the issue of seasonality and trend by changing the series. These pictures shows the result of series decomposition

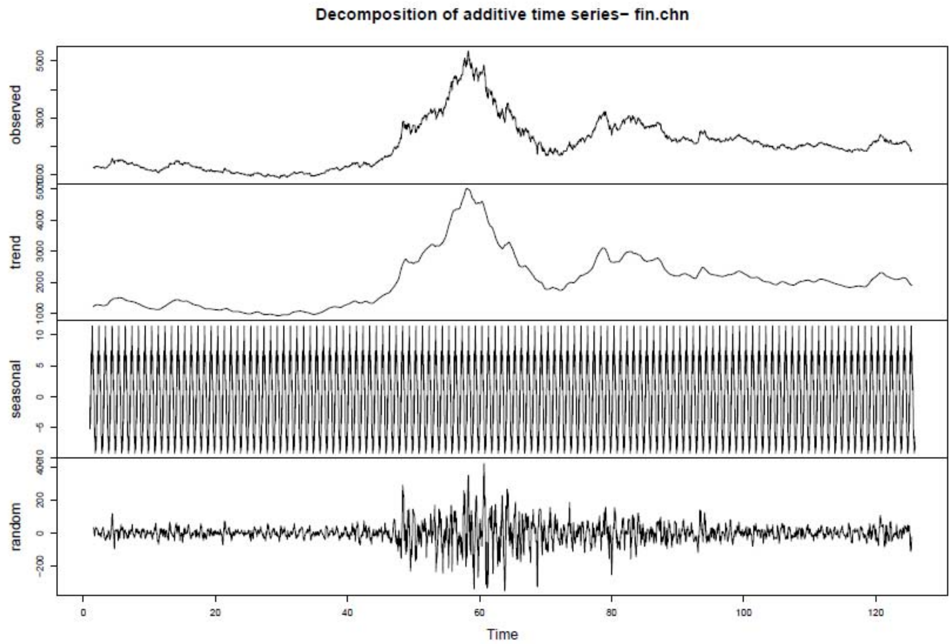


Figure 10: Decomposition of fin.chn series

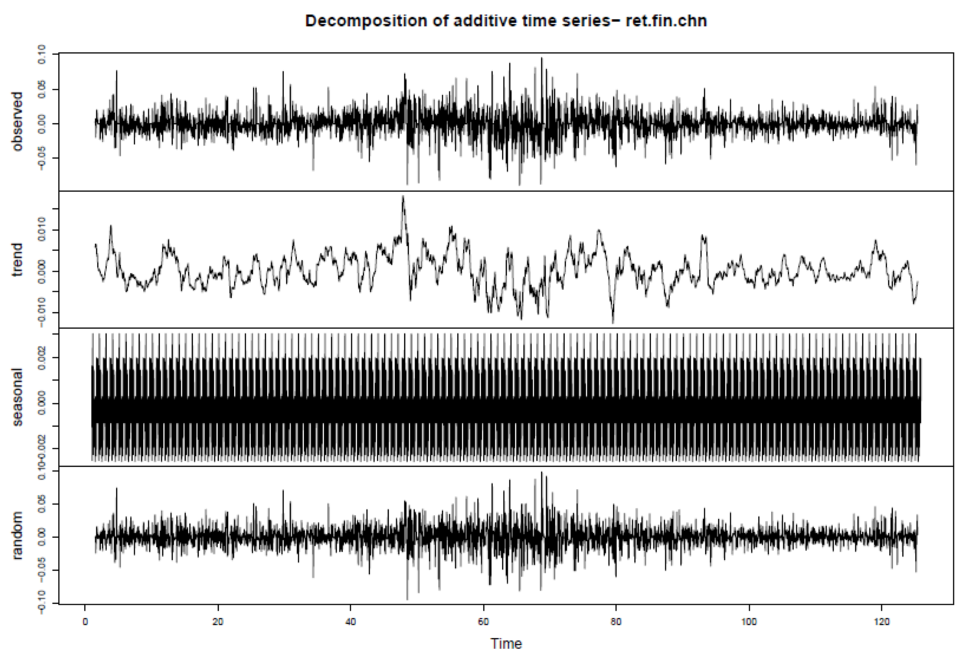


Figure 11: Decomposition of transformed fin.chn (i.e. ret.exch.eur)

After transforming the data, I then checked the descriptive statistics for these series

Table 4.3: Descriptive Statistics

```
> describe(ret.fin)
              var    n mean   sd median trimmed  mad   min  max range  skew
kurtosis se
ret.fin.chn     1 2749    0 0.02      0       0 0.01 -0.09 0.10  0.18  0.03
3.38  0
ret.fin.ger     3 2749    0 0.01      0       0 0.01 -0.10 0.12  0.22 -0.07
7.12  0
ret.fin.gre     4 2749    0 0.03      0       0 0.02 -0.14 0.21  0.36  0.32
6.42  0
ret.fin.id      6 2749    0 0.02      0       0 0.01 -0.11 0.11  0.22  0.00
3.51  0
ret.fin.jp      8 2749    0 0.02      0       0 0.01 -0.12 0.14  0.26 -0.16
5.62  0
ret.fin.my      9 2749    0 0.01      0       0 0.01 -0.09 0.05  0.14 -0.53
7.63  0
ret.fin.sing   10 2749    0 0.01      0       0 0.01 -0.09 0.08  0.17 -0.10
5.55  0
ret.fin.us     15 2749    0 0.02      0       0 0.01 -0.16 0.14  0.30 -0.17
12.78  0
```

The tables above show descriptive statistics of each series, most series exhibit leptokurtosis. This is expected, since the series used are financial data, and recall for chapter 3 that most financial data are found to be leptokurtic.

4.2.1 Normality Test: Jarque-Bera Test

The normality test result shows that all series are not normal, this is expected, since leptokurtosis is a stylized fact for financial data

Table 4.4: Jarque-Bera test

```
> jb.test.ret.fin
             ret.fin.chn ret.fin.ger ret.fin.gre
test stat  1.314622e+03    5818.517    4771.834
p-value   3.416085e-286       0.000       0.000
              ret.fin.id ret.fin.jp ret.fin.my ret.fin.sing
test stat  1.411137e+03   3635.877   6817.722     3540.161
p-value   3.762637e-307      0.000      0.000        0.000
            ret.fin.us
test stat    18742.43
p-value          0.00
```

4.3 Unit Root Test & Stationarity Test

It is a stylized fact that a financial data are mostly non stationary, this part were required to transform our data into stationary data, and check whether there is still unit root left in the data

4.3.1 Preliminary

After the data transformed by log return filter, then we differenced these series to remove unit root by using ndiffs from package forecast in R. The result is that tret.fin.gre had unit root of integrated order 1, hence these series are differenced again once. The series then tested with PP Test and KPSS test to check whether there is unit root remains which implies non-stationarity.

4.3.2 PP Test

PP Test is a unit root test, in other word it test whether a series contain a unit root. To interpret pp test result see if the test statistic of ADF Test < critical value, the null hypothesis of H_0 : series is integrated of order n is not rejected which means that H_0 series have unit root. Below are the values of whether test statistic < critical value, a TRUE means that test statistic < critical value and the H_0 is not rejected.

The result below shows that these series have FALSE values which means that H_0 is rejected implying that these series are didn't have unit root

Table 4.5: PP test

```
> num.pp.ret
                           ret.chn   ret.ger    ret.gre
num.pp.ret.fin.1pct       53.393901 50.073853 160.399430
num.pp.ret.fin.1pct.cval   3.435687  3.435687   3.435688
num.pp.ret.fin.5pct       53.393901 50.073853 160.399430
num.pp.ret.fin.5pct.cval   2.863097  2.863097   2.863098
num.pp.ret.fin.10pct      53.393901 50.073853 160.399430
num.pp.ret.fin.10pct.cval  2.567624  2.567624   2.567624

                            ret.id    ret.jp    ret.my  ret.sing
num.pp.ret.fin.1pct       48.689044 48.985696 46.089525 50.763984
num.pp.ret.fin.1pct.cval   3.435687  3.435687  3.435687  3.435687
num.pp.ret.fin.5pct       48.689044 48.985696 46.089525 50.763984
num.pp.ret.fin.5pct.cval   2.863097  2.863097  2.863097  2.863097
num.pp.ret.fin.10pct      48.689044 48.985696 46.089525 50.763984
num.pp.ret.fin.10pct.cval  2.567624  2.567624  2.567624  2.567624

                             ret.us
num.pp.ret.fin.1pct       61.269519
num.pp.ret.fin.1pct.cval   3.435687
num.pp.ret.fin.5pct       61.269519
num.pp.ret.fin.5pct.cval   2.863097
num.pp.ret.fin.10pct      61.269519
num.pp.ret.fin.10pct.cval  2.567624


> pp.ret
                 ret.chn ret.fra ret.ger ret.gre ret.hk ret.id ret.ita ret.jp
pp.ret.fin.1pct    FALSE   FALSE   FALSE   FALSE  FALSE  FALSE   FALSE  FALSE
pp.ret.fin.5pct    FALSE   FALSE   FALSE   FALSE  FALSE  FALSE   FALSE  FALSE
pp.ret.fin.10pct   FALSE   FALSE   FALSE   FALSE  FALSE  FALSE   FALSE  FALSE

                 ret.my ret.sing  ret.us
pp.ret.fin.1pct   FALSE    FALSE  FALSE
pp.ret.fin.5pct   FALSE    FALSE  FALSE
pp.ret.fin.10pct  FALSE    FALSE  FALSE
```

4.3.3 KPSS Test

KPSS test is a stationarity test, it tests whether a series is stationary. The null hypothesis is

H_0: series is stationary, do not reject null hypothesis when test statistic < critical value.

The result implies that H_0 is not rejected hence implying that these series are stationary

Table 4.6: KPSS Test

```
> num.kpss.ret[,1:5]
```

```
                              ret.chn    ret.ger     ret.gre
num.kpss.ret.fin.1pct       0.1954875 0.17731974 0.002344577
num.kpss.ret.fin.1pct.cval  0.3470000 0.34700000 0.347000000
num.kpss.ret.fin.5pct       0.1954875 0.17731974 0.002344577
num.kpss.ret.fin.5pct.cval  0.4630000 0.46300000 0.463000000
num.kpss.ret.fin.10pct      0.1954875 0.17731974 0.002344577
num.kpss.ret.fin.10pct.cval 0.5740000 0.57400000 0.574000000

> num.kpss.ret[,6:10]
                                ret.id    ret.jp     ret.my  ret.sing
num.kpss.ret.fin.1pct       0.04319371 0.3005279 0.09702253 0.1616399
num.kpss.ret.fin.1pct.cval  0.34700000 0.3470000 0.34700000 0.3470000
num.kpss.ret.fin.5pct       0.04319371 0.3005279 0.09702253 0.1616399
num.kpss.ret.fin.5pct.cval  0.46300000 0.4630000 0.46300000 0.4630000
num.kpss.ret.fin.10pct      0.04319371 0.3005279 0.09702253 0.1616399
num.kpss.ret.fin.10pct.cval 0.57400000 0.5740000 0.57400000 0.5740000

> num.kpss.ret[,11:15]
                                ret.us
num.kpss.ret.fin.1pct        0.1642172
num.kpss.ret.fin.1pct.cval   0.3470000
num.kpss.ret.fin.5pct        0.1642172
num.kpss.ret.fin.5pct.cval   0.4630000
num.kpss.ret.fin.10pct       0.1642172
num.kpss.ret.fin.10pct.cval  0.5740000

> kpss.ret[,1:5]
                   ret.chn ret.ger ret.gre
kpss.ret.fin.1pct     TRUE    TRUE    TRUE
kpss.ret.fin.5pct     TRUE    TRUE    TRUE
kpss.ret.fin.10pct    TRUE    TRUE    TRUE

> kpss.ret[,6:10]
                   ret.id ret.jp ret.my ret.sing
kpss.ret.fin.1pct    TRUE   TRUE   TRUE     TRUE
kpss.ret.fin.5pct    TRUE   TRUE   TRUE     TRUE
kpss.ret.fin.10pct   TRUE   TRUE   TRUE     TRUE
```

4.3.4 Confirmatory Data Analysis

Recall from chapter 3 that confirmatory data analysis is done by combining result from pp test and kpss test

ADF/PP	KPSS
$H_0: y_t \sim I(1)$	$H_0: y_t \sim I(0)$
$H_0: y_t \sim I(0)$	$H_0: y_t \sim I(1)$

With four possible outcomes:

1. Reject H_0 and do not reject H_0
2. Do not reject H_0 and reject H_0
3. Reject H_0 and reject H_0
4. Do not reject H_0 and do not reject H_0

Where condition 1 imply strong probability of being stationary while condition 3 imply that it is highly probable that the series are not stationary

The result of PP Test and KPSS Test on the previous part overwhelmingly suggest outcomes 1 hence our series are confirmed stationary.

4.4 ARIMA Order Detection

ARIMA order detection is needed in order to calculate DCC MGARCH. Traditionally, one need to calculate the ACF[15] -PACF[16] of the data then, examining every possible combination of likeltraditionally, one need to calculate the ACF-PACF of the data then, examining every possible combination of likely ARIMA model, then choosing one model which yild more favorable information criterion.

However, the package "forecast" in R had provided another means to our calculation, the "auto.arima" function from that package calculate ACF, PACF, and ARIMA model for a series then return the one medel found to yield more favorable information criteria

Since the series are stationary, hence I will exclude the integration order in the output. The "auto.arima" function automatically calculate the order or AR(p), I(d), and MA(q), this function also automatically calculate for information criterion AIC, AICc, BIC.

Table 4.7: Example of "auto.arima" function output

```
>auto.arima(ts(ret.fin.chn),trace=TRUE,allowdrift=TRUE
,approximation=FALSE,parallel=TRUE,num.cores=2)

 ARIMA(2,0,2) with non-zero mean : -14244.15
 ARIMA(0,0,0) with non-zero mean : -14239.24
 ARIMA(1,0,0) with non-zero mean : -14238.14
 ARIMA(0,0,1) with non-zero mean : -14238.16
 ARIMA(1,0,2) with non-zero mean : -14234.87
 ARIMA(3,0,2) with non-zero mean : -14241.58
 ARIMA(2,0,1) with non-zero mean : -14234.98
 ARIMA(2,0,3) with non-zero mean : -14241.63
 ARIMA(1,0,1) with non-zero mean : -14236.14
 ARIMA(3,0,3) with non-zero mean : -14240.2
 ARIMA(2,0,2) with zero mean     : -14245.42
 ARIMA(1,0,2) with zero mean     : -14236.47
 ARIMA(3,0,2) with zero mean     : -14243.32
 ARIMA(2,0,1) with zero mean     : -14236.62
 ARIMA(2,0,3) with zero mean     : -14243.36
 ARIMA(1,0,1) with zero mean     : -14237.85
 ARIMA(3,0,3) with zero mean     : -14241.93

 Best model: ARIMA(2,0,2) with zero mean

Series: ts(ret.fin.chn)
ARIMA(2,0,2) with zero mean

Coefficients:
          ar1      ar2     ma1     ma2
      -0.6364  -0.9631  0.6275  0.9460
s.e.   0.0569   0.0743  0.0656  0.0931

sigma^2 estimated as 0.0003276:  log likelihood=7127.72
AIC=-14245.45   AICc=-14245.42   BIC=-14215.85
```

[15] Autocorrelation Function
[16] Partial Autocorrelation Function

Below are table of AR(p) and MA(q) value of the result for the series used in this thesis

Table 4.8: ARMA(p,q) order

```
> arima.ret.fin
             ARp MAq
ret.fin.chn    2   2
ret.fin.ger    5   0
ret.fin.gre    1   2
ret.fin.id     2   3
ret.fin.jp     2   2
ret.fin.my     0   1
ret.fin.sing   1   1
ret.fin.us     5   0
```

4.5 ARCH Effect Test

We then used the residual from ARIMA filtering to test for the presence of ARCH effect

The R package used for this test is "FinTS", this package is companion to the book "Tsay's Analysis of Financial Time Series 3ed". The null hypothesis for the ARCH LM Test is H_0: series have no ARCH effect, the result below shows that H_0 is rejected hence these series exhibit ARCH effect

Table 4.9: ARCH Test

```
> num.arch.lm.ret.fin
                     pval
ret.fin.chn  3.995659e-11
ret.fin.ger  0.000000e+00
ret.fin.gre  0.000000e+00
ret.fin.id   0.000000e+00
ret.fin.jp   0.000000e+00
ret.fin.my   3.330669e-15
ret.fin.sing 0.000000e+00
ret.fin.us   0.000000e+00
```

```
> arch.lm.ret.fin
              pval
ret.fin.chn  FALSE
ret.fin.ger  FALSE
ret.fin.gre  FALSE
ret.fin.id   FALSE
ret.fin.jp   FALSE
ret.fin.my   FALSE
ret.fin.sing FALSE
ret.fin.us   FALSE
```

4.6 Univariate GARCH (1,1) Fitting

The data is fitted with GARCH (1,1) model, when running the parameter estimation, if the model failed to converge, the input data will be cleaned from outlier through Boudt method. The following table will show an example of R output of "ugarchfit" function for series ret.fin.chn

Table 4.10: Example of result of "ugarchfit" function

```
> ugarch.ret.fin.chn

*---------------------------------*
```

```
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model         : fGARCH(1,1)
fGARCH Sub-Model    : GARCH
Mean Model          : ARFIMA(2,0,2)
Distribution        : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.000119    0.000296   0.40046 0.688821
ar1     0.828738    0.268383   3.08790 0.002016
ar2    -0.711580    0.182632  -3.89626 0.000098
ma1    -0.864128    0.250509  -3.44949 0.000562
ma2     0.754853    0.176208   4.28387 0.000018
omega   0.000001    0.000000   2.16668 0.030259
alpha1  0.024786    0.004981   4.97598 0.000001
beta1   0.972114    0.005819 167.06055 0.000000
```

MLE Standard

Persistence

```
Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000119    0.000317  0.37441 0.708101
ar1     0.828738    0.532395  1.55662 0.119561
ar2    -0.711580    0.333011 -2.13681 0.032614
ma1    -0.864128    0.498138 -1.73472 0.082791
ma2     0.754853    0.326156  2.31439 0.020646
omega   0.000001    0.000001  1.15117 0.249662
alpha1  0.024786    0.009693  2.55717 0.010553
beta1   0.972114    0.011753 82.70915 0.000000

LogLikelihood : 7366.919

Information Criteria
------------------------------------

Akaike       -5.3539
Bayes        -5.3367
Shibata      -5.3539
Hannan-Quinn -5.3477

Q-Statistics on Standardized Residuals
------------------------------------
              statistic p-value
Lag[1]           0.7281  0.3935
Lag[p+q+1][5]    2.0920  0.1481
Lag[p+q+5][9]    6.9554  0.2240
d.o.f=4
H0 : No serial correlation
```

QMLE Standard

```
Q-Statistics on Standardized Squared Resi
------------------------------------
              statistic p-value
Lag[1]           0.2605  0.6098
Lag[p+q+1][3]    0.4676  0.4941
Lag[p+q+5][7]    5.9956  0.3066
d.o.f=2
```

Test of ARCH/GARCH behavior in standardized residuals

If p value > 0.05, do not reject H_0 where
H_0: there is no evidence of serial correlation in squred residual

```
ARCH LM Tests
------------------------------------
             Statistic DoF P-Value
ARCH Lag[2]     0.3707   2  0.8308
ARCH Lag[5]     4.8984   5  0.4284
ARCH Lag[10]    8.3197  10  0.5976


Nyblom stability test
------------------------------------
Joint Statistic:  181.3782
Individual Statistics:
mu      0.18192
ar1     0.07786
ar2     0.04829
ma1     0.09334
ma2     0.05590
omega  19.71649
alpha1  0.19230
beta1   0.18250

Asymptotic Critical Values (10% 5% 1%)
```

Test for coefficient stability (i.e. Structural Change)

If test statistic < critical value, do not reject H_0 where

H_0: there is no evidence that the particular parameter is unstable

```
Joint Statistic:              1.89 2.11 2.59
Individual Statistic:         0.35 0.47 0.75

Sign Bias Test
------------------------------------
                    t-value   prob sig
Sign Bias           0.5092 0.6106
Negative Sign Bias  0.5716 0.5676
Positive Sign Bias  0.5757 0.5648
Joint Effect        2.8443 0.4163
```

Test for leverage effects (i.e. asymmetric effect)

If p value > 0.05, do not reject H_0 where

H_0: there is evidence of asymmetric effect

```
Adjusted Pearson Goodness-of-Fit Test:
------------------------------------
  group statistic p-value(g-1)
1    20     267.1    1.053e-45
2    30     329.7    1.007e-52
3    40     353.5    2.632e-52
4    50     369.0    1.214e-50

Elapsed time : 6.79505
```

Test for distribution goodness of fit

If p value > 0.05, do not reject H_0 where

H_0: there is evidence of normality

4.6.1 Goodness of Fit Test: Testing for Normality

The p-value from the Univariate GARCH fitting, shows that, no series is normal

Table 4.11: Normality Test

```
> gof.test.ret.fin
                        20           30           40           50
ret.fin.chn  3.821555e-43 7.726104e-52 3.199251e-55 3.508305e-53
ret.fin.ger  8.880801e-12 2.921870e-10 1.834969e-09 1.130636e-07
ret.fin.gre  7.195926e-12 2.267982e-12 3.466842e-11 1.315858e-12
ret.fin.id   4.790072e-16 2.415001e-16 1.577727e-14 1.408560e-13
ret.fin.jp   1.630821e-09 2.149643e-09 6.629938e-08 1.065901e-06
ret.fin.my   3.257617e-23 1.485817e-22 4.896007e-23 5.207355e-24
ret.fin.sing 3.338292e-15 4.802318e-15 4.631513e-13 5.632436e-14
ret.fin.us   9.202932e-17 2.063507e-14 4.682057e-13 2.875379e-11
```

4.6.2 Sign Bias Test

Leverage effect was exhibited by all series, therefore we need to construct Asymmetric GARCH Model. The Model used will be EGARCH and GJR GARCH

Table 4.12: Sign Bias Test

```
> signbias.test.ret.fin
               Sign Bias Negative Sign Bias Positive Sign Bias Joint Effect
ret.fin.chn  0.924584842        0.330016245        0.361576381 3.786641e-01
ret.fin.ger  0.778020428        0.451828554        0.038813332 2.180175e-02
ret.fin.gre  0.321933238        0.246851387        0.217538526 4.101153e-01
ret.fin.id   0.362987844        0.041188120        0.679486935 4.179690e-03
ret.fin.jp   0.488753614        0.310677729        0.087931980 1.832019e-01
ret.fin.my   0.236544418        0.742623300        0.341151980 1.463623e-01
ret.fin.sing 0.002039507        0.147101959        0.194171346 1.081846e-04
ret.fin.us   0.001336283        0.266306585        0.337840890 5.603784e-04
```

4.6.3 Asymmetric GARCH Models

Since we had seen through the sign bias test that leverage effect have been observed, we need to construct Asymmetric Univariate GARCH Model to check the whether asymmetric models may be better model to explain the data. The distribution models used in the modelling are normal distribution, student-t distribution, and skew-student distribution (Ghalanos, 2013). In this table they are represented with "norm", "st", and "sstd" code. While the asymmetric model used are EGARCH and GJR GARCH, below are the model that was chosen based on information criteria

The result of sign bias test of the asymmetric model shows that financial sector indices of Singapore and USA exhibit strong sign of Negative Bias which means that investors are more reactive to negative news

Table 4.13: Information Criteria – GARCH Model

```
> comp.infocrit.ret.fin
```

	Distribution	Model	Infocrit
ret.fin.chn	st	egarch	-5.443476
ret.fin.ger	sst	gjr.garch	-6.140344
ret.fin.gre	sst	gjr.garch	-4.897897
ret.fin.id	sst	gjr.garch	-5.472374
ret.fin.jp	st	gjr.garch	-5.506169
ret.fin.my	st	egarch	-6.983969
ret.fin.sing	sst	gjr.garch	-6.430831
ret.fin.us	sst	gjr.garch	-6.057298

Table 4.14: Sign Bias Test of Asymmetric GARCH Models

```
> comp.signbias.test.ret.fin
```

	Sign Bias	Negative Sign Bias	Positive Sign Bias	Joint Effect
st.egarch.ret.fin.chn	0.612428020	0.62364048	0.495625416	**4.056131e-01**
sst.gjr.garch.ret.fin.ger	0.657135359	0.69389126	0.056652394	**2.706873e-01**
sst.gjr.garch.ret.fin.gre	0.159444070	0.44757177	0.197483578	**4.509282e-01**
sst.gjr.garch.ret.fin.id	0.437324789	0.41071068	0.989100029	**3.362286e-01**
st.gjr.garch.ret.fin.jp	0.758290911	0.71554089	0.207838520	6.178961e-01
st.egarch.ret.fin.my	0.155373722	0.66386883	0.930925058	**3.623188e-01**
sst.gjr.garch.ret.fin.sing	**0.007653079**	0.08210941	0.220038287	**1.302700e-03**
sst.gjr.garch.ret.fin.us	**0.002410006**	0.05567102	0.519243478	**3.344916e-03**

4.6.4 Persistence of GARCH Model

To refresh our memory of GARCH model, below shown a GARCH (p, q) model equation

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \sigma_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 \tag{4.1}$$

Equation 32: GARCH (p, q) model

The symbol α is the coefficient for lagged conditional error while β is the coefficient for lagged conditional variance

Below is table of β and α of the univariate GARCH result, it shows that most series exhibit a disproportionately high β, while only a few of them that exhibit α higher that 0.1, this imply that most series experience persistent effect from shocks on volatility. A handful of these series also exhibit relatively high α which describe their susceptibility to sudden volatility.

Table 4.15: GARCH Persistence

```
> comp.persistence.ret.fin
                      alpha      beta persistence
ret.fin.chn  -0.0008269864 0.9973475   0.9965205
ret.fin.ger   0.0038974812 0.9185957   0.9224932
ret.fin.gre   0.0767620105 0.8996283   0.9763904
ret.fin.id    0.0781183824 0.8502238   0.9283422
ret.fin.jp    0.0549102437 0.8911349   0.9460451
ret.fin.my   -0.0365702581 0.9814820   0.9449117
ret.fin.sing  0.0553093885 0.9138039   0.9691133
ret.fin.us    0.0183243888 0.9299348   0.9482591
```

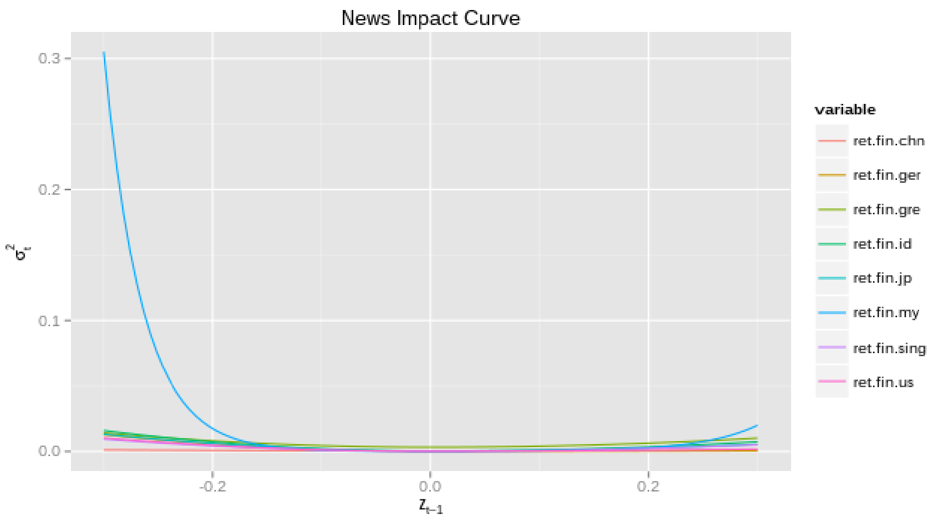
China and Germany exhibit the least sudden volatility variation to shock, with France exhibiting the highest. Indonesia exhibited higher α and lower β, which means that although we can expect high volatility in response to shocks, we can also expect the market to quickly correct iself

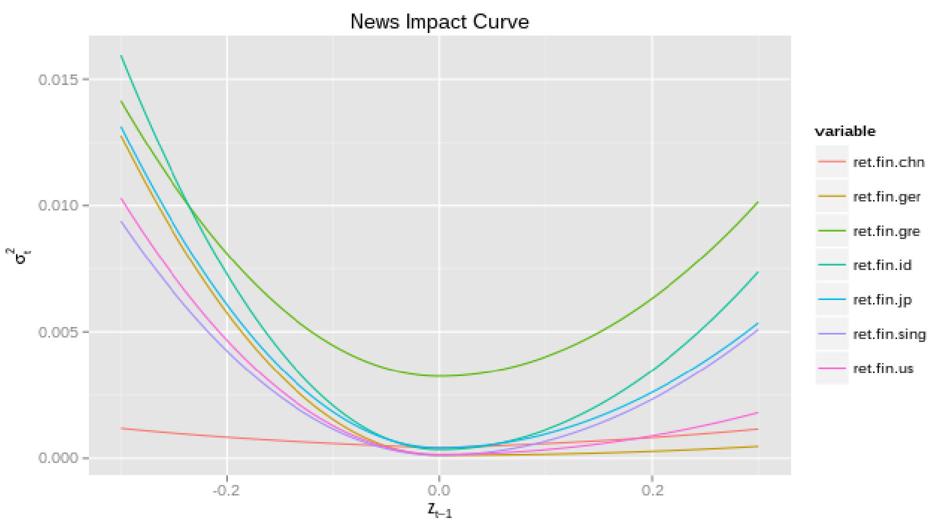
Across all three stock market Indonesia had exhibited similar trend with very high α and very low β compared to other countries. This means the wider volatility band will give investors room for speculating and try to optimize their trading strategy, while the lower persistence effect implies that regardless of these speculation, Indonesian market are quite resilient and will quickly correct itself.

4.6.5 News Impact Curve

To get more representative meaning from these result, let’s also look into news impact curve, the right side of the curve shows how volatility responds to good news while the left side responds to bad news. The use of news impact curve in financial literature itself is attributed to (Engle & Ng, 1993)

The steeper curve on the left half of the news impact curve suggest that particular series is more sensitive to negative news, while the right halve correspond to positive news. The higher the minima of the curve suggest that particular series more volatile than the other.


News Impact Curve
0.3
0.2
0.1
0.0
-0.2
0.0
0.2
z_{t-1}
σ_t^2
variable
ret.fin.chn
ret.fin.ger
ret.fin.gre
ret.fin.id
ret.fin.jp
ret.fin.my
ret.fin.sing
ret.fin.us


News Impact Curve
0.015
0.010
0.005
0.000
-0.2
0.0
0.2
z_{t-1}
σ_t^2
variable
ret.fin.chn
ret.fin.ger
ret.fin.gre
ret.fin.id
ret.fin.jp
ret.fin.sing
ret.fin.us

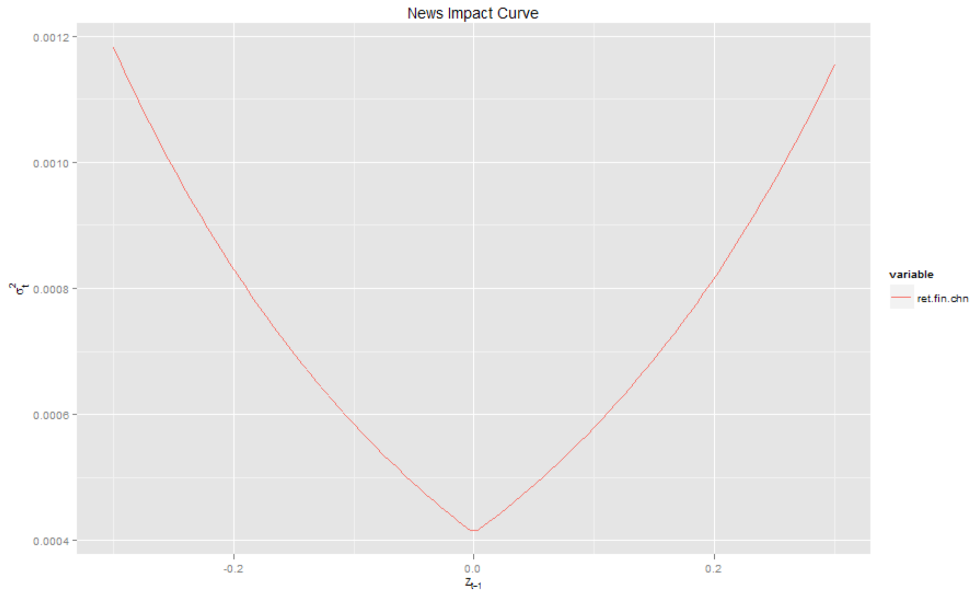


Figure 12: News Impact Curve on Financial Sector Indices

In the financial sector we see that generally the market is more sensitive to negative news. It is interesting to note that Malaysia had a very steep left halve curve. Greece shows the highest volatility of all market, while China had the most gradual curve which shows similar gradient both in the left side and right side, which shows that investor to behave rationally when receiving news about Chinese financial sector

4.7 Testing for Conditional Correlation Structure

Table 4.16: DCC Test

```
> dcc.test.ret.fin
                p.value
ret.fin.chn  0.31007893
ret.fin.ger  0.94213350
ret.fin.gre  0.63883664
ret.fin.id   0.42687594
ret.fin.jp   0.14889844
ret.fin.my   0.82254358
ret.fin.sing 0.97203700
ret.fin.us   0.96933713
```

4.8 Bivariate DCC/ADCC GARCH Analysis

4.8.1 Conditional Correlation Analysis

4.8.1.1 Information Criterion of DCC and ADCC Model

Now, we will then choose the model which shows lower information criteria (bolded number) to choose which model will be showed in news impact surface

Table 4.17: Information Criteria - DCC/ADCC Model

"dcc.fit.fin.id.fin.chn"		**"adcc.fit.fin.id.fin.chn"**	
Akaike	-10.77860	Akaike	**-10.78219**
Bayes	-10.72426	Bayes	**-10.72567**
Shibata	-10.77877	Shibata	**-10.78237**
Hannan-Quinn	-10.75896	Hannan-Quinn	**-10.76176**
"dcc.fit.fin.id.fin.ger"		**"adcc.fit.fin.id.fin.ger"**	
Akaike	-11.57704	Akaike	**-11.58084**
Bayes	-11.51836	Bayes	**-11.51998**
Shibata	-11.57724	Shibata	**-11.58105**
Hannan-Quinn	-11.55583	Hannan-Quinn	**-11.55884**
"dcc.fit.fin.id.fin.gre"		**"adcc.fit.fin.id.fin.gre"**	
Akaike	-10.27693	Akaike	**-10.27885**
Bayes	**-10.22258**	Bayes	-10.22232
Shibata	-10.27710	Shibata	**-10.27903**
Hannan-Quinn	-10.25728	Hannan-Quinn	**-10.25841**
"dcc.fit.fin.id.fin.jp"		"adcc.fit.fin.id.fin.jp"	
Akaike	**-10.90608**	Akaike	-10.90516
Bayes	**-10.85175**	Bayes	-10.84865
Shibata	**-10.90625**	Shibata	-10.90534
Hannan-Quinn	**-10.88644**	Hannan-Quinn	-10.88473
"dcc.fit.fin.id.fin.my"		"adcc.fit.fin.id.fin.my"	
Akaike	**-12.30642**	Akaike	-12.30569
Bayes	**-12.25860**	Bayes	-12.25570
Shibata	**-12.30655**	Shibata	-12.30583
Hannan-Quinn	**-12.28913**	Hannan-Quinn	-12.28761
"dcc.fit.fin.id.fin.sing"		"adcc.fit.fin.id.fin.sing"	
Akaike	**-11.82484**	Akaike	-11.82389
Bayes	**-11.77268**	Bayes	-11.76956
Shibata	**-11.82500**	Shibata	-11.82406
Hannan-Quinn	**-11.80599**	Hannan-Quinn	-11.80425
"dcc.fit.fin.id.fin.us"		**"adcc.fit.fin.id.fin.us"**	
Akaike	-11.53536	Akaike	**-11.53836**
Bayes	-11.47667	Bayes	**-11.47750**
Shibata	-11.53555	Shibata	**-11.53857**
Hannan-Quinn	-11.51414	Hannan-Quinn	**-11.51636**

4.8.1.2 Mean Difference Test – DCC Model

The Student's t-test test for a difference in mean. The Null Hypothesis are whether the mean of conditional correlation between Indonesian return of stock price index of financial sector and aforementioned country index of consumer goods and industrial return of sector stock price index in between certain period is the same, smaller, or greater

$H_{0:1<2}$: period 1 had smaller mean than period 2

$H_{0:1<3}$: period 1 had smaller mean than period 3

$H_{0:2=3}$: period 2 had same mean with period 3

$H_{0:2<3}$: period 2 had smaller than period 3

$H_{0:2>3}$: period 2 had greater than period 3

Table 4.18: Mean Difference Test – DCC Model

> t.test.rcor.fin

	p.val1<2	p.val1<3	p.val2=3	p.val2<3	p.val2>3
ret.fin.chn	9.991982e-01	9.997037e-01	9.421451e-01	0.5289275	4.710725e-01
ret.fin.ger	2.943078e-40	9.627895e-07	4.096642e-18	1.0000000	2.048321e-18
ret.fin.gre	7.279914e-300	1.000000e+00	1.235577e-292	1.0000000	6.177885e-293
ret.fin.jp	**9.169413e-01**	**9.786372e-01**	**6.194904e-01**	**0.6902548**	**3.097452e-01**

```
ret.fin.my    3.386004e-01 5.231650e-01  6.275543e-01 0.6862229  3.137771e-01
ret.fin.sing  9.982691e-01 1.000000e+00  4.539497e-92 1.0000000  2.269749e-92
ret.fin.us    1.918597e-63 1.002065e-17  4.505064e-13 1.0000000  2.252532e-13
```

```
> t.test.rcor.fin>0.05
             p.val1<2 p.val1<3 p.val2=3 p.val2<3 p.val2>3
ret.fin.chn      TRUE     TRUE     TRUE     TRUE     TRUE
ret.fin.ger     FALSE    FALSE    FALSE     TRUE    FALSE
ret.fin.gre     FALSE     TRUE    FALSE     TRUE    FALSE
ret.fin.jp       TRUE     TRUE     TRUE     TRUE     TRUE
ret.fin.my       TRUE     TRUE     TRUE     TRUE     TRUE
ret.fin.sing     TRUE     TRUE    FALSE     TRUE    FALSE
ret.fin.us      FALSE    FALSE    FALSE     TRUE    FALSE
```

In both 2nd and 3rd period the conditional correlation of return of Indonesia with China, Japan, Malaysia, ans Singapore increased in mean, compared to the first period. While Greece had only increased mean in 3rd period

4.8.1.3 Mean Difference Test – ADCC Model

The result for the Asymmetric DCC test are

Table 4.19: Mean Difference Test - ADCC Model

```
> t.test.rcor.a.fin
                 p.val1<2     p.val1<3     p.val2=3  p.val2<3     p.val2>3
ret.fin.chn  9.995537e-01 9.999988e-01 2.856112e-01 0.8571944 1.428056e-01
ret.fin.ger  6.196974e-44 2.867628e-08 1.622883e-17 1.0000000 8.114417e-18
ret.fin.gre  1.293903e-01 9.576379e-01 8.916498e-03 0.9955418 4.458249e-03
ret.fin.jp   7.633148e-04 8.819696e-01 7.466955e-05 0.9999627 3.733478e-05
ret.fin.my   3.821968e-01 5.528676e-01 6.673345e-01 0.6663328 3.336672e-01
ret.fin.sing 1.478476e-01 9.935728e-01 1.931419e-03 0.9990343 9.657097e-04
ret.fin.us   5.781939e-65 1.621012e-14 1.798927e-15 1.0000000 8.994637e-16
```

```
> t.test.rcor.a.fin>0.05
             p.val1<2 p.val1<3 p.val2=3 p.val2<3 p.val2>3
ret.fin.chn      TRUE     TRUE     TRUE     TRUE     TRUE
ret.fin.ger     FALSE    FALSE    FALSE     TRUE    FALSE
ret.fin.gre      TRUE     TRUE    FALSE     TRUE    FALSE
ret.fin.jp      FALSE     TRUE    FALSE     TRUE    FALSE
ret.fin.my       TRUE     TRUE     TRUE     TRUE     TRUE
ret.fin.sing     TRUE     TRUE    FALSE     TRUE    FALSE
ret.fin.us      FALSE    FALSE    FALSE     TRUE    FALSE
```

We see that the conditional correlation of Indonesia with China and Malaysia show greater mean in the 3rd period than the previous periods. Germany shows no higher mean compared to the 1st period, although we saw increase between 2nd to 3rd period. Greece and Japan showed that mean had only increased in the 3rd period. Malaysia and Singapore showed that there's subsequent increase from 1st to 2nd to 3rd period. While US only saw increase in mean in the 3rd period

This result reaffirm the previous result from the Non-Asymmetric DCC Model, that contagion was mainly observed after the occurrence of Europe Sovereign Debt Crisis

4.8.1.4 Median Difference Test - DCC Model

The Wilcoxon Mean Difference Z-test, tests whether the median of conditional correlation of Indonesia with the aforementioned countries in between certain period is the same

$H_{0:1=2}$: period 1 had same median with period 2

$H_{0:1=3}$: period 1 had same median with period 3

$H_{0:2=3}$: period 2 had same median with period 3

Table 4.20: Median Difference Test - DCC Model

```
> wilcox.test.rcor.fin
                  p.val1=2      p.val1=3      p.val2=3
ret.fin.chn   4.091931e-05  1.817179e-03  2.409717e-01
ret.fin.ger   2.070241e-37  4.233765e-06  4.864438e-20
ret.fin.gre  1.308423e-215  3.500015e-46 6.379094e-234
ret.fin.jp    1.001411e-01  5.673686e-03  3.726161e-01
ret.fin.my    5.848837e-01  2.000598e-01  8.031920e-02
ret.fin.sing  3.155825e-03 5.035505e-162  1.102980e-78
ret.fin.us    1.399427e-61  8.615407e-16  1.891657e-15

> wilcox.test.rcor.fin>0.05
             p.val1=2 p.val1=3 p.val2=3
ret.fin.chn     FALSE    FALSE     TRUE
ret.fin.ger     FALSE    FALSE    FALSE
ret.fin.gre     FALSE    FALSE    FALSE
ret.fin.jp       TRUE    FALSE     TRUE
ret.fin.my       TRUE     TRUE     TRUE
ret.fin.sing    FALSE    FALSE    FALSE
ret.fin.us      FALSE    FALSE    FALSE
```

We see that all countries except Japan and Malaysia shows different median when compared to 1st period. While Japan only shows sign of contagion in 3rd period

4.8.1.5 Median Difference Test – ADCC Model

The result for the Asymmetric DCC are

Table 4.21: Median Difference Test - ADCC Model

```
> wilcox.test.rcor.a.fin
                 p.val1=2     p.val1=3     p.val2=3
ret.fin.chn  1.390592e-06 2.871493e-06 6.338514e-01
ret.fin.ger  1.484697e-40 3.653639e-07 6.057498e-20
ret.fin.gre  5.094659e-01 4.392511e-01 1.668388e-01
ret.fin.jp   4.782378e-02 1.122295e-02 2.790975e-05
ret.fin.my   5.714137e-01 2.568376e-01 1.092844e-01
ret.fin.sing 4.331442e-01 2.390264e-03 5.166481e-02
ret.fin.us   6.719961e-62 9.784291e-12 1.290583e-20

> wilcox.test.rcor.a.fin>0.05
             p.val1=2 p.val1=3 p.val2=3
ret.fin.chn     FALSE    FALSE     TRUE
ret.fin.ger     FALSE    FALSE    FALSE
ret.fin.gre      TRUE     TRUE     TRUE
ret.fin.jp      FALSE    FALSE    FALSE
ret.fin.my       TRUE     TRUE     TRUE
ret.fin.sing     TRUE    FALSE     TRUE
ret.fin.us      FALSE    FALSE    FALSE
```

China, Germany, Japan, and US shows different median between each periods, while Greece and Malaysia shows that the median between each periods is relatively the same. Singapore shows that there is difference from the 1st to 2nd and 2^{nd} to 3^{rd} period, but the difference between each subsequent period is less pronounced, hence only 1^{st} and 3^{rd} periods shows difference in median

4.8.1.6 Conditional Correlation Chart

On this chart, the first vertical line represent the starting point of US Subprime Mortgage Crisis, the second vertical line represent the starting point of Eurozone Sovereign Debt Crisis, and lastly the third line represent the ending point of US Subprime Mortgage Crisis. This section exist to provide graphical result of the conditional correlation. While the arrow in the next page represent each periodization, i.e: 1^{st} arrow represent 1^{st} period, and so on

4.8.1.6.1 China

The conditional correlation graph of Chinese Sector and Indonesian Sector shows that the means are relatively constant all through the three period

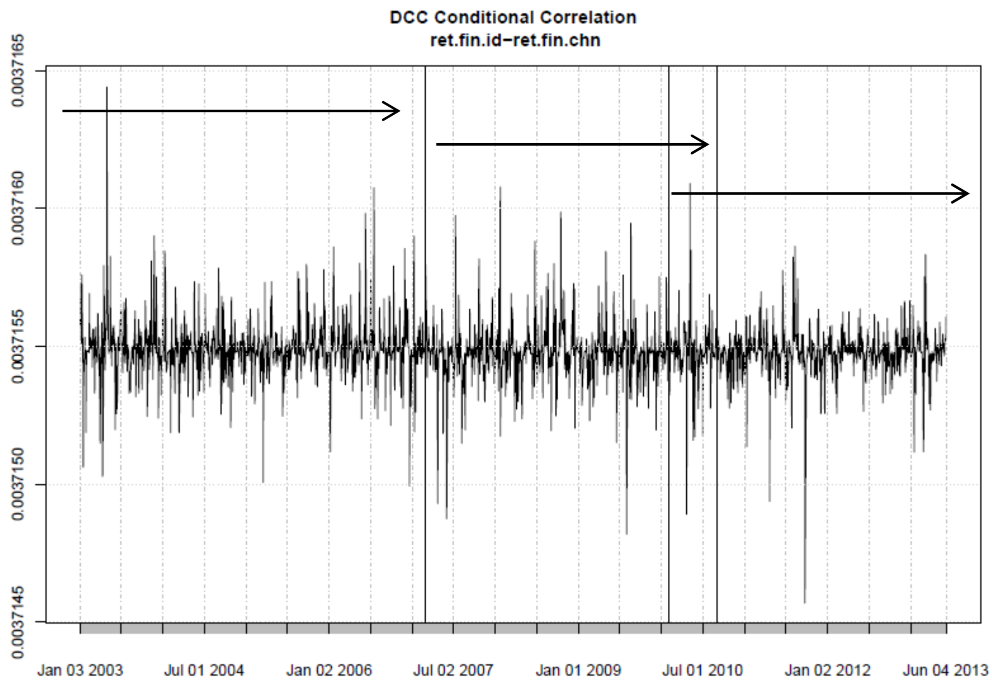


Figure 13: DCC Conditional Correlation FIN.ID - FIN.CHN

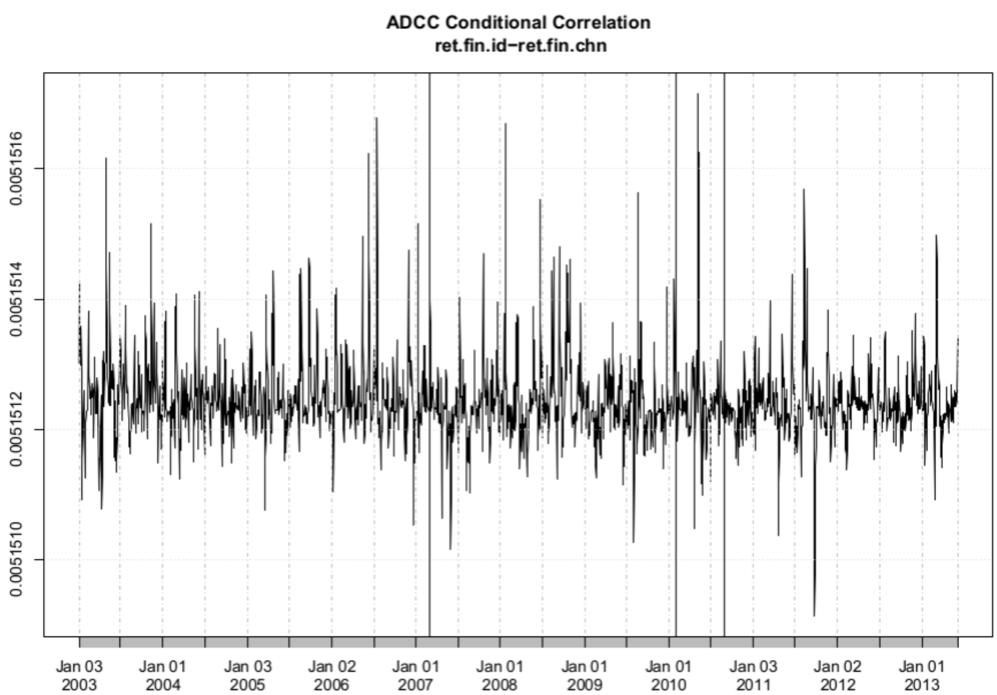


Figure 14: ADCC Conditional Correlation FIN.ID - FIN.CHN

4.8.1.6.2 Germany

The conditional correlation graph of Germany Sector and Indonesian Sector shows that the means are changing all through the three periods

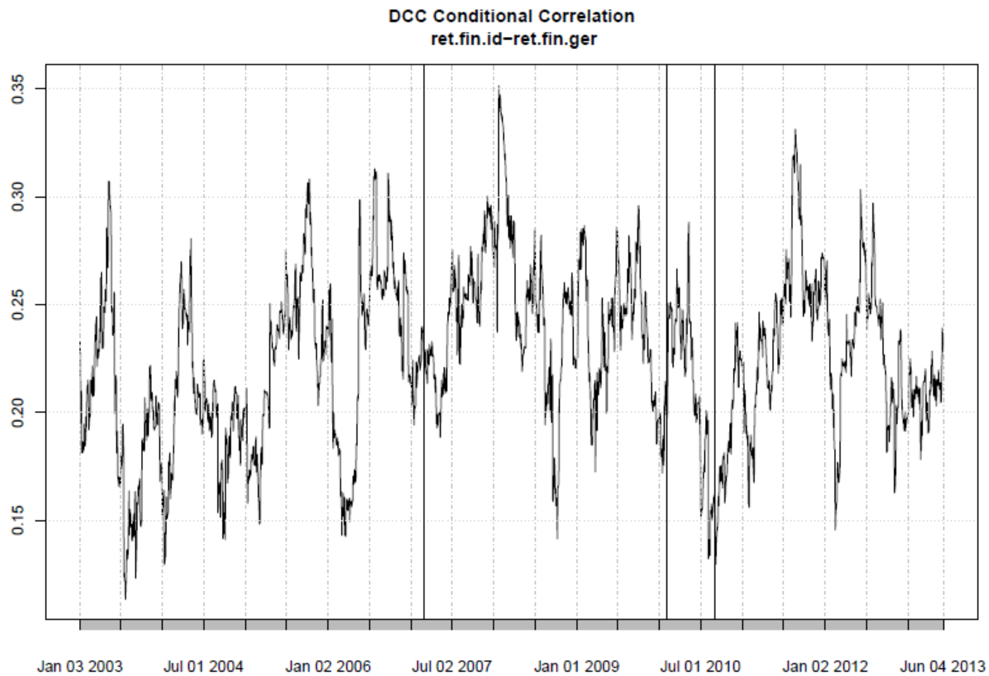


Figure 15: DCC Conditional Correlation FIN.ID - FIN.GER

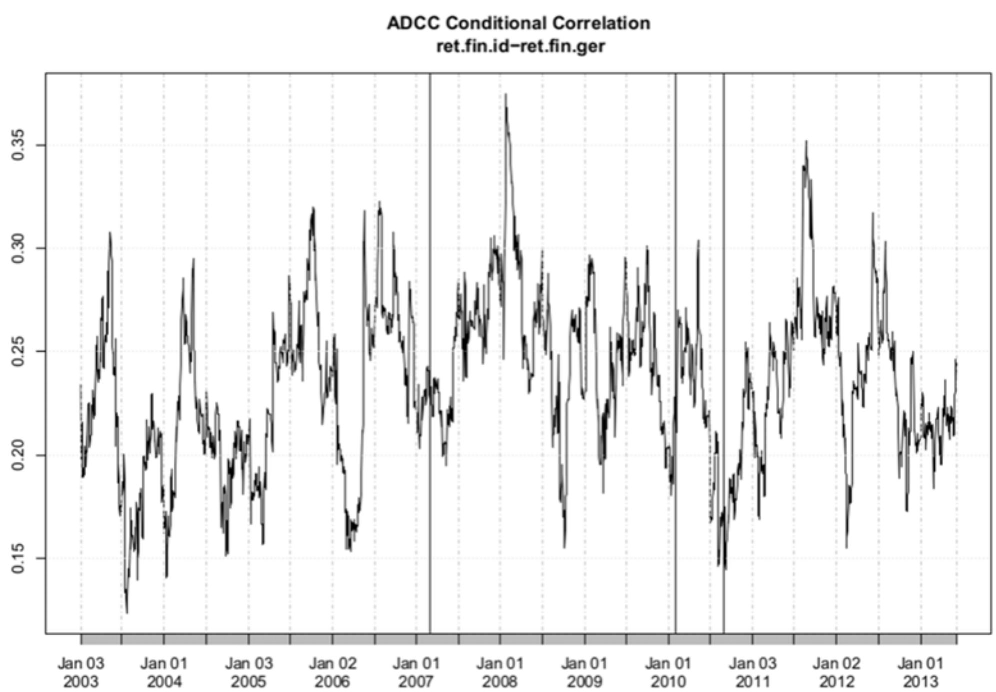


Figure 16: ADCC Conditional Correlation FIN.ID - FIN.GER

4.8.1.6.3 Greece

The conditional correlation graph of Greece Sector and Indonesian Sector shows that conditional correlation of Indonesian financial sector affected by Greece financial sector

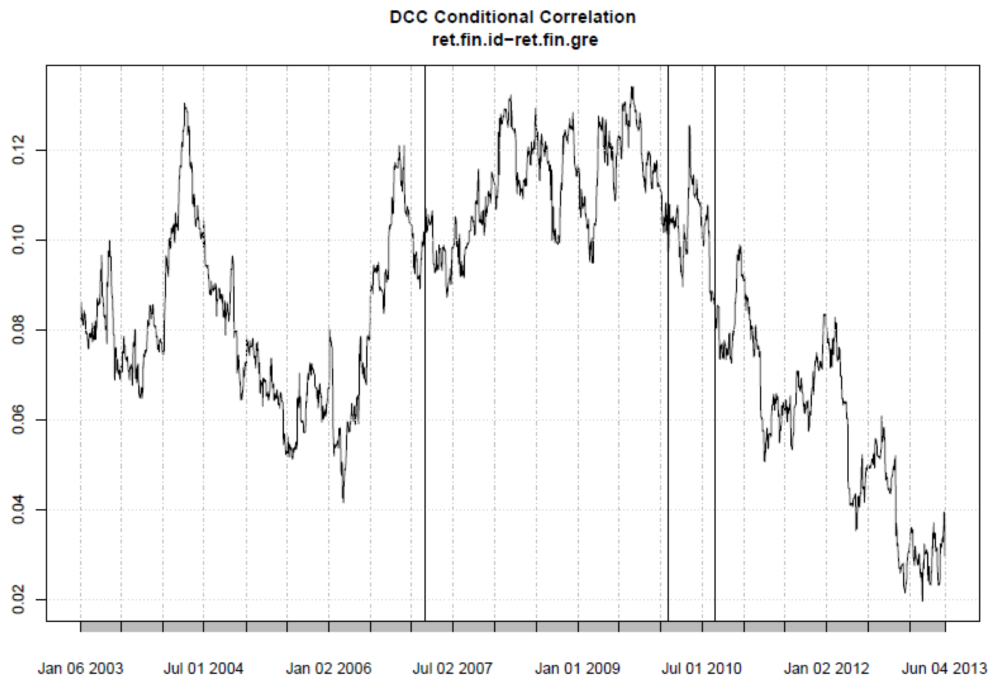


Figure 17: DCC Conditional Correlation FIN.ID - FIN.GRE

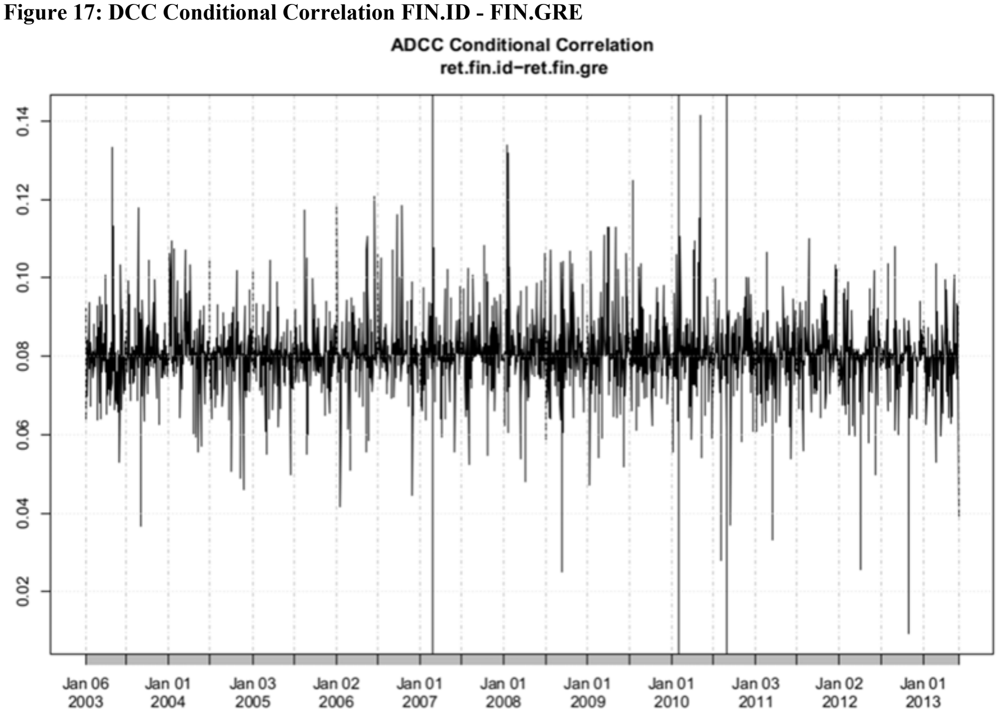


Figure 18: ADCC Conditional Correlation FIN.ID - FIN.GRE

4.8.1.6.4 Japan

Similar to China, Japan's conditional correlation with Indonesian Financial Sector shows stable and relatively constant mean

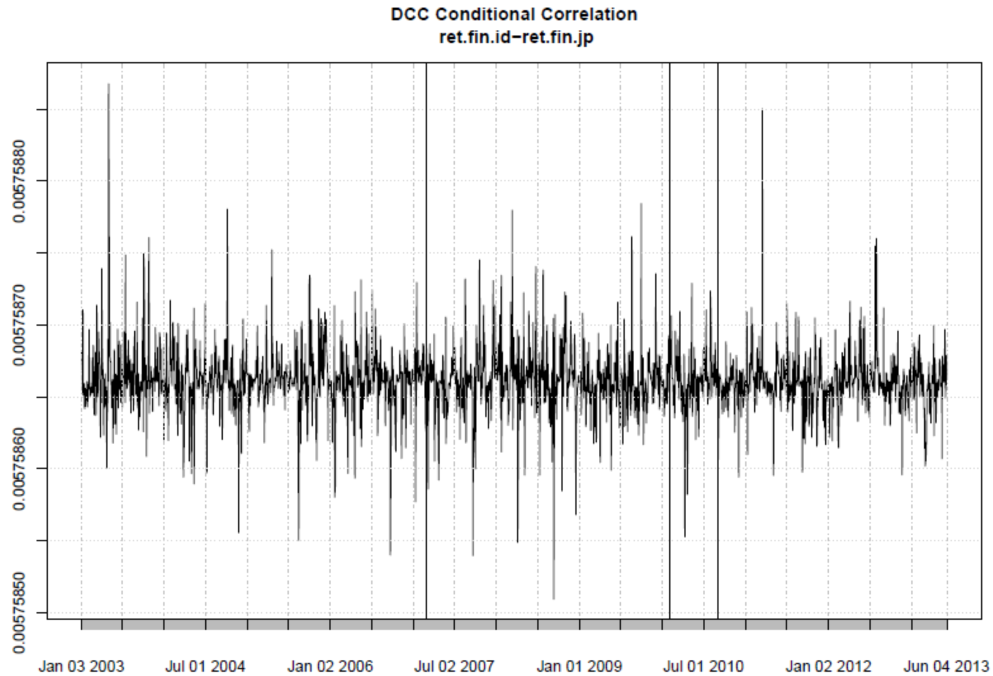


Figure 19: DCC Conditional Correlation FIN.ID - FIN.JP

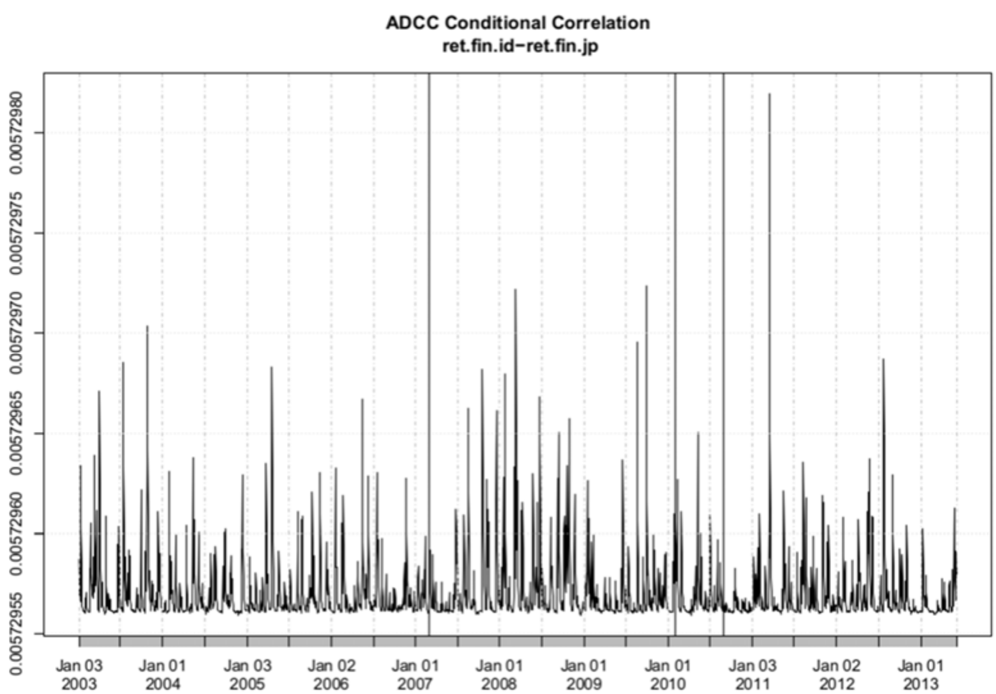


Figure 20: ADCC Conditional Correlation FIN.ID - FIN.JP

4.8.1.6.5 Malaysia

Malaysia result mirrored closely the Chinese and Japanese result, that its shows that means are relatively constant

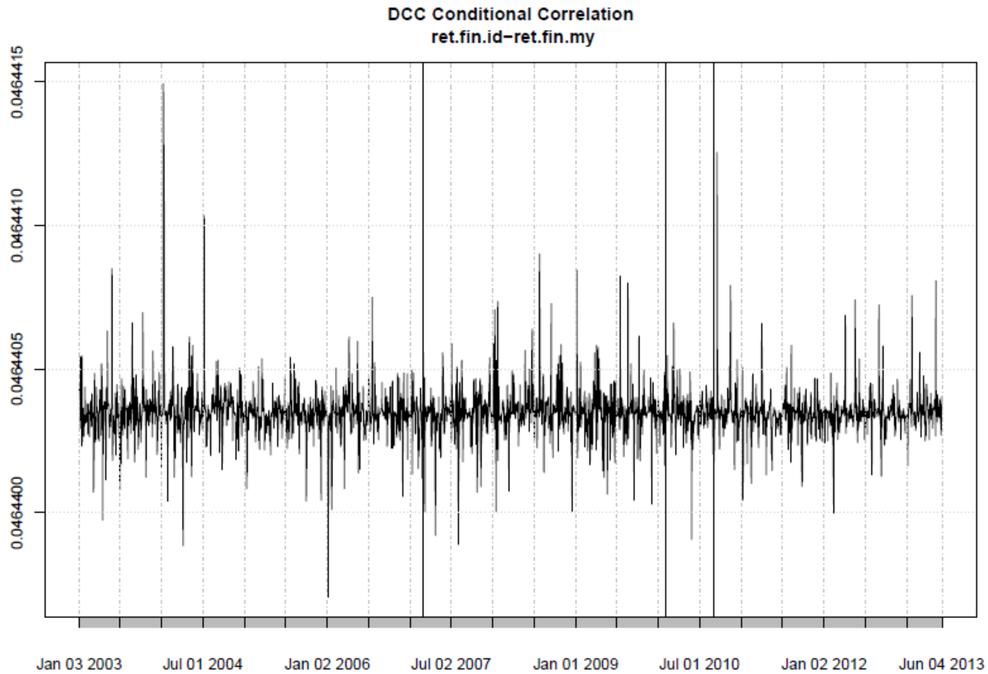


Figure 21: DCC Conditional Correlation FIN.ID - FIN.MY

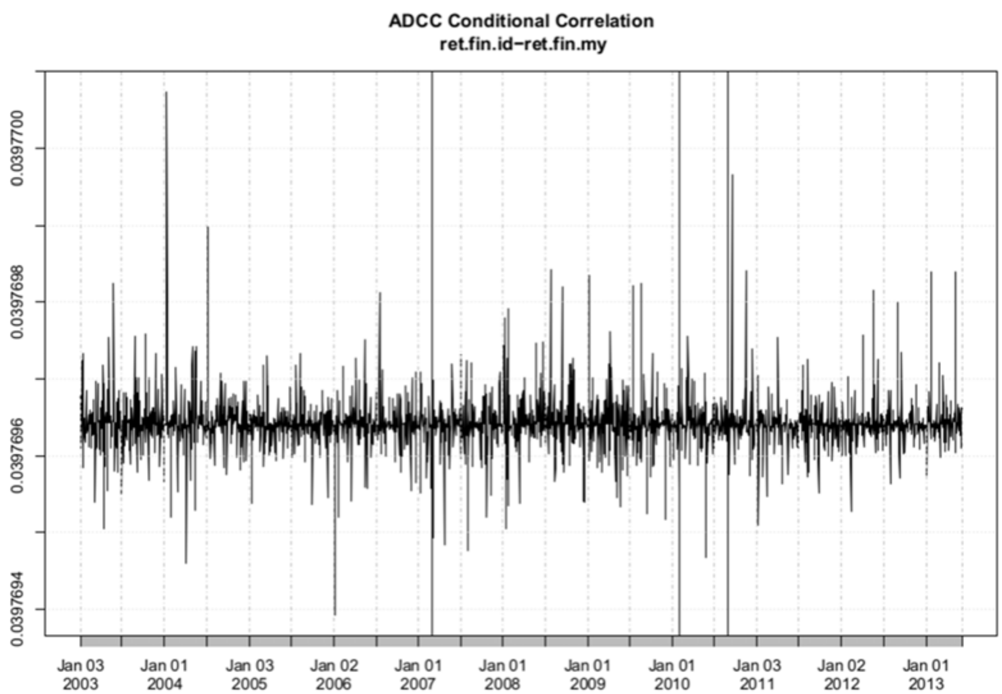


Figure 22: ADCC Conditional Correlation FIN.ID - FIN.MY

4.8.1.6.6 Singapore

Only conditional correlation of Singapore's and Indonesian financial sector sector shows different account, the normal DCC shows non constant means unlike the result from ADCC

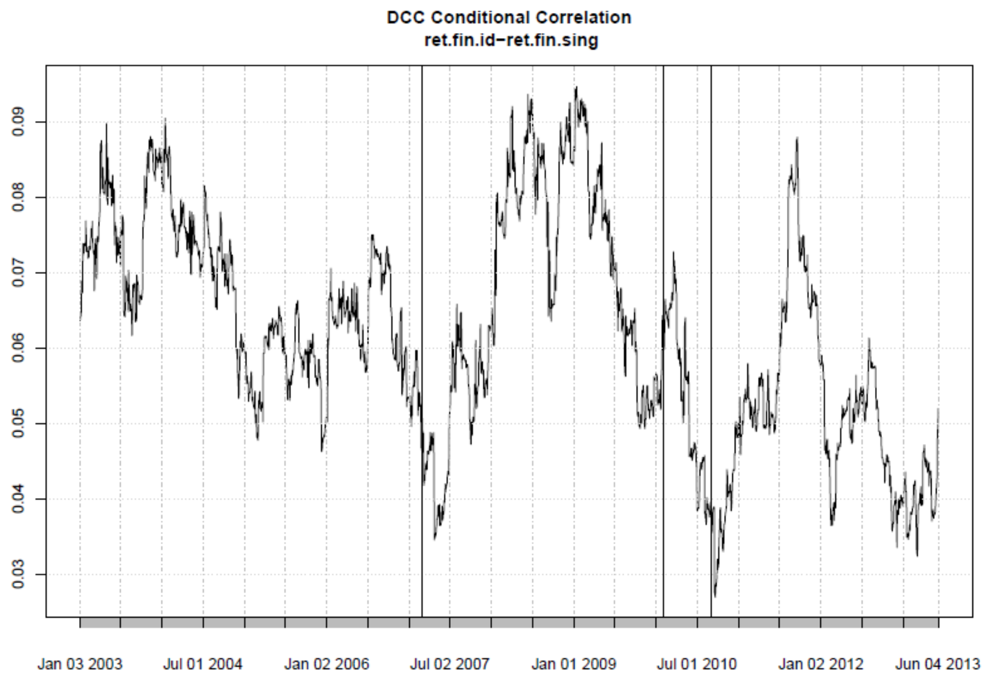


Figure 23: DCC Conditional Correlation FIN.ID - FIN.SING

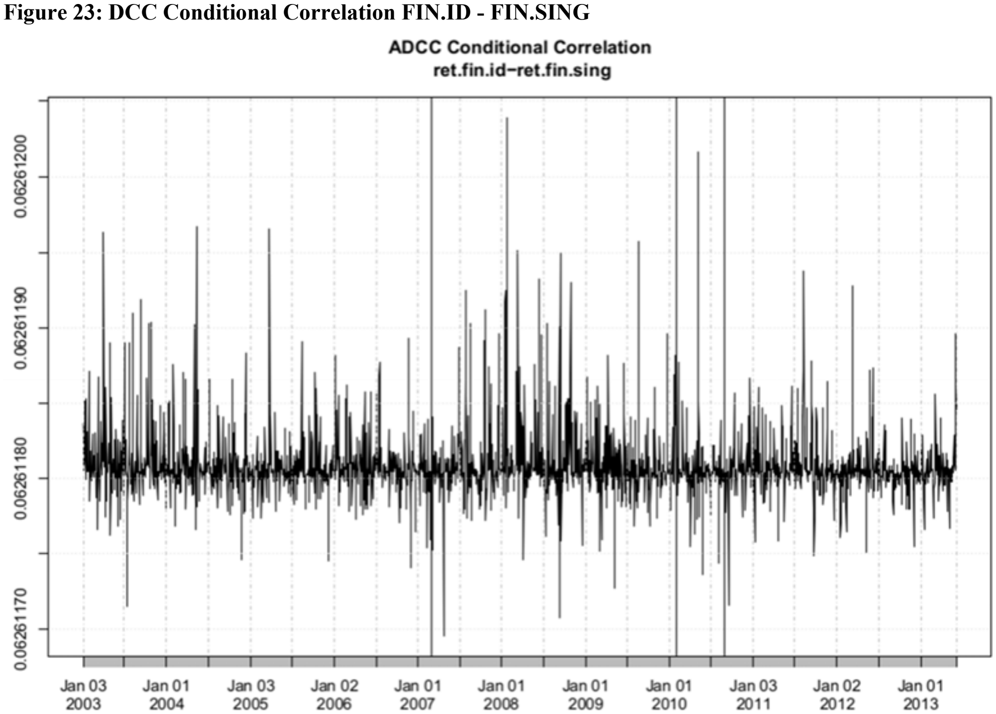


Figure 24: ADCC Conditional Correlation FIN.ID - FIN.SING

4.8.1.6.7 USA

Conditional correlation of US market and Indonesian financial sector are found to exhibit non-constant mean

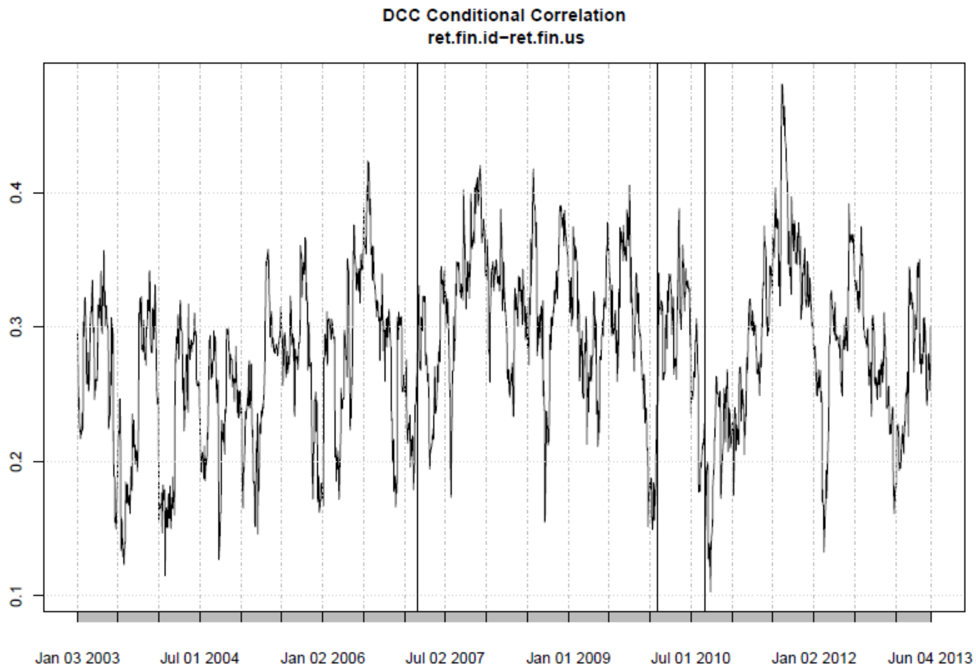


Figure 25: DCC Conditional Correlation FIN.ID - FIN.US

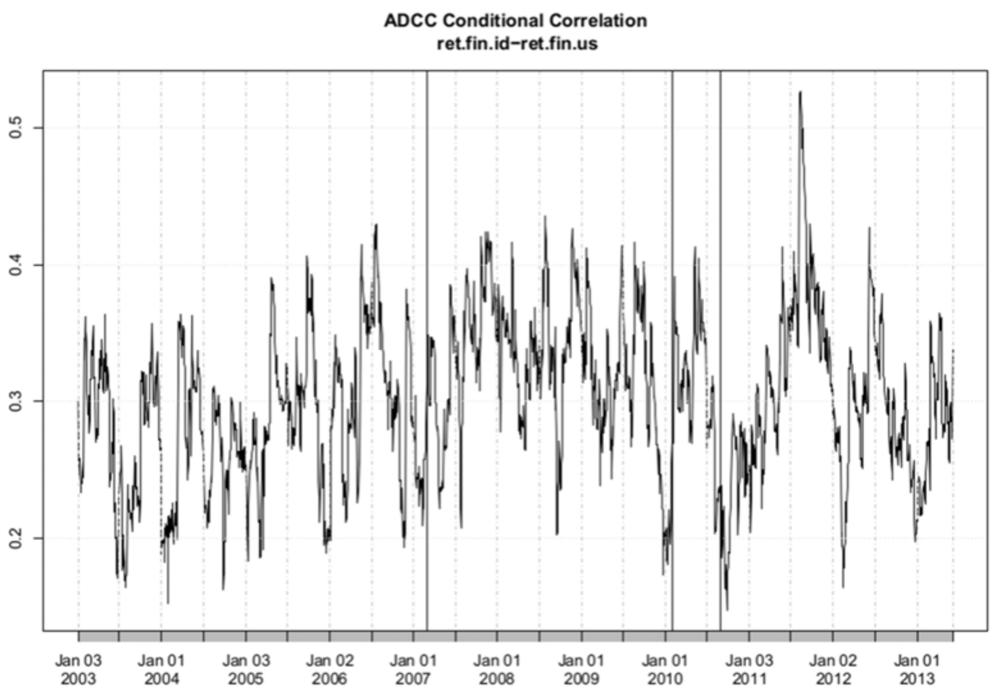


Figure 26: ADCC Conditional Correlation FIN.ID - FIN.US

4.8.1.7 News Impact Surface

To read the news impact surface, the nisurfacex axis represent the return of Indonesian Financial sector, while the nisurfacey axis represent the return of the financial sector of China, Germany, Greece, Japan, Malaysia, Singapore, and USA and nisurfacez represent the magnitude of response toward certain news. The negative/positive numbers in the nisurfacex/nisurfacey axis represent bad/good news.

Each of the picture of 4 sets of picture represent a scenario where a combination of scenario where sectors represented by nisurfacex and sectors represented by nisurfacey was under good/bad, good/good, bad/good, bad/bad news scenario presented in clockwise from top left picture of each sets.

All the news impact surface except on Greece, Malaysia, and Singapore shows that investors are more incited by good news than bad news shows that investors reacts to bad news more reactively than good news

Although investors discriminate on bad news/good news, the news impact surface does not suggest that investors realocate their capital to the other country in the bivariate model as we see consistent pattern in the diminishing response in good/bad and bad/good news corner, unlike what we observed in good/good and bad/bad corner. I suspected that this is the shortfall of the ADCC model

4.8.1.7.1 China

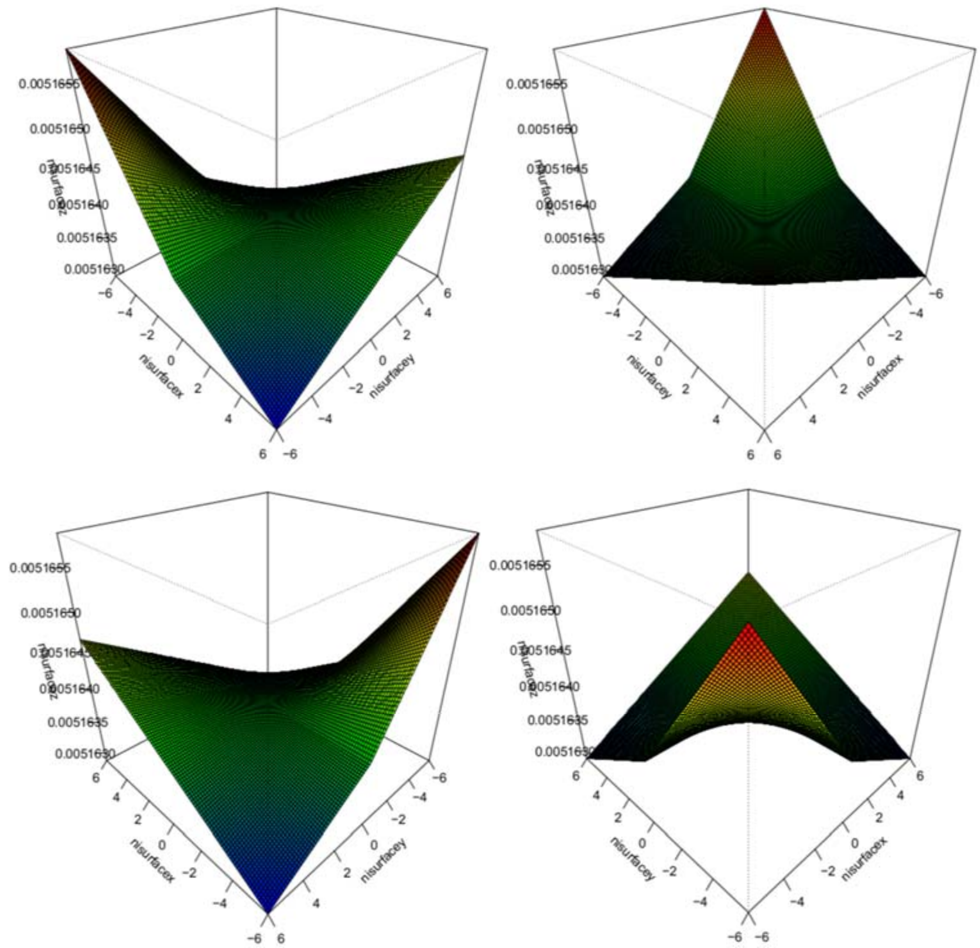


Figure 27: News Impact Surface FIN.ID - FIN.CHN

4.8.1.7.2 Germany

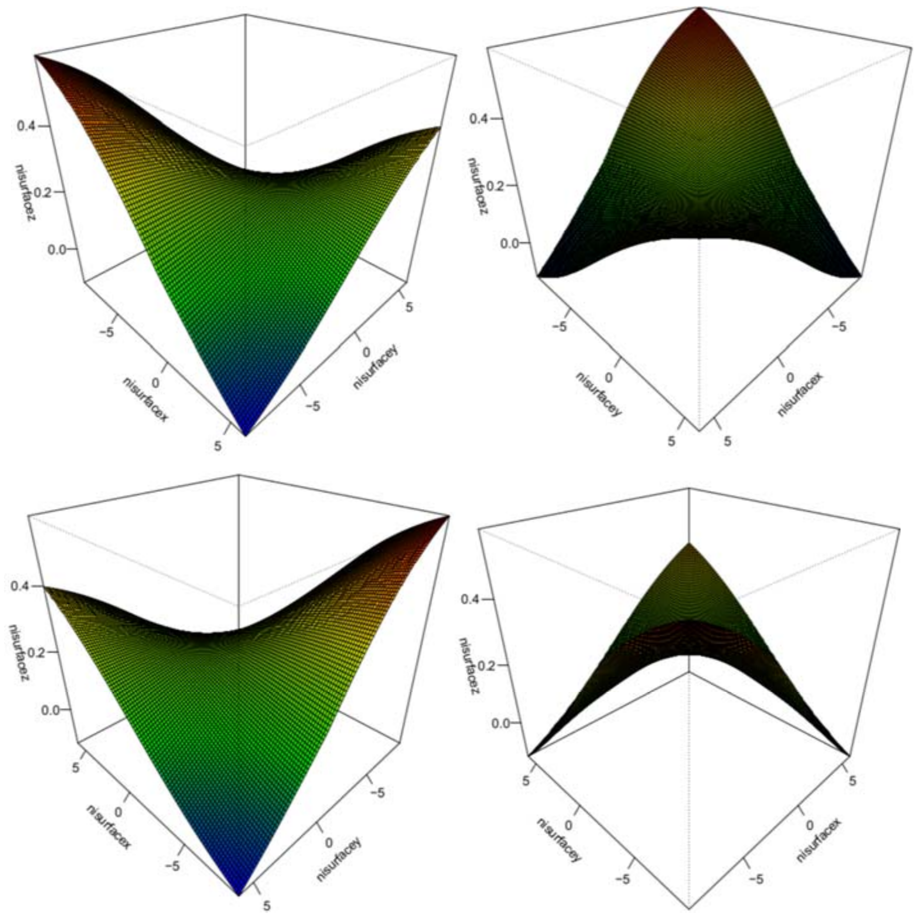


Figure 28: News Impact Surface FIN.ID - FIN.GER

4.8.1.7.3 Greece

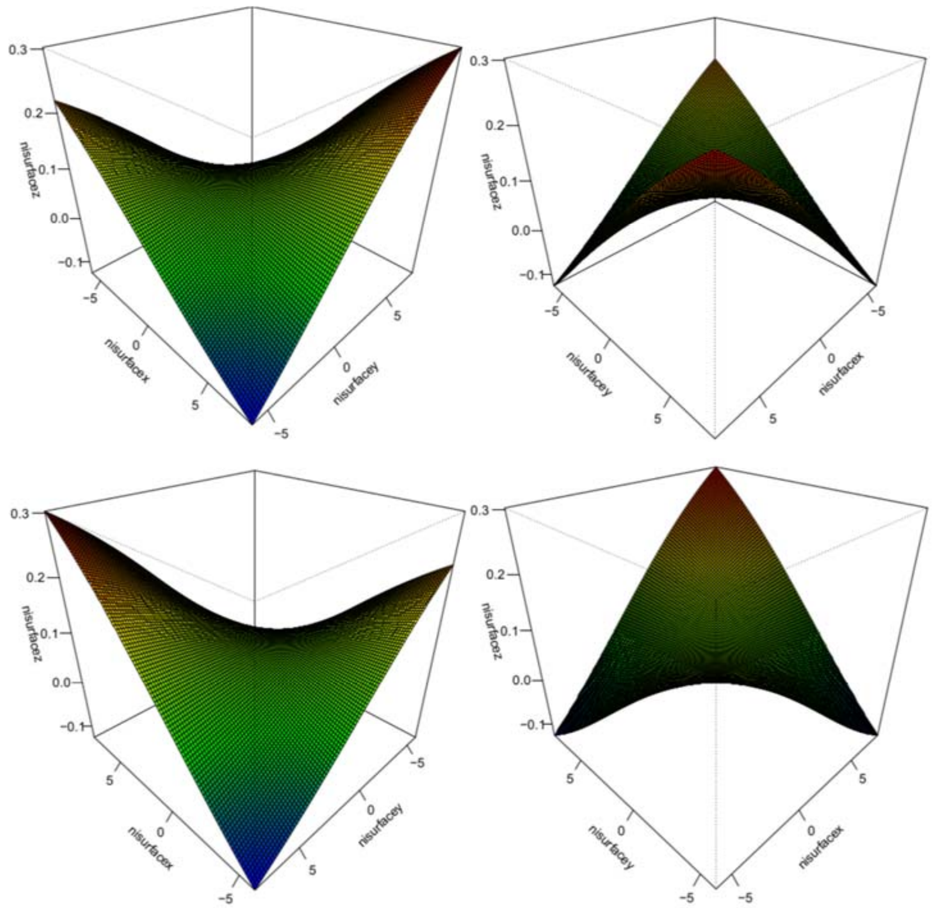


Figure 29: News Impact Surface FIN.ID - FIN.GRE

4.8.1.7.4 Japan

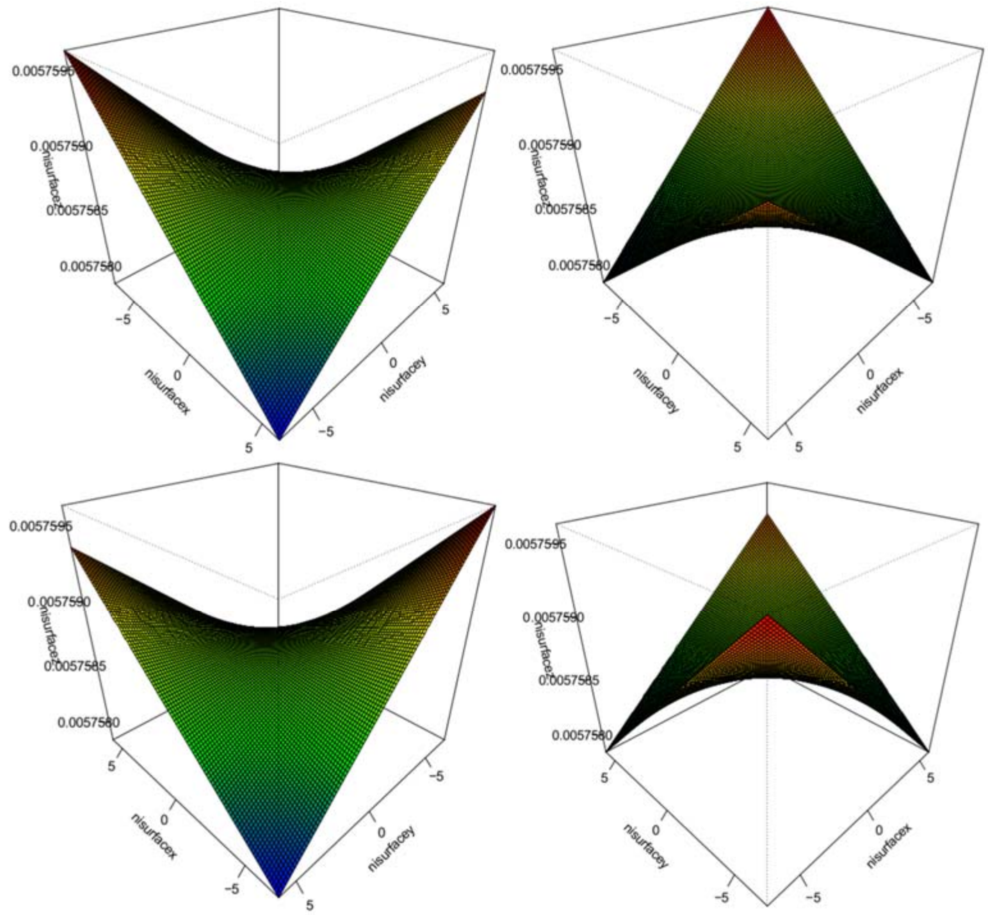


Figure 30: News Impact Surface FIN.ID – FIN.JP

4.8.1.7.5 Malaysia

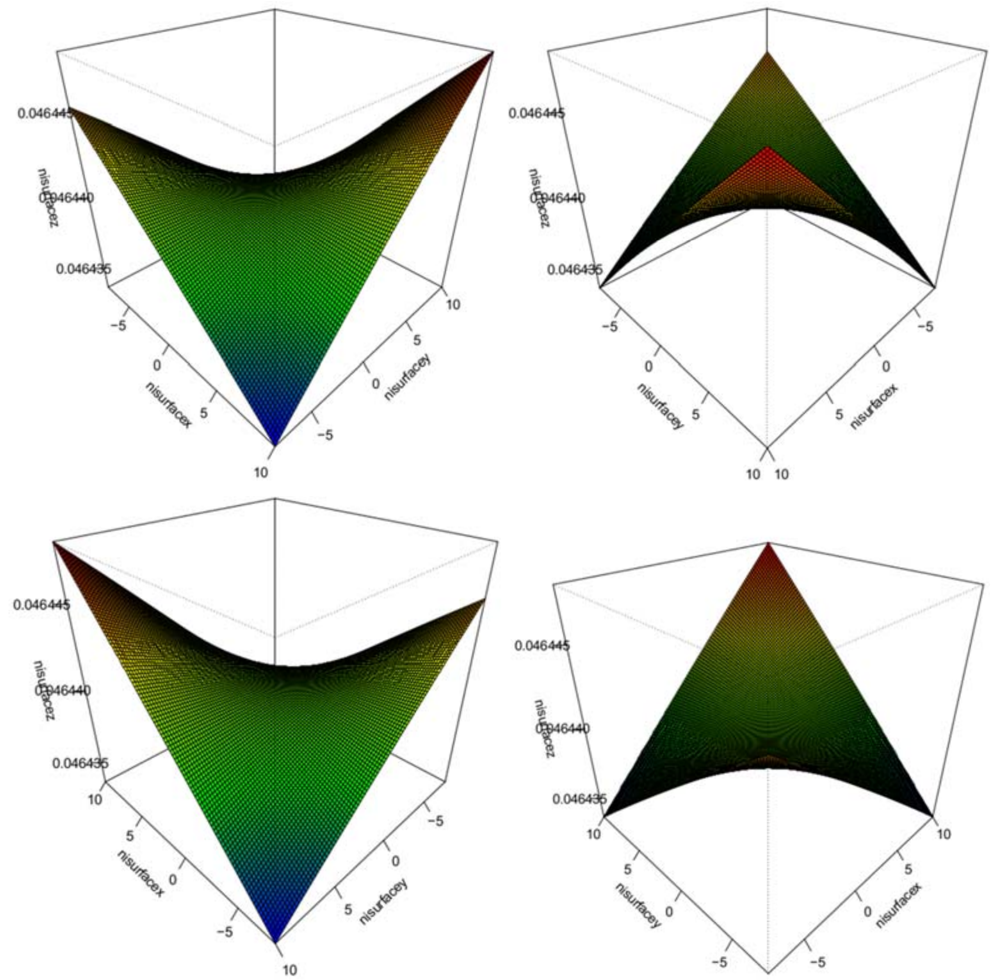


Figure 31: News Impact Surface FIN.ID - FIN.MY

4.8.1.7.6 Singapore

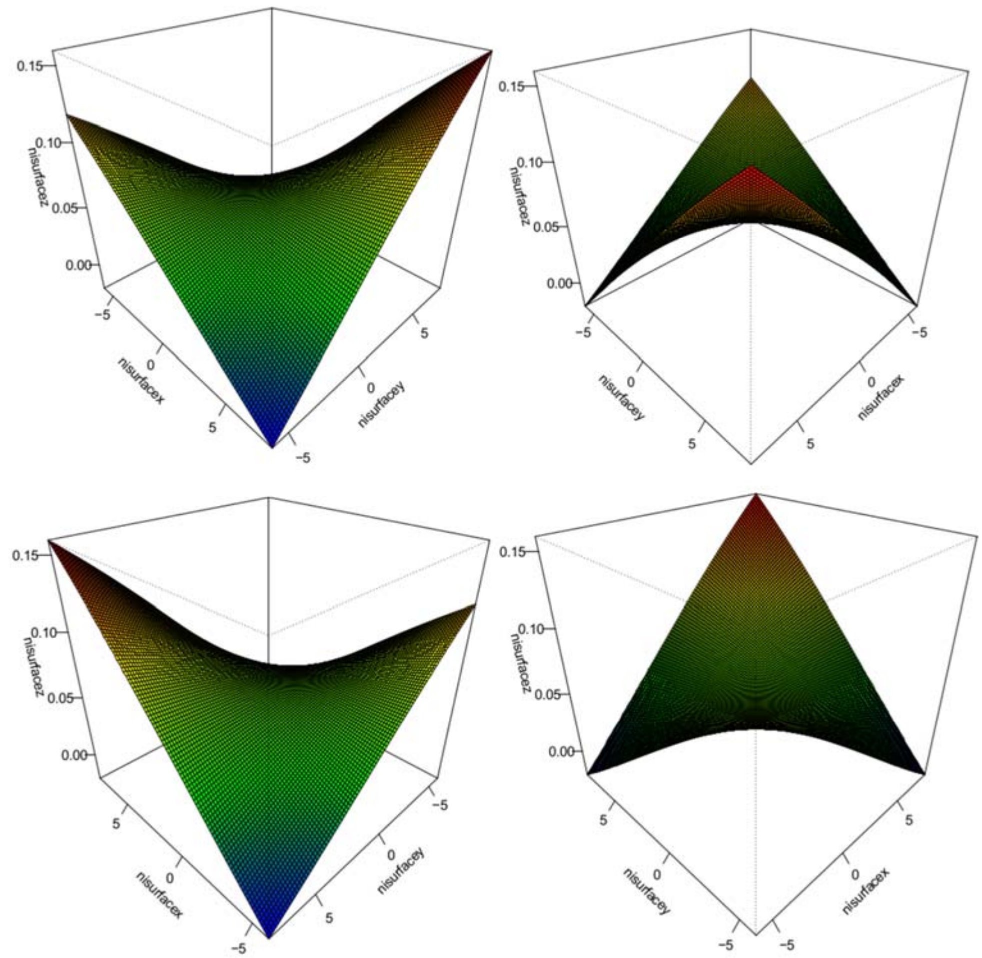


Figure 32: News Impact Surface FIN.ID - FIN.SG

4.8.1.7.7 USA

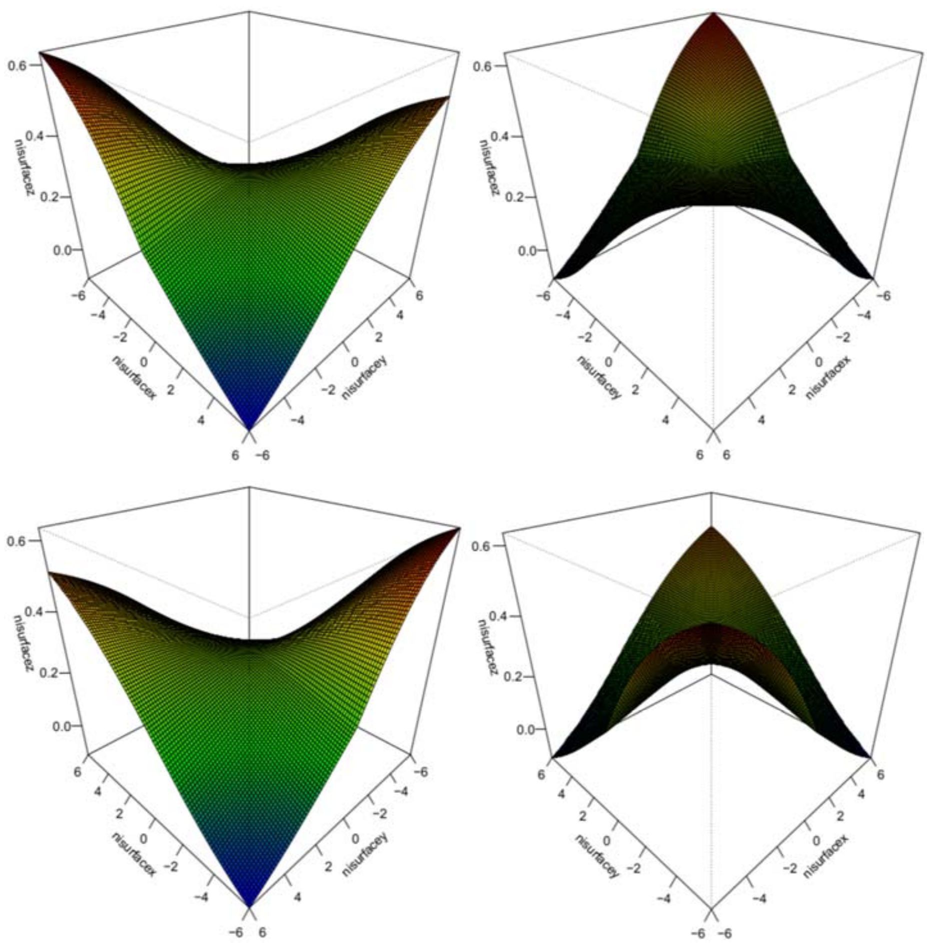


Figure 33: News Impact Surface FIN.ID - FIN.USA

CHAPTER 5
CONCLUSION

5.1 Conclusion of Data Analysis

In chapter 1, we had formulated the problem which we will try to address in this study

1. Does asymmetry effect observed in the financial sector indices of PR China (CHN), Germany (GER), Greece (GRE), Indonesia (ID), Japan (JP), Malaysia (MY), Singapore (SING), USA (US)
2. Does contagion observed between financial sector indices of PR China (CHN), Germany (GER), Greece (GRE), Japan (JP), Malaysia (MY), Singapore (SING), USA (US); with Indonesian financial sector index

Answering the first question, through sign bias test, we've found that Singaporean and US financial sector shows strongest leverage effect

To add into our perspective we had to also note that through observing the news impact surface, we had evidently saw that investors react more to bad news than to good news except on news impact surface between Indonesian financial sectors and Greece, Malaysian, and Singaporean financial sectors; and Indonesian Consumer Goods sector. However, through the news impact surface we also see that investors lacks of interest in good/bad and bad/good news scenario which means that investors are not into diversifying into/from Indonesian financial sector.

Although the model suggests investors discriminate on bad news/good news, the news impact surface does not suggest that investors realocate their capital to the other country in the bivariate model as we see consistent pattern in the diminishing response in good/bad and bad/good news corner, unlike what we observed in good/good and bad/bad corner. However this result may also be attributable that the global financial crisis had affected the entire earth, therefore the notion of diversifiying between financial sectors are not appealing to investors since all market react similarly

Before we answer the second question, let us remind the periodization of the tests used in this study

1. Pre US Subprime Mortgage Crisis
   January 1, 2003 – February 26, 2007
2. US Subprime Mortgage Crisis
   February 27, 2007 – August 30, 2010
   a. Crisis (pre Lehman Brother bankruptcy)
      February 27, 2007 – September 14, 2008
   b. Crisis (post Lehman Brother bankruptcy)
      September 15, 2008 – August 30, 2010
3. Eurozone Sovereign Debt Crisis
   February 2, 2010 –
   a. February 2, 2010 – August 17, 2011
      Sovereign Debt Crisis
   b. August 18, 2011 – …
      Ongoing EMU Economic Downturn

Contagion between Indonesian financial sector with Chinese, Malaysian, Singaporean, and Japanese financial sector was observed on both periods; however, the sign of contagion was more pronouncedly observed in the latter

Contagion between Indonesia and Greece was mainly observed only on the 3rd period, this shows that this crisis's reverberation on Indonesian market than the previous US subprime mortgage crisis.

Contagion between Indonesia and Germany was also observed only in the 3rd period which sends similar message that European Sovereign Debt Crisis was the actor that instigate contagion in this case

We also find an interesting result, contagion between Indonesia and US was mainly observed in the 3rd period instead of the 2nd period, this result shows that European Sovereign Debt Crisis was affect Indonesia, more than US Subprime Mortgage Crisis affect us

Our study shed another light that the contagion following European Sovereign Debt Crisis was more relevant compared to previous US Subprime Mortgage Crisis,

5.2 Limitation of This Study

The limits of this study are:

- The needs for greater computational capability, further study may includes working in bigger size of data hence the greater needs of computational capability
- This study seek to explain contagion from Indonesian major trade partner to Indonesian stock market, therefore we cannot see whether a conditional correlation between Indonesian stock market and another stock market was driven by the same factor, (e.g: whether Indonesian and Japanese Financial Sector conditional correlation was influenced by US stock market)
- We had failed to observe this realocation of capital. Whether this is inadequacy of the model or omitted data. This result shows that perhaps the news impact surface model is not quite capable on capturing investor's behavior particularly about diversification; this is a fact which will be a limitation in this study
- In a hindsight I had left out the analysis of composite stock index, an analysis of conditional correlation analysis of certain sector and the composite index of said country may unravel the condition of it's stock price market perceived by investors, and whether investors had certain preference or bias in constructing their portfolio wihin said country

5.3 Possible improvement of this study and further study which may enrich our understanding of volatility transmission

I suggest for future study, that would be researcher fist take into account on the question of whether volatility pattern is continuous, or changed after an event such as financial crisis, then examine on how investors reacts through their news impact curve

Another improvement would be examining on how stock prices indices from a particular country may affect other countr stock price indices across all sector, so we can begin to draw a picture on how investors perceive the linkage of various sector within a country to another country. This hypothetical study, however, will need to use big data techniques as the computational constrain will be a bottleneck. My incompetence in the field of big data had brought this research only this far, future aspirant may do better by using a better computational machine, or less taxing software as used in this study (i.e R programming language/software), or also better techniques to share the computation across several computational machine

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