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Effects of Global Financial Crisis on Stock Market Volatility

Vliv globální finanční krize na volatilitu akciových trhů

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Description:

1. Introduction
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3. Volatility Models
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References:

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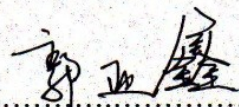Date of submission: 25.04.2015

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"Herewith I declare that I elaborated the entire thesis, including all annexes, independently."

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1. Introduction

Nowadays, financial time series has become an important tool in making quantitative analysis in a broad range of areas. Attentions are focused on financial time series because it provides us with good methodology on making analysis based on the collected data and the established models. What is more, volatility is a factor that almost every investor will take into consideration when it comes to decision making. Financial time series, however, contains many different solutions on measuring volatility according to different situations.

The stock market, which is a component of whole financial market, is closely related to our daily life. For individuals, the stock market broadens our channel on investment activities. For institutions, entities or even the entire country, stock market plays as a mirror which can reflect the current operating situation on economy. For many years, economists are trying to figure out the intrinsic regularity of stock market. Fundament methods and technical methods are the most frequently used terminologies for investigating the pattern of change in stock index. Financial time series, on the other side, leads us to view the changes in indexes from another point by modeling the volatility along a certain period of time.

The main aim of this thesis is to model effect of global financial crisis on volatility of stock markets using conditional volatility models. For the purpose of this thesis, we utilize daily time series of Chinese and Japanese stock markets covering the period from January 2006 till March 2015. Chinese stock market is represented by Shanghai Composite Index while Japanese market is approximated by Nikkei 225 Index.

The main purpose of this thesis is supported by two sub-goals: the first sub-goal is to measure whether the linear or non-linear model can better match the actual volatility on stock index under a certain sub-period for either Chinese market or Japanese market; the second sub-goal is to investigate potential existence of leverage effect for Chinese and Japanese stock market.

The whole thesis can be divided into 6 parts, including the first part "introduction" and the last part "conclusion". Generally speaking, part 2 and part 3 are the description of theory

background and methodology statement while part 4 and part 5 are practical and empirical parts by making analysis.

Since the object for study in this thesis is the index at stock market, chapter 2 will briefly introduce what is financial market, including the structure, basic characteristics, and main participants of financial market. Furthermore, features of stock markets and stock indexes will also be mentioned. To be in harmony with the main goal of the thesis in figuring out the influence of global financial crisis on volatility of stock markets, chapter 2 will take us to a quick review of terminology "financial crisis" and practical examples.

Chapter 3 will state basic approaches for modeling and prediction of volatility. The linear models that are to be introduced contain ARCH model and GARCH model. The non-linear models that are to be introduced contain EGARCH, TGARCH and GJR-GARCH models. The steps in model establishment and criterions on indentifying whether the model is of high quality will be stated. Last but not least, methodologies on choosing good in-sample forecasting model will also be made clear.

In chapter 4, we will firstly state the basic situations on equity market for China and Japan respectively and the financial time series data of daily price will be plotted into figures so that the trending on changes can be more intuitive to see. Then we will adjust the collected empirical data into logarithmic returns and use descriptive statistics to summarize the features on returns. Next, we will establish models for both Chinese and Japanese market using linear volatility models and non-volatility models under the divided three sub-periods of time. These models will undergo diagnostic tests to see whether the general assumptions for financial time series models are fulfilled. Last step in chapter 4 is in-sample forecasting evaluation; we will see the degree of fitting ability of estimated models.

Chapter 5 is going to refine the main conclusions drawn from analysis on chapter 4, with text descriptions and synoptic Tables for summary and comparison.

Chapter 6 is the conclusion part which is dedicated to summarize the whole diploma thesis, evaluate whether the main goals and sub-goals of the thesis are fulfilled and point out potential shortcomings which may be improved.

In this diploma thesis, Figures in chapter 2 and chapter 3 are mainly from the reference of internet. Calculations and outputs of Charts, Figures, and Tables for chapter 4 and chapter 5 are mainly from the statistical software EViews7 and Microsoft Excel 2007.

2. Data on Financial Markets

Chapter 2 will provide a brief description on financial crisis and typical features of financial time series. Definition, constituents, importance, main participants of financial markets will be introduced. Financial crisis will be viewed from two aspects: the first aspect is basic information on financial crisis such as the difference between financial crisis and economic crisis and types of financial crisis. The second aspect describes some practical examples of financial crisis. Methodologies of financial time series will be used in this thesis at later chapters. However, in chapter 2, explanations of some terminologies for financial time series by Andersen (2000), Campbell, Lo and MacKinlay (1997) will be introduced briefly.

2.1 Characteristics of Financial Markets

Even thought financial market is not the main object in our study, basic knowledge on financial market such as its definition, constituent, conditions to form, main participants and so on is necessary. With reference to Burch, Timothy R (2003) and Merrill Lynch (2006), contents in sub chapter 2.1 will lead us to a quick view on comprehensive fundamental information on financial markets.

2.1.1 Comprehensive Fundamental Information on Financial Markets

Financial markets can also be called fund markets. Financial markets provide place for people to conduct activities to adjust capital surplus by means of different financial instruments. This process is what we know as financing.

The constitution of financial market is very complex. It is a huge system which contains a lot of different markets. However, we usually classify financial markets into two categories, money market and capital market. The main difference between money market and capital

market is the maturity to claims. Usually, money market has a maturity of less than 1 year. In contrast, the maturity of capital market is usually longer than 1 year. Figure 2.1 will demonstrate the structure of financial markets.

Figure 2.1: Structure of financial market
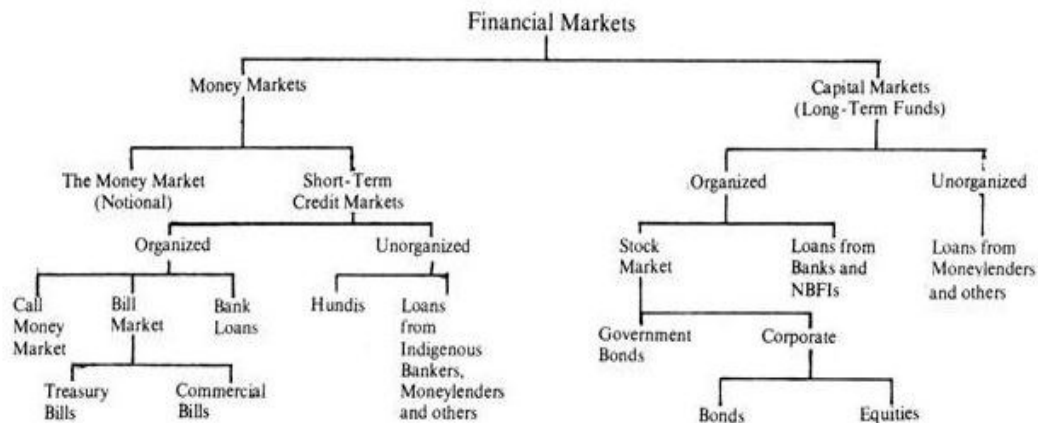
Source from: http://image.baidu.com

Compared with other markets, financial market has its own specialty:

(a) The trading objects in financial market are capitals.

(b) The main relationship in financial market is lending and borrowing, which reflects the separation of the right to use capital and ownership of having the capital.

(c) The financial market can be both tangible market and intangible market.

The conditions for financial market to form can be viewed mainly from four aspects:

(a) With highly developed commodity economy, there exist huge capital supplies and demands.

(b) A variety of financial instruments and derivatives and a lot of transaction methods provided for investors.

(c) A sound financial legislation.

(d) The government can make reasonable and effective intervention on financial market.

2.1.2 Importance and Main Participants of Financial Markets

Financial markets are of great importance in our daily economic life. Main functions of financial markets include:

(a) Possibility to obtain funds, which is the fundamental function of the financial market;

(b) Motivation function, which means that investors are encouraged to invest their money in financial market to gain a certain degree of benefits as compensation;

(c) Price discovery, periodic trading of a security reveals the consensus price which an asset commands on the market. Thus a prospective issuer of new securities knows his costs or at what price level he must set his new bonds or stocks;

(d) Liquidity, which means that investors have the chance to sell the financial instruments to reverse their trades. If the financial markets fail to provide investors with the chance of selling the financial assets, investors would be reluctant to purchase those assets in the first place;

(e) Reducing transaction and search costs. With huge quantities and continuous trading, transaction costs may be kept low. Besides, the financial markets can have other functions like reduction of risk, political function and so on.

The main participants in financial market include banks, pension fund, insurance companies, and investment banking firms, investment companies, savings and loan associations and so on.

Commercial banks are the most important financial intermediary that provides banking and other financial services. Banks service both private and public sectors, and their deposits and lending services are utilized by households, businesses and government agencies. Income of banks mainly derives from investments and fee income, in recent years; banks have begun new services to generate additional income.   Fund is set up by a corporate, a government, a labor union or other organizations to pay the pension benefits of retired workers.

Pension funds receive savings from households' investments which are used for providing

income during the retirement. Moreover, pension funds are frequently part of an employee's benefits package and are managed by investment companies. The fund usually has huge amount available, which are invested in securities until they are withdraw by the employee. Insurance is the business of providing protection against financial aspects of risk. In broad economic sense, insurance transfer risk from individuals to larger group, which is better able to pay for losses. Saving and loan associations are financial institutions which specialized in providing mortgage and issuing mortgage backed securities. Their operations differ from commercial banks, which use most of their funds for business loans and commercial real estate loans. The mortgages usually have long term maturities and can usually be prepaid by borrowers. A mortgage normally involves real estate. Mortgages can be sold in the secondary market.

2.1.3 Stock Market and Stock Indices

In sub-subchapter 2.1.2, we have known that the participants in financial market are various, stock market is one of which. Stock market provides a direct reflection on what is going on in the financial market.

The stock indices summarize the performance of major groupings of stocks, classified by the exchange on which they trade, by region, or any number of classifications that allow investors to benchmark the overall performance of major groupings of stocks.

The situation in financial market can influence the volatility of stock indices. Getting to know the way on how those influence happen, we can tell whether the financial market functions well or not by using the stock indices as a reference. It is the very task that we are going to solve on how changes in financial market effect the volatility of stock indices. Examples of stock indexes include DJI (Dow Jones index), Nikkei index, and HSI (Hang Seng index) and so on. These indexes can reflect the operating situation in stock markets. As what we have usually heard the term "bear market" when the stock index is on the trend of going down or the term "bull market" when the stock index is on the trend of going up.

2.2 Financial Crisis

Subchapter 2.2 contains two parts, the first part is to provide basic ideal on the conception of financial crisis and distinguish between financial crisis and economic crisis. The second part will use some examples in history to make the image on what financial crisis really is deeper. Decades of years ago, economists like Lander, Joel and Martha (1997) and Siegel, Jeremy (2002) had already made comprehensive explanations on concept of financial crisis.

2.2.1 Fundamental Knowledge on Financial Crisis

The term financial crisis refers to the situation where the prices of financial assets drop down sharply or the financial institutions have to close down. Financial crisis is the disaster happens in financial area. Finance has a special characteristic of globalization because financial assets have strong liquidity. The blasting fuses of financial crisis can be the financial products, financial institutions or financial markets from any part of the world or any country.

The term "financial crisis" and "economic crisis" is not the same. Theoretically, finance and economy do not refer to the same thing. Finance is based on currency and capital, whose contrast conceptions are production and consumption. Production and consumption are based on goods and services. Economy has broad conception than finance; it refers to all activities which are related to demand and supply. The basic point in finance is to create value to gain wealth by re-allocation of wealth. Economic crisis refers to the situation where the increase in wealth cannot satisfy the demand of people. Practically, financial crisis and economic crisis are highly related.

Usually, the economic crisis happens along with financial crisis. The main reason is that because currency and capital take steps into the process of production and consumption, the influence of currency and capital in economic become more and more obvious. Let us take production as an example, in the first process of production—investment, capital has already taken a step inside it. During this stage, currency capital transfers into production capital. In the second process, namely, the manufacturing process, capital transfers its form from

investment into goods. In the third process of production, the selling stage, the form of capital transfers from goods to currency again. From the transformation process of currency capital, the input of currency of capital and gain from currency capital is separated by time. Any contingency happens during the production process can cause trouble to the operation situation on capital flow. Once the capital input cannot generate output as expected, credit crisis happens, which can lead to financial crisis. When such contingencies happen in production process frequently, production may have to be terminated because of shortage in capital input. The decrease on output can cause economic crisis. This is the reason why financial crisis and economic crisis always go hand in hand. It can also explain the situation where financial crisis happens before economic crisis.

There are several types of financial crisis:

(a) Currency crisis.

(b) Debt crisis.

(c) Banking crisis.

(d) Subprime crisis.

 Nowadays, financial crisis appears to be more than two types of those circuses.

2.2.2 Practical Examples of Financial Crisis

There are a lot of financial crisis happens in history. In 1873, the economy in Austria and Germany were prosperous, which drew a lot of foreign capital. However, the sudden termination of foreign financing led to the operation difficulty for Jay Cooker Company in America. In 1890, Baring brothers' investment bank was immersed in repaying crisis to Argentina debt. At the same year, financial crisis in New York caused lots of companies into bankrupt in October. Baring brothers failed to survive just one month later.

In the latest decades, the financial crises which have the deepest influence on us are Asia

financial crisis in 1997 and global financial crisis in 2007.

1. Asia financial crisis

The Asia financial crisis can be divided into three different phases. First stage is from June, 1997 to December, 1997. The second stage is from January, 1998 to July, 1998. The last stage is from July, 1998 till the end of 1998.

During the first stage, Thailand abandoned its fixed exchange rate system, turned to floating exchange rate system. The exchange rate of the Thai baht against the dollar depreciated to 17%. Later, currencies of the Philippines, Malaysia, and Singapore were all suffered from great attack. During the second stage, in February of 1998, the Indonesian government announced that it would implement the Indonesian rupiah maintain a fixed exchange rate peg to the dollar, to stabilize the currency. However, this behavior was strongly against by IMF, America and western European countries. IMF announced to give up the assistance to Indonesian government, which put Indonesia into great political and economic crisis. The third stage, the crisis mainly reflects on attack to Hong Kong. From August, 1998, Hansen Stock Index in Hong Kong dropped to as much as 6000 points. Also, during this period, the influence of Asia financial crisis spread beyond Asia to the whole world.

2. Global financial crisis during 2008-2009

Subprime crisis in 2007 happened in America first, later it developed to overall financial crisis and permeated to the whole world.

Trust, the ultimate glue of all financial systems, began to dissolve in 2007—a year before Lehman's bankruptcy—as banks started questioning the viability of their counterparties.

The collapse of Lehman Brothers, a sprawling global bank, in September 2008 almost brought down the world's financial system.

Figure 2.2 shows the serious effect of 2008 financial crisis on American stock market. Before 2006, the price of houses in America went up sharply. A lot of low income people make loans from banks to buy houses. However, in the beginning of 2007, American government announced that the real estate industry has come to the top point and the price

should go down. Thus, those who used real estate as a way of investment suffered from great loss, they could not afford the repayment to banks. The small and medium size financial intermediaries had to close down because of relatively low risk tolerance. Later, the mortgage crisis intensified, bankrupt happened to real estate companies and a lot of large investment banks.

Figure 2.2: Dow Jones Industrial Average

Source from: http://research.stlouisfed.org/
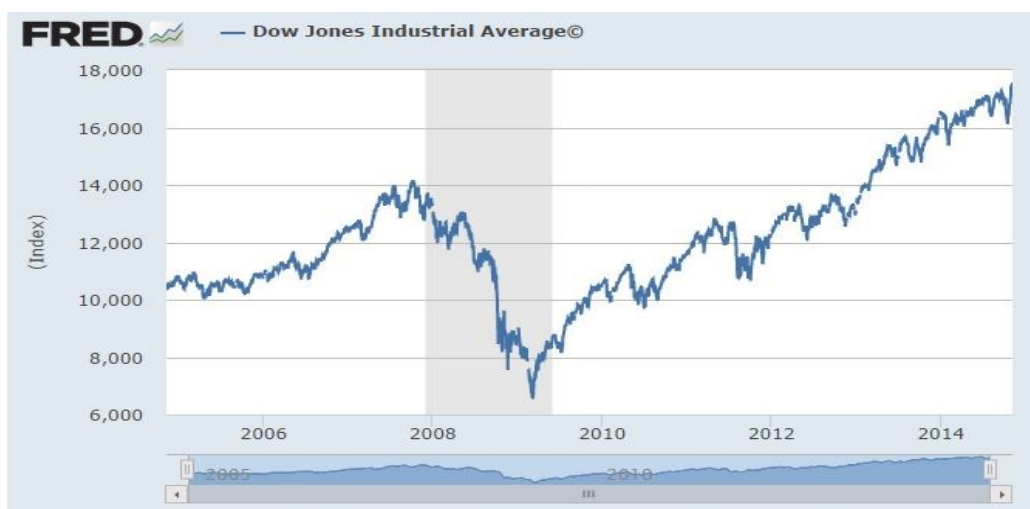
What warning did American financial crisis convey to us?

Start with the folly of the financiers. The years before the crisis saw a flood of irresponsible mortgage lending in America. Loans were lent out to borrowers with poor credit histories record which shows these borrowers have to struggle hard to repay the loan back. These risky mortgages were passed on to financial engineers at the big banks, who turned them into securities that are supposed to be of low risk but without actual prove. Pooling itself does make profits if the risks of each loan are uncorrelated. The big banks insisted that the property markets in different American areas would behave independently from one another. Unfortunately, this belief was turned out to be wrong. Starting in 2006, America suffered a nationwide house-price slump.

The pooled mortgages were used to form securities known as collateralized debt obligations (CDOs), which were sliced by degree of exposure to default. Investors bought the

safer tranches because they trusted the triple-A credit ratings assigned by agencies such as Moody's and Standard & Poor's. This was another mistake. The agencies were paid by. The direct result is that those rating agencies which enjoy high reputation fell to credit the financial institutions with objectivity and fairness.

Failures in finance were at the heart of the crash. But bankers were not the only people to blame. Central bankers and other regulators bear responsibility, too. Because their behavior of mishandling the crisis, failing to keep economic imbalances in check and failing to exercise proper oversight of financial institutions.

The U.S. financial crisis presents two marked characteristics:

(a) Domestic investment banks, securities business, the credit business of commercial banks and insurance companies business are intertwined, which can easily lead to the interaction of risk.

(b) Second, as the opening of financial markets from different countries, America has made a lot of real estate mortgage bonds sold to other countries, which can easily lead to the spread of crisis to international markets.

These characteristics tell us that the financial liberalization must be doubly cautious. Another lesson we should learn from the 2007 financial crisis is that the development of virtual economy must be closely integrated with the real economy. Without the support from real economy and corresponding control measures, the virtual economy will gradually evolve into speculative economy. Last but not least, it is urgent to put more supervision on financial derivatives. Financial derivatives could have been used to spread risk, improve the work efficiency of financial intermediaries. But on the other hand, it can work as a risk channel if the risk is high enough. The lesson of American warns us that corresponding supervision must be strengthened in the development of financial derivatives. We should avoid excessive development of financial derivatives to control the size of the risk.

2.3 Financial Time Series and Their Characteristics

Chapter 2.3 will explain some important terminologies for financial time series by Ghysels (2000), Lyons (2001), Tsay (2001), and Wood (2000). This subchapter cannot be ignored because we will use the methodology of financial time series to deal with the market data, so that the analysis on stock markets can be more concrete.

2.3.1 Volatility Clustering

In traditional classical capital market theory, the variance of return rate is assumed to be constant when the econometric model is used. Even though the method and assumption meet the requirements of efficient market theory in financial market, a large number of empirical studies have shown that this assumption is unreasonable in some situations, as noted by Mandelbrot (1963), that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." A quantitative manifestation of this fact is that absolute returns $|r_t|$ or their squares display a positive, significant and slowly decaying autocorrelation function: $\text{corr}(|r_t|, |r_{t+\tau}|) > 0$ for τ ranging from a few minutes to a several weeks.

Figure 2.3 shows that under volatility clustering, low volatilities are following previously smaller changes while high volatilities are following previously bigger changes.

Figure 2.3: Volatility clustering and not volatility clustering
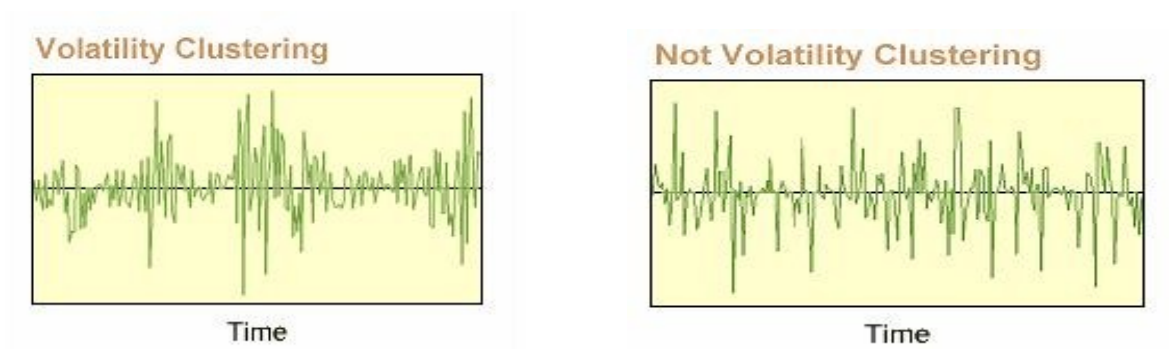
Source from: http://www.riskglossary.com/link/volatility_clustering.htm

2.3.2 Asymmetric Volatility

Empirically, it seems that the volatility in stock markets is asymmetric: returns and conditional volatility are negatively related, that is, the negative (positive) returns are usually related with upward (downward) revisions of the conditional volatility. To make better explanation in the following chapters which concerns to the analysis on stock markets, we should figure out the basic knowledge on asymmetric volatility.

Black (1976) and Christie (1982) were among the first to make an explanation on the phenomenon of asymmetric volatility in stock market. An important conclusion from their research is the leverage effect hypothesis, that is, a drop in the value of the stock (negative return) can increase the financial leverage, thus, the stock will become more risky and the volatility will increase as well. For a period of time, the term "leverage effect" has been the synonymous with asymmetric volatility. However, there is another factor which can also be used to explain asymmetric volatility, namely, volatility feedback effect.

The mechanism of volatility feedback effect is not complex. The increase in volatility means potentially higher risk. When the risk is higher, investors usually require for higher level of required rate of return, which is negatively related to stock price.

Practically, both leverage effect and volatility feedback can influence the stock market. Suppose an immediate event happens in the stock market, which increases the volatility of stock prices, the effect of such volatility shock is often reflected in the traders' reluctance to buy and willingness to sell in anticipation towards the whole stock market. As a result, stock price has to drop to meet the balance requirement in buying and selling volume. The anticipation of volatility leads to the drop of stock price, as what is explained by "volatility feedback hypothesis". The drop in stock price increases the leverage ratio, which leads to the increase of potential risk and therefore a further volatility in stock market, as what has been explained by "leverage effect hypothesis".

2.3.3 Leptokurtic Distribution

Even though there are a variety of forms of distribution for a set of data, it seems that the data from financial markets usually present a leptokurtic distribution. Because it is possible that we will use leptokurtic distribution in our later analysis, we will briefly introduce the conception of leptokurtic distribution here.

Leptokurtic describes a distribution that is more peaked than a normal distribution. Compared with normal distribution, leptokurtic distribution has more returns clustered around the mean and the tail is fatter than normal distribution. In leptokurtic distribution, there is a relatively greater possibility that an observed value being either close to the mean or far from the mean. Let us take a look at an example about comparison between normal distribution and leptokurtic distribution.

Figure 2.4: Comparisons between normal distribution and leptokurtic distribution
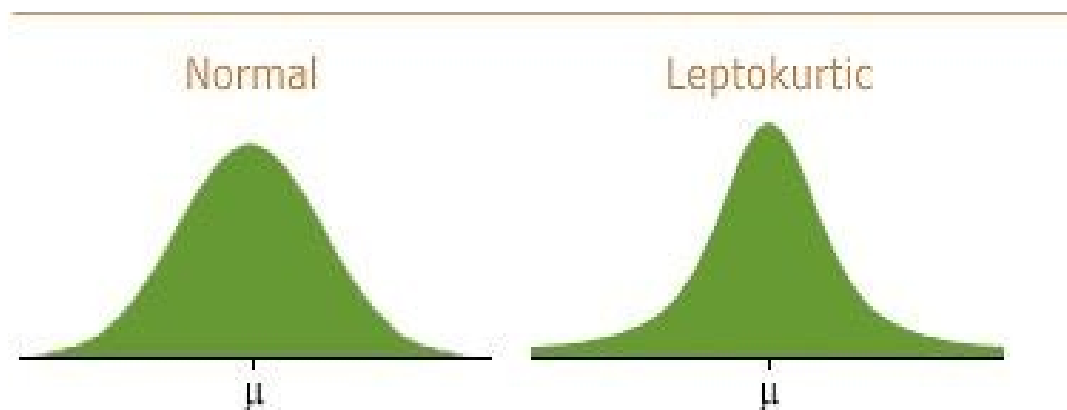
Source from: http://www.riskglossary.com/link/stable_paretian_distributions.htm

As Figure 2.4 shows that a leptokurtic distribution means that small changes happen less frequently because historical values have clustered by the mean. However, this also means that large fluctuations are more likely within the fat tails.

3. Volatility Models

A volatility model must be able to forecast volatility, which is the basic requirement in almost all applications of financial time series. In this chapter we will outline some fundamental facts about volatility that should be incorporated in a model by Robert F. Engle (1982), Bollerslev (1986) and Taylor (1986)

Virtually all the financial uses of volatility models entail forecasting aspects of future returns. A risk manager must know today the likelihood that his portfolio will decline in the future. An option trader will want to know the volatility that can be expected over the future life of the contract. A portfolio manager may want to sell a stock or a portfolio before it becomes too volatile. A market maker may want to set the bid–ask spread wider when the future is believed to be more volatile.

3.1 Volatility and its Consequences

Volatility is a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from the same security or market index. Generally, higher level of volatility means much risky of an asset.

In other words, volatility refers to the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time.

If an asset price such as a currency, commodity, stock price, or bond price made a big move yesterday, there is a high possibility that it will make a big movement today as well.

In Figure 3.1, we can see the returns of the S&P 500 around the stock market crash of October 19, 1987. Before the stock market crash, the standard deviation of returns was about 1% per day.

Figure 3.1: Stock returns after the October 19, 1987 stock market crash

Source from: http://cims.nyu.edu/~almgren/timeseries

Although the stock market crash on October 19, 1987 is an extreme example, we can see that large moves in prices lead to more large moves. Before the stock market crash, the standard deviation of returns was about 1% per day. On October 19, the S&P 500 was down 20%, which as a 20 standard deviation move, in 4 of the 5 following days, the market moved over 4%, it appears that volatility continued increasing after the stock market crash, rather than remaining at 1% per day.

Volatility does not only appear during a crisis, it will eventually drop back to approximately the same level as it did before the crisis. Over the decades, proofs have appeared again and again, such as the Great Depression, Watergate, the 1987 stock market crash, Long Term Capital Management's collapse in 1998, the September 11 terrorist attacks, and the bankruptcy of WorldCom in 2002. There are also examples in the foreign exchange market, such as the Mexican Peso crisis in 1994, the East Asian currency crisis in 1997, EMS crises in 1992 and 1993. In all these cases, volatility remained high for a while, and then dropped back to pre-crisis levels.

Figure 3.2 shows that during the financial crisis last fall, the VIX index hit a high of 80%, and then gradually reverted over the last year back to a volatility of 21%.

Figure 3.2: Implied volatilities after the 2008 financial crisis

Source from: http://cims.nyu.edu/~almgren/timeseries

The volatility in American stock market is extremely high when it is compared to the pre-crisis time period and post-crisis time period. The stationary of data is broken by occur of certain event.

3.2 Volatility Modeling and Volatility Forecasting Using High Frequency data

The forecasting of volatility (variance) can be regarded as a significant problem of establishing a mathematic model for predicting, because the volatility is an important parameter in financial risk management and it can be applied to lots of areas such as option pricing, portfolio creation, VaR methodology and so on.

The three main purposes of forecasting volatility are:

1. Risk management. A large part of risk management is measuring the potential future losses of a portfolio of assets, and in order to measure these potential losses, estimates must be made for future volatilities and correlations.

2. Asset allocation. The Markowitz approach of minimizing risk for a given level of expected returns has become a standard approach, and of course an estimate of the variance-covariance matrix is required to measure risk.

3. The most challenging application of volatility forecasting, however, is to use it for developing a volatility trading strategy. Option traders often develop their own forecast of volatility, and based on this forecast they compare their estimate for the value of an option with the market price of that option.

The idea of using high frequency data for more reliable volatility estimation appeared more than twenty years ago. In order not to lose all the information about the price process in between, Officer (1973) computed annual volatilities from monthly returns, later on, Merton (1980) used daily returns to measure monthly volatilities. Recently the idea of using higher frequency intra-daily data for estimating daily volatility came up. Schwert (1998) was working with 15-minute returns, while Taylor and Xu (1997) as well as Andersen et al. (1998) apply 5-minute returns to estimate daily exchange rate volatilities.

For the issue concerning forecasting volatility, high frequency data have been valuable in a number of ways:

1. High frequency data helps us to understand the dynamic properties of volatility which is important for forecasting.

2. High frequency data have improved the evaluation of volatility forecasts in important ways.

3. Realized measures have made it certain on the development of new volatility models which provide more accurate forecasts.

4. Realized measures can assistant and improve the accuracy in estimation of complex volatility models, such as continuous time volatility models. The reduction in the parameter uncertainty will improve predictions based on such models.

5. High frequency data have improved our understanding about the fundamental forces of volatility and their relative importance. For instance, high frequency data have enabled a detailed analysis of news announcements and their effect on the financial markets.

Volatility forecasting using high frequency data can be divided into two main parts, which we refer to as reduced form volatility forecasting and model based forecasting, respectively.

The reduced-form approach deals with cases where the realized measures are modeled with a time series model such as ARIMA and the estimated model is used to produce volatility forecasts. An influential paper in this area is Andersen et al. (2003) who constructed and analyzed long-memory Gaussian vector autoregressive (VAR) models for a vector of realized variances. This approach has subsequently been used in numerous other studies. A related type of reduced-form volatility forecasts are the regression based forecasts, such as those based on the HAR structure by Corsi (2009) and MIDAS by Ghysels, Santa-Clara & Valkanov (2006).

The other approach, namely, the model-based approach to volatility forecasting is established from a model for returns, such as a GARCH type model that describes the entire distribution of returns. The name for this type of forecasting is to estimate the model's parameters and use the estimated model to predict volatility. High frequency data have been used in two different ways in this context. One is to enhance an existing volatility model by including a realized measure into the model, the other one is to utilize high-frequency based statistics for improving or simplifying the estimation of the statistical model.

3.3 Linear Volatility Models

The aim of this thesis is to develop models for the collected financial data and compare whether the linear or non linear model can better reflect the relationship between these financial data and its response time series. For the purpose of this thesis, it is the conditional volatility models that will be used.

Introductions for linear volatility models are mainly from the references with Engle (1982) and Bollerslev (1986).

3.3.1 ARCH Model

Practically speaking, the risk or the volatility of an asset's return is specified as the conditional variance empirically. Generally, the fluctuation of asset's return is not constant, the variance of return can be different based on what time it is, for example, during the financial crisis time period, the variance of asset return was more fluctuate. This

phenomenon of time-varying volatility can be observed in many empirical data. Because of such phenomenon, the assumption of a constant variance for the set up of regression model cannot hold, because homoscedasticity is met. As a result, we should construct econometric models which can be used even when the variance changes over time.

The first model that will be introduced is the simplest one, ARCH model, which is the short term of Autoregressive Conditional Heteroscedasticity. Engle (1982) suggests the heteroskedastic of conditional variance can be formulated as a linear function of past squared errors. The ARCH model comes from the fact that these models are autoregressive models in squared returns, Heteroscedasticity means non constant volatility.

In a standard linear regression where $Y_i = \alpha + \beta x_i + \varepsilon_i$, when the variance of the residuals, ε_i is constant, we call that homoscedastic and use ordinary least squares to estimate α and β. If, on the other hand, the variance of the residuals is not constant, we call that heteroscedastic and we can use weighted least squares to estimate the regression coefficients.

Let us assume that the return on an asset is:

$$r_t = \mu + \sigma_t \epsilon_t. \tag{3.1}$$

We will define the residual return at time t, as

$$a_t = \sigma_t \epsilon_t. \tag{3.2}$$

In an ARCH model, first developed by Engle (1982):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2, \tag{3.3}$$

where $\alpha_0 > 0$ and $\alpha_1 \geqslant 0$ to ensure positive variance. Under an ARCH model, if the residual return is large in magnitude, our forecast for next period's conditional volatility σ_{t+1} will be large. We say that in this model, the returns are conditionally normal.

However, the formula (3.3) is called ARCH(1) model, because the conditional variance of the random variable Y_t depends only on one lagged value. To test whether the change of dependent variable Y_t is in the linear regression model, we can expand the formula as:

$$Y_t = b_0 + b_1 * x_1 + b_2 * x_2 + \mu_t, \qquad \mu_t \sim NI(0, \sigma_t^2), \tag{3.4}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2. \tag{3.5}$$

The implications we can see from formula (3.3) are that μ_{t-1}^2 and μ_t^2 are correlated. If we

express the unconditional variance μ_t and marked it as σ^2, we will find:

$$\sigma^2 = E(\mu_t^2) = \alpha_0 + \alpha_1\mu_{t-1}^2. \tag{3.6}$$

While for $0 \leq \alpha_1 < 1$, the formula above has stationary solution, which can be written as:

$$\sigma^2 = \frac{\alpha_0}{1 - \alpha_1}. \tag{3.7}$$

Since the ARCH(1) states that the conditional variance depends only on 1 lagged value, what if the conditional variance depends on 2 or more lagged factors? This leads to a simple extension of ARCH(1) model, which is the ARCH(q):

$$\sigma_t^2 = \alpha_0 + \alpha_1\mu_{t-1}^2 + \cdots + \alpha_q\mu_{t-q}^2. \tag{3.8}$$

To transfer the conditional variance for expectations, we can get:

$$E(\sigma_t^2) = E(\alpha_0 + \alpha_1\mu_{t-1}^2 + \cdots + \alpha_q\mu_{t-q}^2)$$

$$= \alpha_0 + \alpha_1\sigma_{t-1}^2 + \cdots + \alpha_q\sigma_{t-q}^2. \tag{3.9}$$

To fulfill the conditions of covariance stationary of ARCH(q), the long term conditional variance σ_{t-i}^2 are consistent and equal to unconditional variance σ^2. Out of this reason, we can say that:

$$\sigma^2 = \alpha_0 + \alpha_1\sigma^2 + \cdots + \alpha_q\sigma^2. \tag{3.10}$$

Although the ARCH(1) model implies heavy tails and volatility clustering, it does not in practice generate enough of either. ARCH(q) for q lag does a bit better but at a price in terms of parsimony. There are also many inequality restrictions to impose that can be violated otherwise.

3.3.2 GARCH Model

In ARCH model, next period's variance only depends on last period's squared residual so a crisis that caused a large residual would not have the sort of persistence that we observe after actual crises. What is more, in the empirical applications of ARCH(q) models, a long lag length and a large number of parameters are often needed. In order to improve these shortcomings, Bollerslev (1986) suggested the generalized ARCH, or GARCH model. The GARCH model specified the conditional variance to be a function of lagged squared errors

and past conditional variance. The simplest equation of GARCH model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{3.11}$$

where $\alpha_0 \geq 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ to meet the non-negative conditional variance σ_t^2 so that our next period forecast of variance will fall into the required bands.

If we define the process of $\varepsilon_t = \mu_t^2 - \sigma_t^2$, formula (3.11) can be then reverted into:

$$\mu_t^2 = \alpha_0 + (\alpha_1 + \beta_1)\mu_{t-1}^2 - \beta_1 \varepsilon_{t-1} + \varepsilon_t. \tag{3.12}$$

The equation (3.12) is ARMA(1,1). The random variable ε_t is uncorrelated to time, but it show unstable volatility around the average, which brings it to heteroskedasticity problem. The root if autoregressive part is $\alpha_1 + \beta_1$. If the value of $\alpha_1 + \beta_1$ is close to 1, it means that the persistence of volatility is significant. Also, the GARCH(1,1) is undated to IGARCH (1,1), which is:

$$\mu_t^2 = \alpha_0 + \mu_{t-1}^2 - \beta_1 \varepsilon_{t-1} + \varepsilon_t. \tag{3.13}$$

Sometimes it is not enough only to forecast next period's variance of returns, but also to make a forecast several intervals forwards. Again starting from the GARCH(1,1) equation, we can derive our forecast for next period's variance:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

$$\widehat{\sigma_{t+1}^2} = \alpha_0 + \alpha_1 E\left[\frac{\alpha_t^2}{I_{t-1}}\right] + \beta_1 \sigma_t^2,$$

$$= \alpha_0 + \alpha_1 \sigma_t^2 + \beta_1 \sigma_{t-1}^2$$

$$= \sigma^2 + (\alpha_1 + \beta_1)(\sigma_t^2 - \sigma^2)$$

$$\widehat{\sigma_{t+2}^2} = \alpha_0 + \alpha_1 E\left[\frac{\alpha_{t+1}^2}{I_{t-1}}\right] + \beta_1 E\left[\frac{\sigma_{t+1}^2}{I_{t-1}}\right],$$

$$= \alpha_0 + (\alpha_1 + \beta_1)\,\sigma_{t+1}^2$$

$$= \sigma^2 + (\alpha_1 + \beta_1)^2(\sigma_t^2 - \sigma^2)$$

$$\bullet\bullet\bullet$$

$$\widehat{\sigma_{t+n}^2} = \sigma^2 + (\alpha_1 + \beta_1)^n(\sigma_t^2 - \sigma^2). \tag{3.14}$$

From the above equation we can see that $\widehat{\sigma_{t+n}^2} \to \sigma^2$ as $n \to \infty$. So as the forecast

horizon goes to infinity, the variance forecast approaches the unconditional variance α_t .

To use p as the length of delay μ_t^2 , q as the maximum length of delay σ_t^2, conditional variance for GARCH(p,q) can be specified as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} a_i \mu_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 .$$
(3.15)

Even though the GARCH(p,q) is widely accepted and is treated as a useful way in modeling establishment, there are still some limitations for application Husek(2007):

1. Some of the estimated parameters do not meet the requirement of non-negativity when establishing the model.

2. The GARCH models meet obstacles when we are to describe level effect.

3. It is hard to get the feedback between conditional variance and conditional average of regression model.

3.4 Nonlinear Volatility Models

Both ARCH and GARCH models assume that positive and negative error terms have a symmetric effect on the volatility. Or, good and bad news have the same effect on the volatility in this model, which is caused by the fact that conditional variance in equations is a function of the squared lagged values of residuals. However, this assumption is frequently violated in reality, in particular by stock returns, because the volatility increases more after bad news than after good news. This so called leverage effect appears firstly in Black (1976).

It seems that not only does the magnitude of α_t^2 affect future volatility, but the sign also affect future volatility. However, it is not clear why volatility should increase more when the level of stock prices drop compared to a stock price rise. This subchapter contains a brief introduction of nonlinear models.

Nelson (1991) made the first step in describing asymmetric effect. The model is the exponential GARCH or EGARCH model.

$$ln\, \sigma_t^2 = \omega_t + \sum_{k=1}^{\infty} \beta_k g(Z_{t-k}),$$
(3.16)

where ω_t and β_k are deterministic coefficients and:

$$g(Z_t) = \theta Z_t + \gamma(|Z_t| - E|Z_t|). \tag{3.17}$$

The function $g(Z_t)$ in (3.17) is piecewise linear. It contains two parameters which define the "size effect" and the "sign effect" of the shocks on volatility. The uniqueness of this function that distinguishes it from GARCH model is the second effect, namely, the leverage effect. The term $(|Z_t| - E|Z_t|)$ determines the size effect and the term θZ_t determines the sign effect. The parameter γ is thus typically positive and θ is negative.

To combine (3.16) and (3.17) together, we can derive the general form of EGARCH model as follows:

$$log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \, log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \tag{3.18}$$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that γ_i is less than 0, the impact is asymmetric if γ_i is not 0.

The EGARCH model shows some differences from GARCH models:

1. Volatility of the EGARCH model, which is measured by the conditional variance σ_t^2, is an explicit multiplicative function of lagged innovations. On the contrary, volatility of the standard GARCH model is an additive function of the lagged error terms ε_t, which causes a complicated functional dependency on the innovations.

2. Volatility can react asymmetrically to the good and bad news.

3. For the general distributions of Z_t, the parameter restrictions for strong and covariance-stationary coincide.

One important advantage for EGARCH model is that it has no parameter restrictions, thus the possible of instabilities of optimization routines are reduced.

The idea of the Threshold ARCH (TARCH) models is to divide the distribution of the innovations into different intervals and then estimate a piecewise linear function for the conditional standard deviation by Zakoian (1991), and the conditional variance respectively,

Glosten (1993). Suppose that there are two intervals, the division is normally at zero, which means the influence of positive and negative innovations on the volatility is differentiated.

Rabemananjara and Zakoian(1993) extend this model by including the lagged conditional standard deviations (variance respectively) as a repressor, this new creation lead to TGARCH model. In TGARCH model, conditions for covariance-stationary are also taken into consideration. TGARCH and TARCH models are basically the same; the one important difference is that the TGARCH model in the function is the conditional standard deviation and not the conditional variance. The general form of this model can be viewed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_1 \sigma_{t-1}^2, \qquad (3.19)$$

where

$$S_{t-i} \begin{cases} 1, \text{ if } \varepsilon_{t-i} < 0 \\ \\ 0, \text{ if } \varepsilon_{t-i} \geq 0. \end{cases}$$

Here we can see that when there is good news, namely ε_{t-i} is positive, total effect is given by $\alpha_i \varepsilon_{t-i}^2$. When there is bad news, namely ε_{t-i} is negative, the total effect is given by $(\alpha_i + \gamma_i)$. These are the reasons why TGARCH model can be used to convey the information of leverage effect. When γ_i is positive, bad news will increase volatility and we say that there is a leverage effect.

The Volatility-Switching GARCH (VS-GARCH) model of Fornari&Mele (1997) extends the asymmetry in GJR-GARCH model to the other components of the model:

$$\sigma_t^2 = \alpha_0 + \varphi_0 sin(\mu_{t-1}) + \{\alpha_1 + \varphi_1 sin(\mu_{t-1})\}\mu_{t-1}^2 + \{\beta_1 + \varphi_{21} sin(\mu_{t-1})\}\sigma_{t-1}^2. \quad (3.20)$$

The idea of this model is to show the leverage effect which may appears in stock return series. This effect reflects itself as an asymmetry: a negative shock has a greater impact on the conditional variance than the positive one with the same absolute value.

3.5 The Construction of Volatility Models

As we have a brief idea about the mechanism of linear and nonlinear volatility models, we should also develop an idea about the establishing process of volatility models. Inclán&Tiao (1994) summarized the generally process in model establishing:

1. The choice of whether linear or nonlinear model should be used is based on the specified time series.

2. Make a significant test for the hypothesis of conditional homoskedasticity against the alternative hypothesis of conditional heteroskedasticity for linear and nonlinear type.

3. Estimate the parameters for chosen model of conditional heteroskedasticity.

4. Verify the suitability the given model.

5. Modification of the model when necessary.

6. Use the model for descriptive or predictive purposes.

3.5.1 Test of Conditional Heteroskedasticity

The general form of significant test can also be applied to the test of conditional heteroskedasticity. By constructing a regression model:

$$\widehat{\mu_t^2} = a_0 + a_1 * \widehat{\mu_{t-1}^2} + \cdots + a_q * \widehat{\mu_{t-q}^2} + \varepsilon_t. \tag{3.21}$$

The first step for hypothesis testing is to make H_0 as $a_1 = a_2 = \cdots a_q = 0$. The alternative hypothesis H_a is that at least one of the parameter is different from zero.

The second step is the choice of significant level, which is marked as α.

The third step is calculating the test statistic value. We are to use F-test here with the test formula as:

$$F_{LM} = \frac{(SSE_0 - SSE_1)/q}{SSE_1/(T-q-1)}. \tag{3.22}$$

The forth step is to see whether the value calculated from step three falls in the reject area or not.

3.5.2 Estimation on Parameters

The estimation for parameters can be estimated by the maximum likelihood estimation (MLE). Maximum likelihood estimate provides a method of a given observation data to estimate the model parameters, namely, model has been set, but parameters are unknown. We don't have the enough material resources to the country's everyone's height, but by sampling, we can get some heights, and then get the above assumptions by maximum likelihood estimate of the mean value and variance of the normal distribution.

First, we make assumptions the sampling x_1, x_2, x_3…are independently and identically distributed, parameter θ is treated as the model parameter; f is the model that has been established. Based on the independent identically distributed hypothesis, model f with parameters θ can be expressed as:

$$f(x_1, x_2 \dots x_n | \theta) = f(x_1|\theta)^* f(x_2|\theta) \dots f(x_n|\theta), \tag{3.23}$$

Back to the notion of "model has been set, but parameters are unknown", at this point, we have known x_1, $x_2 \dots x_n$, with θ unknown. So the likelihood is defined as:

$$L(\theta|x_1, x_2 \dots x_n) = f(x_1, x_2 \dots x_n|\theta) = \prod_{i=1}^{n} f(x_i|\theta) \tag{3.24}$$

Commonly used in practice are on both sides of the exponential, get the formula is as follows:

$$\ln L(\theta|x_1, x_2 \dots x_n) = \sum_{i=1}^{n} \ln f(x_i|\theta) \tag{3.25}$$

What we usually referred to as the maximum likelihood for the biggest logarithmic average likelihood is stated as follows:

$$\widehat{\theta_{mle}} = \arg\max \hat{\gamma}(\theta|x_1, x_2 \dots x_n), \ \hat{\gamma} = \frac{1}{n} \ln L \tag{3.26}$$

The general solving process of the maximum likelihood estimation is:

1. Write a likelihood function.

2. Take the logarithm form for likelihood function.

3. Derivation process for the function.

4. Solve the likelihood equation.

3.5.3 Verification the Suitability of the Given Model

The estimations of parameters for both linear and nonlinear models have to fulfill certain conditions. Simply speaking, we need to verify whether the variance of residuals is constant or not, whether these residual items have autocorrelation and whether the independent variables have the problems on multicollinearity.

The test for constant variance of residuals is based on the creation of artificial regression with added constant. The model can be expressed as:

$$\hat{\mu}_t^2 = a_0 + a_1\hat{\mu}_{t-1}^2 + \varepsilon_t. \tag{3.27}$$

Since the estimation for parameters is using the OLS method, we can create a model based on the artificial regression:

$$\hat{\mu}_t^2 = a_0 + a_1\hat{\mu}_{t-1}^2 + a_2\hat{\mu}_{t-2}^2 + \cdots + a_q\hat{\mu}_{t-q}^2 + \varepsilon_t. \tag{3.28}$$

We can use $H_0: a_1 = a_2 = a_3 = \cdots = a_q$ for the assumption of conditional homoskedasticity with the test statistic $T*R^2$ has distribution $\chi^2(q)$.

Verification of autocorrelation problem can be tested by using the selective autocorrelation function:

$$\hat{\rho}_k = \frac{\sum_t \hat{\mu}_k \hat{\mu}_{t-k}}{\sum_t \hat{\mu}_t^2}. \tag{3.29}$$

If the model does not have the autocorrelation problem, the value of the function should lie within the interval $\pm 2\sqrt{T}$ suppose a 95% confidence interval.

Another option to analyze autocorrelation problem is to use portmanteau test. The H_0 is set as $\rho_1 = \rho_2 = \cdots = \rho_k = 0$, and the H_a is set as ρ_k where k=1,2....K are auto correlated components of the model for the lag k. The statistic of the well constructed model is stated as:

$$Q = T \sum_{k=1}^{K} \hat{\rho}_k^2. \tag{3.30}$$

A shortcoming of test statistic of equation (3.30) is that it is only available for large sample distributions, while for small samples, it is not effective. Ljung and Box invented the statistic:

$$Q = T（T + 2）\sum_{k=1}^{K} \hat{\rho}_k^2 （T - k)^{-1}. \tag{3.31}$$

The equation (3.31) is called modified portmanteau statistic, whose values are also compared with the distribution $\chi^2(K - p - q)$, which is used for testing the autocorrelation.

There are two methods for detecting multicollinearity:

1. *T*-test indicates that none of the individual coefficient is significantly different from zero, however, the *F*-test indicates overall significance and the R^2 is high.

2. The absolute value of the sample correlation between any two independent variables is greater than 0.7.

Methods to correct the problem can be: omit one or more of the correlated independent variables.

Next, we can use Jarque-Bera test to verify normality. Skewness of normal distribution equals to 0 (*S*=0). Kurtosis of normal distribution equals to 3 (*K*=3). If samples come from normal population, they are near 0 to 3. Based on this, there is a statistic test as follows:

$$JB = \frac{n-k}{6}\left\{S^2 + \frac{(K-3)^2}{4}\right\}$$
(3.32)

Jarque and Bera proved that under normality assumption, if the associated probability of *JB* statistic value is less than the probability of set, reject the null hypothesis; deny the supposed probability that sample is normal distribution.

3.5.4 Criteria for Model Selection

There can be more than one acceptable estimated model whole the same set of data is provided. There are some methods available to choose the optimal one. The idea for choosing the best estimated model is to compare the residuals of each estimated model by the summary statistics. The criteria are Akaike information criteria (AIC), Bayes information criteria (BIC) and Schwartz-Bayes information criteria (SBC) by Arlt (2003).

Akaike function can be expressed as:

$$AIC(M) = T ln\ \hat{\sigma}_\mu^2 + 2M. \tag{3.32}$$

The M equals to $p+q$ is the number of parameters in ARMA(p,q) model and $\hat{\sigma}_\mu^2$ is the residual variance of this model. The result of minimum value of this criterion is chosen.

The Schwartz-Bayes criteria can be expressed as:

$$SBC\ (M) = T ln\ \hat{\sigma}_\mu^2 + M\ ln\,T. \tag{3.33}$$

The difference between (3.23) and (3.33) is that in equation (3.33), T represents the number of observations, which is equal to the number of residuals obtained from the model. The choose principal is the same for both equations, which means that the model with the minimum value of criterion is chosen.

3.6 Loss Functions

To verify whether the model we have established is accurate enough for prediction, we can use loss functions to make estimation about the size of differences between the theoretical result and actual result.

Root-Mean-Square Error (RMSE) is frequently used as a measure for differences between estimated data and the actual observed data. Basically, the RMSE represents the sample standard deviation of the differences between predicted values and observed values. Formula of RMSE is express as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\widehat{y_t}-y)^2}{n}}. \tag{3.34}$$

Besides, there are also other ways to measure the difference between estimation data and actual data, such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil's coefficient (Theil's U).

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |\hat{\sigma}_t - \sigma_t|, \qquad (3.35)$$

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \frac{|\hat{\sigma}_t - \sigma_t|}{\sigma_t}, \qquad (3.36)$$

$$Theil's\ U = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^{T} |\hat{\sigma}_t - \sigma_t|}}{\sqrt{\frac{1}{T} \sum_{t=1}^{T} \sigma_t^2} + \sqrt{\frac{1}{T} \sum_{t=1}^{T} \hat{\sigma}_t^2}}. \qquad (3.37)$$

The choice of a loss function is not arbitrary. It is very restrictive and sometimes loss function may be characterized by its desirable properties.

Sound economical prediction practice requires selecting an estimator consistent with the actual acceptable variation experienced in the context of a particular applied problem. As a result, in the applied use of loss functions, we should be careful when deciding which statistical method to use to model an applied problem.

4. Empirical Findings

Chapter 4 will combine the stated methods from time series analysis with the financial data to show how to establish a good model for a large set of data and how to make further analysis for the established models based on ideas of Franke (2011).

All the Tables and Figures of this subchapter are from own calculation with the help of Excel 2007 and EViews7.

4.1 Description of Investigated Stock Markets

The purposed markets of our objects are Chinese stock markets and Japanese stock markets. Since these two markets are both from Asia and have similar tradition and regional culture, it will be interesting to see the difference of influence of financial crisis to these two markets. What is more, the results of comparison between developing market and developed market is quiet attractive.

4.1.1 Chinese Stock Market

The data which will be used for this thesis are collected from SSE (Shanghai stock exchange). SSE is the first biggest equity exchange located in the east part of China. Stock indexes and trading volumes in SSE are treated as important reference as how the financial market is operating in China. Subchapter 4.1 will present some information as to how the Chinese equity market is right now.

Generally speaking, the characteristics of Chinese equity market can be viewed from 4 aspects:

1. Chinese stock market is in the stage of adjustment.

China's Shanghai and Shenzhen stock market are developed from a local stock market to a national market. In December 1990 business formally, from the number of shares listed, only a few stocks from small scaled firms take part in. Moreover, stock is essentially the Shanghai or Shenzhen's local stock, such as the Shanghai old stereotype in only one is beyond the stock. In the development of the stock market, due to a lack of strategic consideration, a money expansion appears. However, expansion of stock is not proportional to money expansion. What needs to be specified here is that for capital expansion, expansion and its speed is much faster than the stock.

During the period from 1991 to 1996, the stock sales from dozens of expanded to nearly 3000, the market capital increased from initial level of more than one hundred million Yuan to the level of more than 3000 one hundred million Yuan, and the listed company only increases from nearly 20 up to more than 400 and only 30 billion shares of tradable shares. Stock market supply and demand imbalances, thus causing the share price in the first two years in the situation of increasing rapidly.

The Shanghai stock market from the beginning in December 1990 to its firs points, the end of 1992, the initial points rose to 780 points, the average annual rate of 179%; Shenzhen stock market developed a little bit late. Since April 1991 began first points, rose to 241 points by the end of 1992, the annual average rose by 68.5%. Because share prices have risen by excessive at the start of two years, with the capacity of stocks, shares in the first half of 1993 after reaching the height of the historic, stock prices started to stagnate, Shanghai and Shenzhen stock market went into the hard phase of adjustment. In 1993, the Shanghai and Shenzhen stock market closing index at 833 points and 238 points respectively, 1994 closing index at 647 points and 140 points respectively, 1995 closing index at 555 points and 113 points respectively. According to the foreign stock index rise speed and the actual situation of our country, our country stock market the adjustment expected to quite a time. If countries do not appear serious inflation, the Shanghai composite index in 1000, probably it will take more than 5 years.

2. Demand exceeds supply

Chinese stock market investors and the market invested capital amount are big, but tradable shares are less as compared to the former two, stock market presents the obvious demand should not supply situation.

According to preliminary statistics, by the end of October 1996, registered investors in the Shanghai and Shenzhen stock market were about 18 million, at the same time period, Shanghai and Shenzhen stock market had the size of about 30 billion, resulting in the average people have only nearly 1700 shares of stock. According to preliminary estimates, Chinese city company 1995 after-tax profit is less than 0.30 Yuan per share, split off, most people income per capita is only 500 Yuan, according to the market capital of 20000 Yuan per capita calculation, stock investment yields (excluding tax, fee) is only 2.5%, only the equivalent of current savings interest rates. And because people frequently traded in the stock market, the sum of the paid fees and transaction tax is often more than the sum of after-tax profits of tradable shares.

3. Excessive stock market trading

Because shareholder in China tends to have higher level of speculative, the motivation is the main for scraping price difference on market, so many people put investing in stocks as their main jobs. Changes in stock markets can drive them to sell, then buy back and the cycle is hard to stop. These behaviors drive the stock market appear to be extremely active. Compared with the same maturity level of stocks, overseas market share less than 40% of the average annual turnover rate, however the average annual turnover rate of Chinese stock market is more than 600%, which is the 15 times than foreign mature stock market.

4. The stock market is yet to be regulated

Chinese stock market is developed from the local stock market; however, the regulation on the stock market by the central government started from the second half of 1992, as the stock market operation also has yet to be regulated. The shortages of Chinese stock market can be viewed from the following aspects:

a) Lack of unified understanding of the stock market, the specific performance reflects on the relevant policy continuity, the lack of scientific and listed such as the stock market expansion and index method of control is still using limit control.

b) The lack of long-term planning for the development of the stock market, such as issues like how to complete the combination of state shares and legal person share, a specified progress does not exist.

c) The regulation on the stock market, such as information disclosure regulation. For example, how to stop large institutions to manipulate the stock market its problem are still inadequate.

4.1.2 Description of Shanghai Composite Stock Index

Stock index is made by the stock exchange or compiled by the financial services agency as a reference indicator for the stock market. The stock price goes ups and downs frequently, so that investors face the market price risk. For a specific kind of stock price's changes, investors are able to understand the change, but, for a variety of stock price's changes, it is not easy to figure out the change .In order to solve this problem, some financial services use their business knowledge and market advantage with information to develop the stock price index as the index of market price movements.

The Shanghai stock index can be divided into 7 groups: component index, comprehensive index (like business index, real estate index and so on), industrial index, style index (mainly division is growth stock and value stock), subject index, fund index, bond index.

As for the method to calculate the stock index, the Shanghai composite index series adopts franchise weighted formula of composite price index. The differences for different types of index's calculation are the choice of weight for computing, for example, the fund index is weighted based on the issued amount of funds that have been issued.

The components of index will be contained in annexes in CD on the back of this thesis.

4.1.3 Japanese Stock Market

On the Japanese stock market, issued stocks can be divided into two kinds, one is issued for financing and the other one is issued for a specified purpose.

Similar to other countries, Japan's circulation of stock market also points exchange market and OTC market two parts. After the war, in order to form fair securities prices, Japan generally prohibit shares listed in the OTC, which led to the stock exchange become the center of circulation of stock market.

The transaction of the exchange can be divided into three kinds according to delivery day:

a) The first is a general trading, accounting for 99% of the total volume, The general trading can be divided into spot transactions and credit transactions further;

b) The second is specified date settlement deal, but the longest maturity must not exceed 15 days.

c) The third is the issue of settlement, namely, the actual delivery is dealt with after the new share issue.

OTC market is mainly used for newly issued shares and does not meet the conditions of exchange of stock trading. Due to the three major stock exchanges opened the second market, the slow development of OTC transactions.

Japan has eight stock exchanges, which are located in Tokyo, Nagoya, Fukuoka, Niigata, Kyoto, and Hiroshima. Sapporo. Tokyo enjoys the most important statue as the country's central market. To centralize the stock trading into the exchange, Tokyo, Osaka and Nagoya in October 1961, set up a so called second market respectively.

Japanese stock market has very special features: the price of the stock is almost manipulated by foreign investment institutions. Among shares listed on the Tokyo stock exchange, foreign investment institutions accounted for 30% and its volume can account for 60% due to the frequent trading, so the Japanese stock market is very likely to be influenced by foreign investment agency.

The Nikkei stock index futures does not only exchange in Japanese exchange market, it also has trading activities Singapore stock exchange (SGX) and the Chicago mercantile exchange (CME) respectively, so it is easy to be influenced by the fluctuation of the American capital market.

Japanese stock index basically has two. One is the Nikkei stock average, including the Nikkei 225 stock and the Nikkei 500 stock. The other one is the Topix index to the Tokyo stock exchange.

4.1.4 Description of Nikkei Stock Index

The Nikkei index is used to reflect the average change of price for stocks which are trading in the Tokyo stock exchange.

The types of the index can be divided according to the amount of sample and way of calculating, the main types can be divided in to two groups as follows:

1. The Nikkei 225 index. This index has long duration and has very good comparability,it is most frequently used to measure the Japanese stock market long-term evolution and the latest changes.
2. The Nikkei 500 index. Its representative is relatively more widely, but its sample is not fixed, every year in April, the compostition for the index will be changed according to operating performance of listed companies, trading volume and market value or some other factors.

Compositions of samples come from construction, transportation, electricity and gas industries, warehousing, aquaculture, mining, real estate, finance and services industries. The index has a wide cover, besdides various industries, the choice of most representative of the company shares issued shares as a sample.

For our thesis , the type of index that will be used is Nikkei 225 stock index. The components of Nikkei 225 stock index will be contented in CD on the back of this thesis.

4.2 Data Sample Description

Samples of data for this thesis come from the stock index of two Asia stock exchange market, Shanghai and Tokyo. The stock index is a relatively good indicator of the overall market situation. The Shanghai composite stock index and Nikkei 225 index are measures to mirror the operating situation of overall economic situation for China and Japan respectively. All the data which are used for this thesis are downloaded from fee-paying economic situation information research software which is created by a Chinese consultant company.

The aim of this sub chapter is to explain the trend of the index curve from financial time series' point of view. The linear and non-linear model will be established based on the given indexes. Later, we will compare whether linear or non-linear model is better and whether the conclusion about choice of model is the same for both Chinese and Japanese markets.

4.2.1 Data Sample from China

As what has been mentioned in sub-subchapter 4.1.1, Shanghai stock exchange is the first exchange market established in China and Shanghai stock index is one of the most important indexes to mirror the whole economic situation of China. The daily data from 3/1/2006 to 3/1/2015 is collected. With the help of EView 7, we can plot the large sum of data into line graph to form a basic idea on the trending of stock index.

The reason for the choice of the period from 3/1/2006 to 3/1/2015 is out of the consideration for financial crisis. It would be interesting to see how the line chart changes around the crisis. What is more, the idea of financial time series focus more on predicting of future rather than to find explanations for what have already happened. As time gets closer to present, the effect on the future gets stronger.

In Figure 4.1, the whole periods are divided into three sub-periods by two man-made lines. The logic of time dividing is based on the trend of stock prices. The first period will start from 1/3/2006 to 15/10/2007, because the trend line is going up and it seems that during this

period, the time series data of daily stock index shows a good linear regression relationship. The second period will start from 15/10/2007 to 26/10/2008, which is the period under the influence of financial crisis. The third period will start from 26/10/2008 to 3/1/2015, the period after the crisis show a relatively high volatile.

Figure 4.1: Daily data of closed price for Shanghai composite stock index

4.2.2 Data Sample from Japan

The overall time period we choose for Japanese stock market is almost the same as China. Similar time will produce better comparison while due to the differences of exchange day and other factors such as regional differences, it is almost impossible to put the time totally the same for two different countries' market.

The Nikkei index is not only an important index within Japanese domestic market; it also plays an important role in the global financial market. As Japan is a developed country with a relative more mature financial market than China.

In Figure 4.2, we can see the overall trending of stock price for Japanese market is similar to that of Chinese stock market. However, the differences of the shapes for stock price and the volatilities are also obviously to see.

Figure 4.2: Daily data of closed price for Nikkei 225 stock index
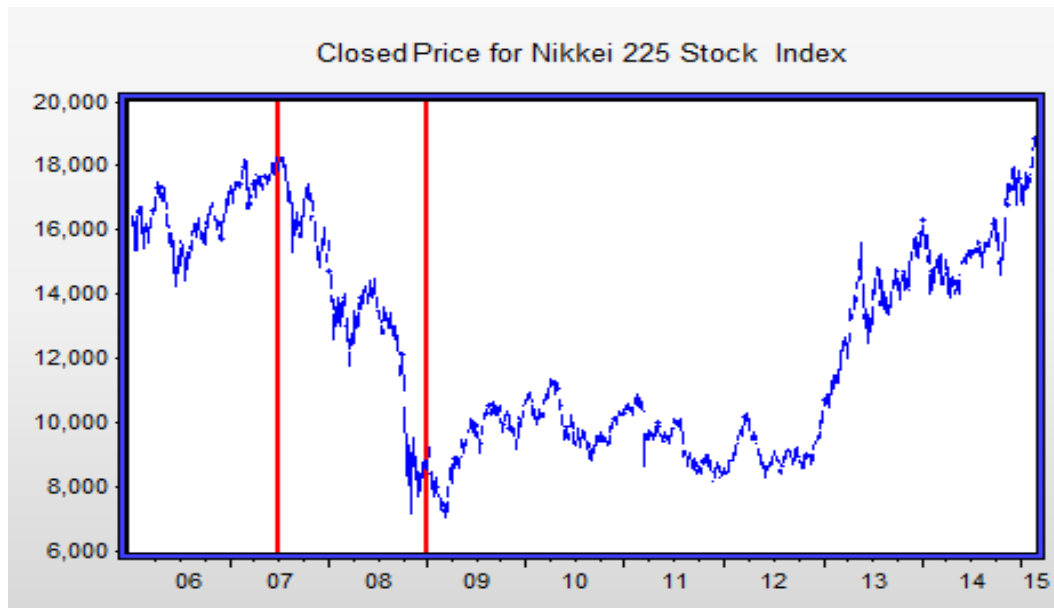
The division of time is the same as China, the total period will be divided as before the crisis, during the crisis and after the crisis, even though the shape of trending for Japan seems to be different from that of China in great degree. To specify, the first period starts from 14/6/2006 to 21/6/2007. The second period starts from 21/6/2007 to 11/3/2009 and the third period starts from 11/3/2009 to 8/2/2015. The division of time periods for Japan is different than that of China, because our division is mainly out of the consideration of before crisis period, during crisis period and after crisis period. And the country specified situation of China and Japan is different. There is an interesting phenomenon in Japan that since 8/11/2012, there seems to be a rapid recovery pace. We will focus our attention on this point of time and make explanations for it for both qualitative analysis and quantitative analysis.

4.3 Logarithmic Returns

Figure 4.1 and Figure 4.2 showed that the developments of the observed indexes are non-stationary, to develop a good regression model, it is suggested that the use of stationary data would be better. One of the ways of altering non-stationary data into stationary data is to create a time series of daily returns and continue using the time series of daily returns in all

calculations showing below.

Generally P_t represents the price of an asset in the time t, in our case for analysis, it is the closed price of stocks. Suppose we hold the asset from the time $t-1$ will bring the investor a brutto return which is defined as:

$$(1+R_t) = \frac{P_t}{P_{t-1}}. \tag{4.1}$$

Netto return can be derived as:

$$R_t = \frac{P_t}{P_{t-1}} - 1 = \frac{P_t - P_{t-1}}{P_{t-1}}. \tag{4.2}$$

However, this time series of daily returns do not confirm the assumptions made by normal distribution. We can change the inference into logarithmic returns to confirms stationary of the daily return time series and normal distribution.

$$r_t = \ln(1 + R_t) = \ln\frac{P_t}{p_{t-1}} = \ln P_t - \ln P_{t-1}. \tag{4.3}$$

The equation (4.3) is the absolute incremental of logarithmic price and is called logarithmic return. If we apply this equation on the daily index for both Shanghai stock index and Nikkei stock index, we will see the stock's closed price's daily logarithmic return time series, as Figure 4.3 and Figure 4.4 domenstates.

On Figure 4.3 and Figure 4.4, it appears that the influence of financial crisis is mainly reflected at higher volatility degree than other time series. According to the beginning and ending of high volatility, we divide the whole sample time period into three sub-periods, as what the red lines show. Division of time makes it possible for us to estimate models for detailed periods. Furthermore, separating the period of crisis apart from others can lubricate the process of comparison. Another information we can get from Figure 4.3 and 4.4 is that the degree of volatility during crisis time period for Chinese market and Japanese market is different, so that we can image these distinguishes will result in different consequences in modeling estimation process.

Figure 4.3: Daily logarithmic returns of Shanghai composite stock index
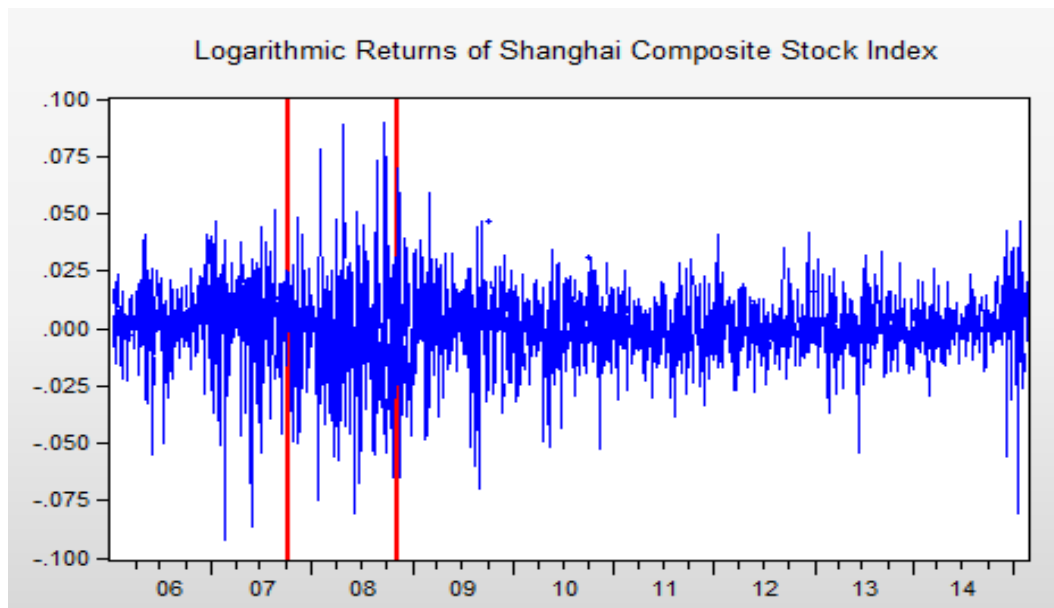
Figure 4.4: Daily logarithmic returns of Nikkei 225 stock index
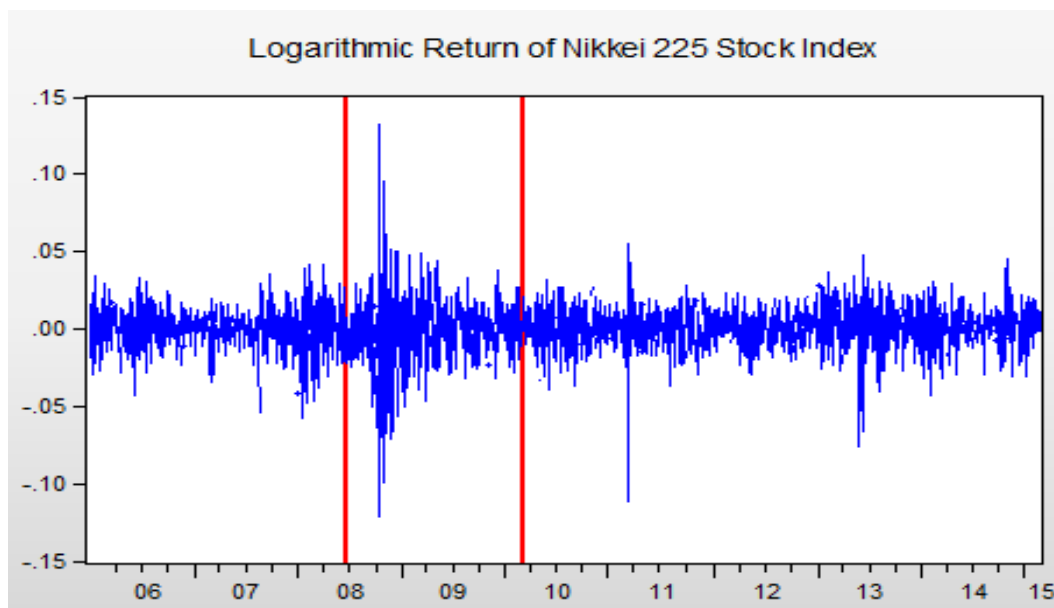
4.4 Descriptive Statistic for Return Series

Since we have divided the whole period into three sub-periods for both Chinese and Japanese stock market, we have collected totally 6 groups of sample data based on two markets and three sub-periods respectively.

Table 4.1: Descriptive statistics of daily returns

	pre-crisis period	crisis period	post-crisis period	pre-crisis period	crisis period	post-crisis period
	shanghai compostie stock index			Nikkei 225 stock index		
observation	395	254	1504	253	423	1450
mean	0.003872	-0.004847	0.000375	0.000985	-0.002194	0.000604
medium	0.004985	-0.005295	0.000563	0.000776	-0.001186	0.000721
maximum	0.051945	0.090348	0.070196	0.033007	0.132346	0.055223
minimum	-0.092562	-0.080437	-0.069827	-0.034007	-0.12111	-0.111534
standard deviation	0.018493	0.027436	0.014104	0.010154	0.024657	0.014128
skewness	-1.173276	0.262697	-0.334346	-0.16528	-0.256172	-0.548383
kurtosis	6.864142	4.083163	5.886744	4.075331	8.059919	7.062278
Jarque-bera	336.37	15.33821	550.241	13.3416	455.8756	1069.677
probility	0.00000	0.000467	0.00000	0.001267	0.00000	0.00000

Table 4.1 shows the basic descriptive statistic. We can see that the mean return for both Chinese and Japanese markets are negative during crisis period, which shows that the finance crisis does have some negative to the Asia stock market more or less. As expected, the JB test rejects normality at the 5% level for all series. As what we can imagine, the volatility during crisis is larger than the other two periods for both markets as what the index standard deviation has shown.

4.5 Empirical Analysis and Model Estimation

This chapter is aimed at estimating models for the three different periods for both markets. Linear and non-linear model are both to be presented. Later, we will discuss whether linear or non-linear model is better to suit the certain market at a certain period of time.

4.5.1 Model Estimation for Chinese Market

Firstly, we will use the GARCH model to link the relationship of returns for Chinese markets. The linear model which is to be used is GARCH(1,1) and the non-linear which is to be used is EGARCH(1,1).

Pre-Crisis Period

Table 4.2: Chinese market, pre-crisis period using GARCH(1,1) model

Variance Equation				
C	4.36E-06	2.58E-06	1.690991	0.0908
RESID(-1)^2	0.073233	0.014871	4.924474	0.0000
GARCH(-1)	0.919939	0.015917	57.79474	0.0000
R-squared	-0.003431	Mean dependent var		0.003872
Adjusted R-squared	-0.003431	S.D. dependent var		0.018493
S.E. of regression	0.018525	Akaike info criterion		-5.241874
Sum squared resid	0.135210	Schwarz criterion		-5.201581
Log likelihood	1039.270	Hannan-Quinn criter.		-5.225909
Durbin-Watson stat	2.039009			

From Table 4.2, we can see that the *p*-value for both ARCH item and GARCH item are lower than 0.05, which means that both of them are statistically significant.

Table 4.3: Chinese market, pre-crisis period using EGARCH(1,1) model

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4) *RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variance Equation				
C(2)	-0.092598	0.033306	-2.780260	0.0054
C(3)	0.048143	0.022029	2.185418	0.0289
C(4)	0.086239	0.015526	5.554344	0.0000
C(5)	0.993118	0.003506	283.2261	0.0000
R-squared	-0.001476	Mean dependent var		0.003872
Adjusted R-squared	-0.001476	S.D. dependent var		0.018493
S.E. of regression	0.018507	Akaike info criterion		-5.287961
Sum squared resid	0.134947	Schwarz criterion		-5.237595
Log likelihood	1049.372	Hannan-Quinn criter.		-5.268005
Durbin-Watson stat	2.042990			

In Table 4.3, since the *p*-value for all the parameters are lower than 0.05, the estimated model is statistically significant. Since parameter γ_i is positive, we fail to accept the existence of leverage effect. If we relate Table 4.2 and Table 4.3 together, the result shows that on the basis of AIC result, it is suggested that the choice for non-linear model under pre-crisis period for Chinese market is preferred, as what has been indicated in sub-subchapter 3.5.4, the result of lower value derived from AIC show be chosen.

Crisis Period

Table 4.4: Chinese market, crisis period using GARCH(1,1) model

Variance Equation				
C	0.000126	0.000185	0.684369	0.4937
RESID(-1)^2	0.032416	0.033785	0.959476	0.3373
GARCH(-1)	0.801188	0.262673	3.050131	0.0023
R-squared	-0.000044	Mean dependent var		-0.004847
Adjusted R-squared	-0.000044	S.D. dependent var		0.027436
S.E. of regression	0.027437	Akaike info criterion		-4.331922
Sum squared resid	0.190456	Schwarz criterion		-4.276216
Log likelihood	554.1541	Hannan-Quinn criter.		-4.309512
Durbin-Watson stat	1.993531			

In Table 4.4, we can see that the *p*-value of ARCH term is higher than 0.05, which means we can ignore this parameter and this model is not suitable for this period. However, after trying other models such as GARCH(0,1), we meet the same problem as what has been shown in GARCH(1,1), which means that the linear model may not be used for crisis period.

Table 4.5: Chinese market, crisis period using EGARCH(1,1) model

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
    *RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variance Equation				
C(2)	-11.18304	3.663221	-3.052788	0.0023
C(3)	0.121229	0.107831	1.124256	0.2609
C(4)	0.106822	0.065410	1.633118	0.1024
C(5)	-0.537969	0.509799	-1.055258	0.2913
R-squared	-0.000173	Mean dependent var		-0.004847
Adjusted R-squared	-0.000173	S.D. dependent var		0.027436
S.E. of regression	0.027439	Akaike info criterion		-4.332206
Sum squared resid	0.190481	Schwarz criterion		-4.262574
Log likelihood	555.1902	Hannan-Quinn criter.		-4.304194
Durbin-Watson stat	1.993274			

Table 4.5 shows the estimation of non-linear model for Chinese stock market under crisis period. Unfortunately, it also fails to pass the significant test. Except the EGARCH(1,1), we cannot find any other better option from non-linear models for the crisis period within Chinese market. Table 4.4 and Table 4.5 show that both GARCH(1,1) and EGARCH(1,1) are not suitable for modeling and forecasting for Chinese stock market under crisis period.

Post-Crisis Period

Table 4.6: Chinese market, post-crisis period using GARCH (1,1) model

Variance Equation				
C	2.97E-06	7.85E-07	3.789037	0.0002
RESID(-1)^2	0.042962	0.006224	6.903009	0.0000
GARCH(-1)	0.939143	0.008778	106.9898	0.0000
R-squared	-0.000278	Mean dependent var		0.000375
Adjusted R-squared	-0.000278	S.D. dependent var		0.014104
S.E. of regression	0.014106	Akaike info criterion		-5.842096
Sum squared resid	0.299059	Schwarz criterion		-5.827958
Log likelihood	4397.256	Hannan-Quinn criter.		-5.836829
Durbin-Watson stat	1.999898			

Table 4.6 shows that the *p*-value for all parameters is less than 0.05, so that these parameters are statistically significant and that the GARCH(1,1) model can be used for the post-crisis period in Chinese market.

Table 4.7: Chinese market, post-crisis period using EGARCH (1, 1) model

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
   *RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variance Equation				
C(2)	-0.220458	0.041793	-5.275047	0.0000
C(3)	0.103864	0.013483	7.703097	0.0000
C(4)	0.001530	0.006196	0.246865	0.8050
C(5)	0.983617	0.004278	229.9324	0.0000
R-squared	-0.000123	Mean dependent var		0.000375
Adjusted R-squared	-0.000123	S.D. dependent var		0.014104
S.E. of regression	0.014105	Akaike info criterion		-5.841931
Sum squared resid	0.299012	Schwarz criterion		-5.824259
Log likelihood	4398.132	Hannan-Quinn criter.		-5.835349
Durbin-Watson stat	2.000208			

Table 4.7 shows the *p*-value for C(4) is higher than 0.05, which means that the leverage effect can be ignored, because it is not statistically significant. However, this model can be used for the post-crisis period as whole. To combine Table 4.6 and Table 4.7 together, we can see that the linear model GARCH(1,1) takes a little bit advantage over non-linear model EGARCH(1,1) on the basis of comparison on AIC result.

To sum up, for Chinese stock market, the GARCH(1,1) model and EGARCH(1,1) model can be used for both the pre-crisis period and post-crisis period. However, when we are comparing models on the basis of AIC, it seems that non-linear model is more suitable for pre-crisis period while linear model is more suitable for post-crisis period. For the crisis period, no suitable model has been found.

4.5.2 Model Estimation for Japanese Market

Now that we have plotted both the linear and non-linear model for Chinese stock markets for the three divided periods of time, the same operation will be used for model establishment for Japanese markets. Even though the division of time is not totally the same as China, the basic logic is the same, the three sub-periods of time is divided according the financial crisis.

The process in valuing the suitability of whether the linear or non-linear model can be used is almost the same as what have been done for Chinese market. For Japanese market, the linear model that will be used is also GARCH(1,1), while the non-linear model that will be used is TGARCH(1,1).

Pre-Crisis Period

Table 4.7: Japanese market, pre-crisis period using GARCH(1,1) model

Variance Equation				
C	3.31E-06	2.00E-06	1.655627	0.0978
RESID(-1)^2	0.035520	0.016478	2.155533	0.0311
GARCH(-1)	0.924648	0.033165	27.88031	0.0000
R-squared	-0.000216	Mean dependent var		0.000985
Adjusted R-squared	-0.000216	S.D. dependent var		0.010154
S.E. of regression	0.010155	Akaike info criterion		-6.377429
Sum squared resid	0.025987	Schwarz criterion		-6.321565
Log likelihood	810.7448	Hannan-Quinn criter.		-6.354953
Durbin-Watson stat	2.049482			

Table 4.7 shows that p-value for the constant item is higher than 0.05, which means that this parameter is not statistically significant. However, we still can conclude that the GARCH(1,1) model is acceptable for pre-crisis period on the whole because the ARCH term

and GARCH term are both statistically significant.

Table 4.8: Japanese market, pre-crisis period using TGARCH (1, 1) model

Variance Equation				
C	1.93E-05	4.61E-06	4.193969	0.0000
RESID(-1)^2	-0.079548	0.014914	-5.333784	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.330586	0.085875	3.849640	0.0001
GARCH(-1)	0.719473	0.062190	11.56895	0.0000
R-squared	-0.006024	Mean dependent var		0.000985
Adjusted R-squared	-0.006024	S.D. dependent var		0.010154
S.E. of regression	0.010184	Akaike info criterion		-6.406594
Sum squared resid	0.026138	Schwarz criterion		-6.336764
Log likelihood	815.4341	Hannan-Quinn criter.		-6.378499
Durbin-Watson stat	2.037650			

Table 4.8 shows that p-value for all parameters are lower than 0.05, which means all the parameters are statistically significant. What is more, since the parameter γ is higher than 0, leverage effect can be measured if non-linear model is used. To combine Table 4.7 and Table 4.8 together, it seems that the non-linear model is preferred for the pre-crisis period because non-linear model can not only measure the leverage effect; it has a better AIC result as well.

Crisis Period

Table 4.9: Japanese market, crisis period using GARCH(1,1) model

Variance Equation				
C	9.43E-06	4.49E-06	2.097227	0.0360
RESID(-1)^2	0.137355	0.030082	4.566040	0.0000
GARCH(-1)	0.852013	0.032194	26.46489	0.0000
R-squared	-0.001017	Mean dependent var		-0.002194
Adjusted R-squared	-0.001017	S.D. dependent var		0.024657
S.E. of regression	0.024670	Akaike info criterion		-5.035365
Sum squared resid	0.256832	Schwarz criterion		-4.997092
Log likelihood	1068.980	Hannan-Quinn criter.		-5.020243
Durbin-Watson stat	2.139671			

Table 4.9 shows that the p-value for all parameters is less than 0.05, which means that all the parameters are statistically significant. The linear model can be used for crisis period.

Table 4.10: Japanese market, crisis period using TGARCH(1,1) model

Variance Equation				
C	1.03E-05	3.27E-06	3.166302	0.0015
RESID(-1)^2	-0.063308	0.029102	-2.175396	0.0296
RESID(-1)^2*(RESID(-1)<0)	0.236832	0.042951	5.514061	0.0000
GARCH(-1)	0.916587	0.021399	42.83344	0.0000
R-squared	-0.000052	Mean dependent var		-0.002194
Adjusted R-squared	-0.000052	S.D. dependent var		0.024657
S.E. of regression	0.024658	Akaike info criterion		-5.094052
Sum squared resid	0.256584	Schwarz criterion		-5.046211
Log likelihood	1082.392	Hannan-Quinn criter.		-5.075148
Durbin-Watson stat	2.141736			

Table 4.10 shows that in non-linear model, all the parameters are statistically significant because p-value for all parameters is less than 0.05 and the model can measure leverage effect because parameter γ is positive. Table 4.9 and Table 4.10 show that both the linear and non-linear model can be used for crisis period in Japanese market. However, non-linear model can be a preferred choice because it can measure leverage effect and what is more, it has a better AIC result.

Post-Crisis Period

Table 4.11: Japanese market, post-crisis period using GARCH(1,1) model

Variance Equation				
C	9.20E-06	2.39E-06	3.843137	0.0001
RESID(-1)^2	0.107885	0.011920	9.050677	0.0000
GARCH(-1)	0.845837	0.019166	44.13246	0.0000
R-squared	-0.000070	Mean dependent var		0.000604
Adjusted R-squared	-0.000070	S.D. dependent var		0.014128
S.E. of regression	0.014128	Akaike info criterion		-5.795843
Sum squared resid	0.289233	Schwarz criterion		-5.781279
Log likelihood	4205.986	Hannan-Quinn criter.		-5.790408
Durbin-Watson stat	2.061462			

Table 4.11 shows that all the parameters are statistically significant, p-value for all parameters is less than 0.05, and even the constant term is meaningful from statistical point of view. Till now we cannot reject the linear model GARCH(1,1) for Japanese market under post-crisis time period.

Table 4.12: Japanese market, post-crisis period using TGARCH(1,1) model

Variance Equation				
C	9.89E-06	2.45E-06	4.034685	0.0001
RESID(-1)^2	0.056897	0.014418	3.946253	0.0001
RESID(-1)^2*(RESID(-1)<0)	0.088818	0.014768	6.014196	0.0000
GARCH(-1)	0.846971	0.022206	38.14195	0.0000
R-squared	-0.000068	Mean dependent var		0.000604
Adjusted R-squared	-0.000068	S.D. dependent var		0.014128
S.E. of regression	0.014128	Akaike info criterion		-5.803619
Sum squared resid	0.289232	Schwarz criterion		-5.785414
Log likelihood	4212.624	Hannan-Quinn criter.		-5.796825
Durbin-Watson stat	2.061466			

Table 4.12 shows that the non-linear model is statistically significant, what is more, it can also measure the leverage effect because parameter γ is positive. To combine Table 4.11 and Table 4.12 together, we can see that even though both the linear and non-linear models are suitable for post-crisis period, TGARCH(1,1) can be a better choice because it can measure leverage effect and it has a better AIC result.

To sum up, at the Japanese stock market, both linear and non-linear models can be used for all the sub-periods. However, the non-linear model takes advantage over linear model in that it can measure the leverage effect and it has better AIC result than linear model.

4.6 Diagnostic Tests for Estimated Models

As what have been described in chapter 3.5, after estimation of models, it is necessary to verify the suitability for given model because a good regression model has to fulfill certain conditions such as constant residuals, no autocorrelation and the model should not have normal distribution.

The diagnostic test is used to test whether the estimated models have met the required conditions with methodologies at Tsay (2005). Chapter 4.6 is to demonstrate results of diagnostic test of estimated models for both markets under specified period of time.

4.6.1 Normality Test

As what has been stated in sub-subchapter 3.5.3, *JB* test is the goodness-of-fit test to see whether the sample data meet the normal distribution of skewness and kurtosis. The original assumption is H_0: skewness is 0, kurtosis is 3 (because of the normal distribution's characteristic of skewness equals to 0, kurtosis equals to 3). *JB* statistics show that the deviation in skewness for 0 and kurtosis for 3 will make the *JB* increase.

By making the H_0 as the residual items of the model follow normal distribution.

Table 4.13: Normality test for Chinese market under GARCH(1,1)

GARCH(1,1)	Periods		
	pre-crisis	crisis	post-crisis
Jarque-Bera	237.24	13.24	189.64
Probability	0.00000	0.0013	0.00000

Table 4.14: Normality test for Chinese market under EGARCH(1,1)

EGARCH(1,1)	Periods		
	pre-crisis	crisis	post-crisis
Jarque-Bera	128.88	10.63	171.8
Probability	0.00000	0.0013	0.00000

Table 4.13 and Table 4.14 show the normality test for Chinese market under linear and non-linear model respectively. We can see that the *JB* test for both linear and non-linear model under all these three periods is significant different from 0, which means that the assumption of skewness being 0, kurtosis being 3 can be rejected. What is more, the *p*-value is less than 0.05, which means that at the 5% significant level, the assumption of residual items are following normal distribution can be rejected.

Table 4.15: Normality test for Japanese market under GARCH(1,1)

GARCH(1,1)	Periods		
	pre-crisis	crisis	post-crisis
Jarque-Bera	25.42	10.09	124.11
Probability	0.000003	0.006436	0.00000

Table 4.16: Normality test for Japanese market under TGARCH(1,1)

TGARCH(1,1)	Periods		
	pre-crisis	crisis	post-crisis
Jarque-Bera	9.15	5.91	208.5
Probability	0.010300	0.052247	0.00000

Table 4.15 shows normality test for Japanese market under linear model GARCH(1,1), we can see that the *JB* test for all these three periods is significant different from 0, which means that the assumption of skewness being 0, kurtosis being 3 can be rejected. And, the *p*-value is less than 0.05, which means that at the 5% significant level, the assumption of residual items are following normal distribution can be rejected.

Table 4.16 shows normality test for Japanese market under non-linear model TGARCH(1,1). For pre-crisis period and post-crisis period, the *JB* test is significantly different from 0 and the *p*-value is less than 0.05. For pre-crisis period and post-crisis period, the assumption of residuals items being following the normal distribution can be rejected. For crisis period, we fail to reject the null hypothesis because *p*-value is higher than 0.05.

4.6.2 Autocorrelation Test

As what has been introduced in sub-chapter 3.5, the verification of autocorrelation problem will be exercised by using portmanteau test. Results in Ljung-Box *Q* statistics show the answers. By making the H_0 as the residual items of the model do not have autocorrelation.

The reason for choosing 4 time lags is that the closer of time to estimated point, the bigger of possibility of autocorrelation may happen. If there is no problem concerned with autocorrelation with 4 time lags, the null hypothesis of residual items being in no autocorrelation cannot be rejected.

Here we are going to use 5% significant level.

Chinese Stock Market

Table 4.17: Autocorrelation test for pre-crisis period

		AC	PAC	Q-Stat	Prob
GARCH(1,1)	1	-0.014	-0.014	0.082	0.774
	2	-0.066	-0.066	1.803	0.406
	3	0.045	0.043	2.596	0.458
	4	0.065	0.062	4.288	0.369
EGARCH(1,1)	1	-0.014	-0.014	0.08	0.777
	2	-0.065	-0.066	1.786	0.409
	3	0.057	0.056	3.106	0.376
	4	0.073	0.071	5.257	0.262

Table 4.18: Autocorrelation test for crisis period

		AC	PAC	Q-Stat	Prob
GARCH(1,1)	1	-0.004	-0.004	0.004	0.953
	2	-0.074	-0.074	1.43	0.489
	3	0.02	0.02	1.538	0.673
	4	0.055	0.05	2.337	0.674
EGARCH(1,1)	1	-0.019	-0.019	0.095	0.758
	2	-0.079	-0.079	1.687	0.43
	3	0.015	0.012	1.745	0.627
	4	0.072	0.067	3.097	0.542

Table 4.19: Autocorrelation test for post-crisis period

		AC	PAC	Q-Stat	Prob
GARCH(1,1)	1	0.025	0.025	0.9104	0.336
	2	0.026	0.026	1.954	0.376
	3	0.019	0.018	2.511	0.473
	4	0.007	0.005	2.581	0.63
EGARCH(1,1)	1	0.025	0.025	0.9104	0.34
	2	0.025	0.024	1.849	0.397
	3	0.019	0.018	2.407	0.492
	4	0.008	0.006	2.499	0.645

Table 4.17, 4.18 and 4.19 show the autocorrelation test for Chinese stock market for estimated models with 4 time lags. We can see that p-value for all these test is higher than 0.05, which means we fail to reject the hypothesis of no autocorrelation.

Japanese Stock Market

Table 4.20: Autocorrelation test for pre-crisis period

		AC	PAC	Q-Stat	Prob
GARCH(1,1)	1	-0.027	-0.027	0.183	0.669
	2	0.044	0.044	0.686	0.71
	3	0.021	0.024	0.804	0.849
	4	-0.111	-0.113	4.022	0.403
TGARCH(1,1)	1	-0.037	-0.037	0.343	0.558
	2	-0.018	-0.019	0.424	0.809
	3	0.001	-0.001	0.424	0.935
	4	-0.083	-0.083	2.188	0.701

Table 4.21: Autocorrelation test for crisis period

		AC	PAC	Q-Stat	Prob
GARCH(1,1)	1	-0.049	-0.049	1.035	0.309
	2	0.028	0.026	1.378	0.502
	3	-0.061	-0.058	2.959	0.398
	4	0.059	0.053	4.464	0.347
TGARCH(1,1)	1	-0.058	-0.058	1.415	0.234
	2	0.015	0.012	1.513	0.469
	3	-0.068	-0.067	3.484	0.323
	4	0.077	0.069	5.996	0.199

Table 4.21: Autocorrelation test for post-crisis period

		AC	PAC	Q-Stat	Prob
GARCH(1,1)	1	-0.009	-0.009	0.117	0.732
	2	0.028	0.028	1.276	0.528
	3	0.014	0.015	1.575	0.665
	4	-0.027	-0.028	2.649	0.618
TGARCH(1,1)	1	-0.015	-0.015	0.345	0.557
	2	0.027	0.027	1.402	0.496
	3	0.015	0.016	1.733	0.63
	4	-0.021	-0.022	2.403	0.662

Table 4.19, 4.20 and 4.21 show the autocorrelation test for Japanese market under all these three periods. The test results are similar as that of Chinese market, *p*-value for all these test is higher than 0.05, which means we fail to reject the hypothesis of no autocorrelation for

Japanese market as well. In other words, autocorrelation does not exist for all the models which have been established.

To sum up, based on the Ljung-Box Q statistics, all of the models (no matter linear models or non-linear models) for both Chinese and Japanese market for all the three sub-periods fail to reject the null hypothesis of no autocorrelation.

4.6.3 Test of Heteroskedasticity

To test whether the residual items have constant variance, we are going to use the ARCH test to provide with further proof on the existence of heteroskedasticity from statistical point of view. By making the H_0 as the model does not have heteroskedasticity.

Chinese Stock Market

Table 4.22: Heteroskedasticity test for pre-crisis period

	RESID^2(-1)	Prob	RESID^2(-2)	Prob	RESID^2(-3)	Prob	RESID^2(-4)	Prob
GARCH(1,1)	-0.006	0.903	-0.008	0.875	0.039	0.435	0.009	0.861
EGARCH(1,1)	0.048	0.329	-0.029	0.568	0.058	0.248	0.012	0.814

Table 4.23: Heteroskedasticity test for crisis period

	RESID^2(-1)	Prob	RESID^2(-2)	Prob	RESID^2(-3)	Prob	RESID^2(-4)	Prob
GARCH(1,1)	0.069	0.281	-0.078	0.224	-0.026	0.685	0.049	0.447
EGARCH(1,1)	0.026	0.687	-0.057	0.375	-0.019	0.762	0.051	0.43

Table 4.24: Heteroskedasticity test for post-crisis period

	RESID^2(-1)	Prob	RESID^2(-2)	Prob	RESID^2(-3)	Prob	RESID^2(-4)	Prob
GARCH(1,1)	-0.027	0.2968	0.041	0.113	0.004	0.872	-0.032	0.215
EGARCH(1,1)	-0.023	0.373	0.043	0.099	0.006	0.834	-0.032	0.21

Table 4.22, 4.23 and 4.24 show the results of test of heteroskedasticity for Chinese market. We can see that under all the three periods for both linear and non-linear models, by testing up to 4 days lag and a significant level of 0.05, the p-value for each lag is higher than 0.05. So, at a significant level of 5%, we fail to reject the null hypothesis that there is no heteroskedasticity.

Japanese Stock Market

Table 4.25: Heteroskedasticity test pre-crisis period

	RESID^2(-1)	Prob	RESID^2(-2)	Prob	RESID^2(-3)	Prob	RESID^2(-4)	Prob
GARCH(1,1)	-0.049	0.443	0.014	0.818	0.201	0.068	0.047	0.456
TGARCH(1,1)	-0.107	0.092	0.069	0.257	0.015	0.804	0.139	0.072

Table 4.26: Heteroskedasticity test for crisis period

	RESID^2(-1)	Prob	RESID^2(-2)	Prob	RESID^2(-3)	Prob	RESID^2(-4)	Prob
GARCH(1,1)	-0.046	0.346	0.079	0.346	0.072	0.146	0.022	0.653
TGARCH(1,1)	-0.082	0.095	0.001	0.987	0.049	0.319	0.024	0.625

Table 4.27: Heteroskedasticity test for post-crisis period

	RESID^2(-1)	Prob	RESID^2(-2)	Prob	RESID^2(-3)	Prob	RESID^2(-4)	Prob
GARCH(1,1)	0.071	0.068	0.021	0.437	-0.007	0.781	-0.032	0.227
TGARCH(1,1)	0.015	0.569	0.006	0.831	-0.005	0.847	-0.037	0.155

Table 4.25, 4.26 and 4.27 show the results of test of heteroskedasticity for Japanese market. We are going to test up to 4 days lag and use a significant level of 0.05; the *p*-value for each lag is higher than 0.05, which means that we fail to reject the null hypothesis that there is no heteroskedasticity.

4.7 In-sample Forecasting of Estimated Models

This sub-chapter is actually an in-sample forecasting, which means we are going to test whether the results of volatility derived from our models can be a good match for the real volatility situation derived from the real historical data. The difference between in-sample forecasting and out-of-sample forecasting is that the former one is tested against the empirical data while the latter one is tested against future expected data. We will use loss functions RMSE, MAE and Theil's inequality coefficient as described in the sub-chapter 3.6 to identify the quality of the established models. Based on the logic that the lower is value of loss functions, the higher is the predictive ability of the estimated model, Bauwens (2012). We have got the results as sub-subchapter 4.7.1, 4.7.2 and 4.7.3.

4.7.1 Forecasting on Chinese stock market

The results in Table 4.28 show that models in crisis period seem to have the weakest power in prediction because the results from RMSE, MAE and Theil's U have the lowest value for models during crisis period. Identification for pre-crisis and post-crisis periods draw the same result, which is the non-linear model has better prediction power over the linear model.

Table 4.28: Forecasting ability of models in Chinese stock market

periods	models	RMSE	MAE	Theil's coefficient
pre-crisis	GARCH(1,1)	0.00076023	0.00038081	0.20186412
	EGARCH(1,1)	0.00075156	0.00037278	0.20135392
crisis	GARCH(1,1)	0.00140283	0.00081398	0.37637875
	EGARCH(1,1)	0.00135564	0.00080955	0.37232944
post-crisis	GARCH(1,1)	0.00041573	0.00021944	0.26492906
	EGARCH(1,1)	0.00041321	0.00021751	0.26448591

Figure 4.5: Model forecasting, Chinese market, pre-crisis period
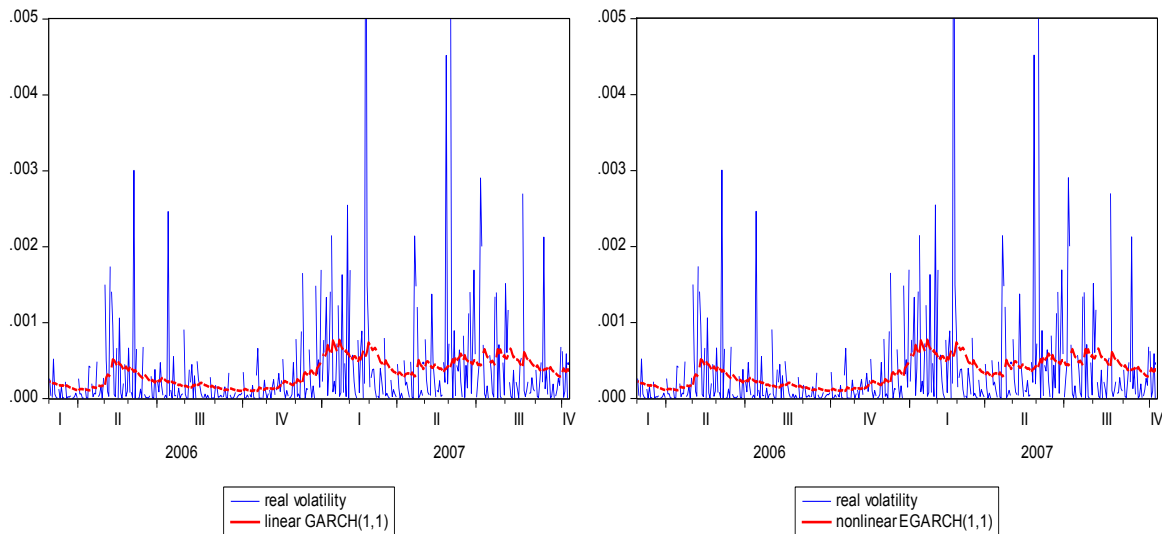
From Figure 4.5, it may not be easy to tell the differences in forecasting power between linear model and non-linear model for Chinese market under pre-crisis time period. However, the estimated pattern of volatility is almost with the same pattern of real volatility. Reasons which may account for the high volatility from the end of 2006 to the beginning of 2007 can be viewed as the appreciation of Chinese RMB, growth of real estate, coupled with the beneficiary to the financial and insurance areas appear, these sectors became to promote the prosperous of stock market.

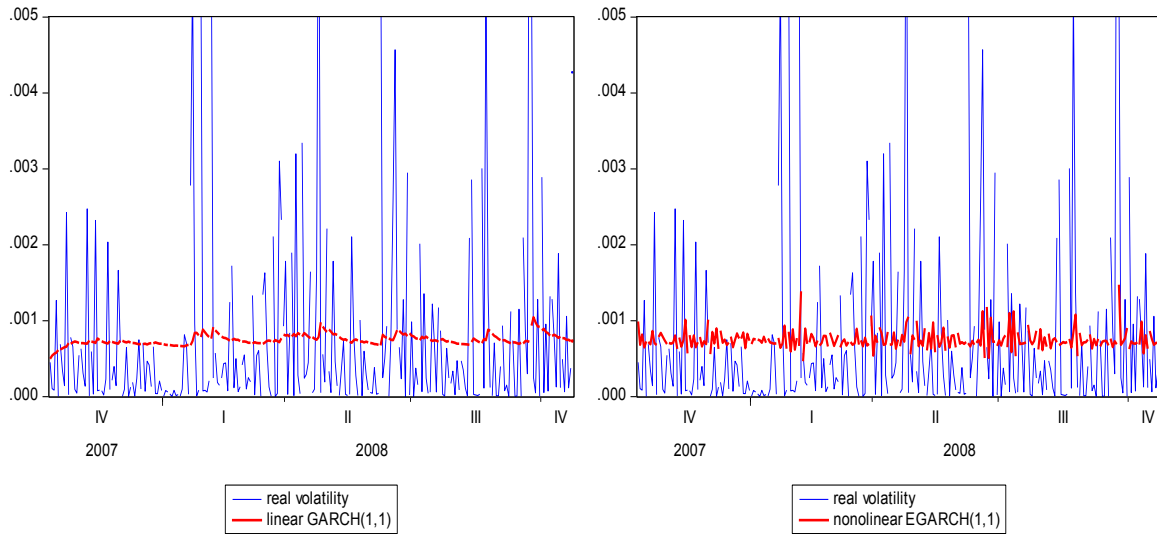Figure 4.6: Model forecasting, Chinese market, crisis period

Figure 4.6 indicates that during crisis time period, both linear and non-linear model fail to exert good forecasting power on volatility. The estimated volatility derived from models appears to be constant, while it is not content with the actual situation.

From Figure 4.7, forecasting power between linear and non-linear model is not easily to be seen, while both GARCH(1,1) and EGARCH(1,1) can be a good match for the real fluctuation of stock index. High volatility in 2009 is mainly due to the policy reason. To revitalize the top ten industrial, stimulation efforts and support from governments are strong, which results in the relevant industry stocks out of the soaring prices.

Figure 4.7: Model forecasting, Chinese market, post-crisis period
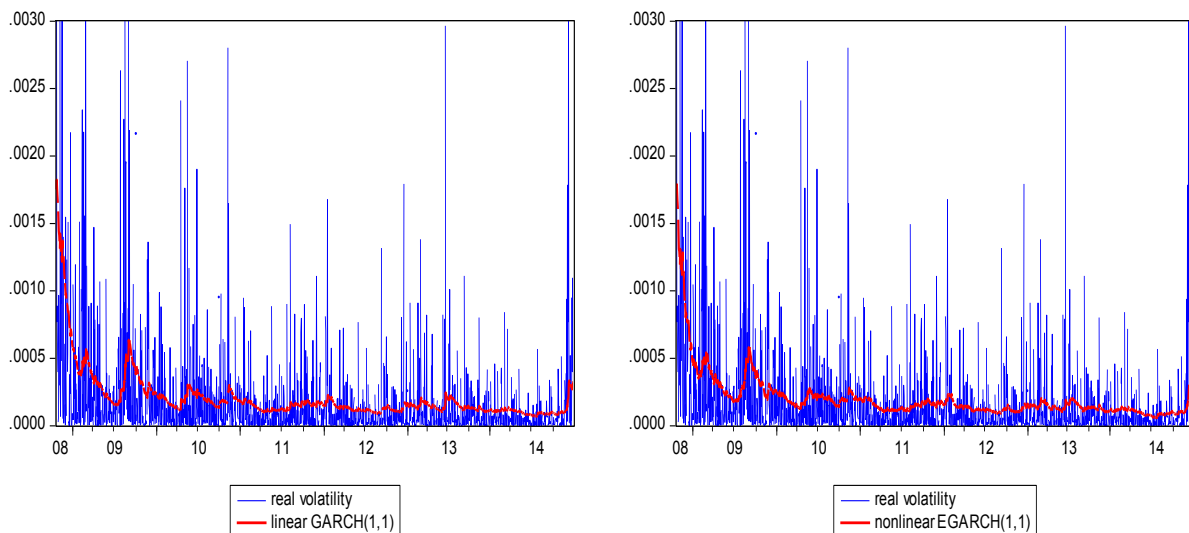
4.7.2 Forecasting on Japanese stock market

On Table 4.29, the situation in Japanese stock market is similar as that of Chinese stock market. Models established for crisis time period is of low quality in forecasting when compared with the other two periods. For pre-crisis period, all the indicators show that the linear model can be preferred over non-linear model. For post-crisis period, the non-linear TGARCH(1,1) has stronger prediction power over linear GARCH(1,1) model.

Table 4.29: Forecasting ability of models in Japanese stock market

periods	models	RMSE	MAE	Theil's coefficient
pre-crisis	GARCH(1,1)	0.00017478	0.00010661	0.13767496
	TGARCH(1,1)	0.00017625	0.00010732	0.13839751
crisis	GARCH(1,1)	0.00106988	0.00060591	0.38556258
	TEGARCH(1,1)	0.00101945	0.00058174	0.37129533
post-crisis	GARCH(1,1)	0.00047283	0.00020813	0.23602151
	TGARCH(1,1)	0.00047054	0.00020732	0.23170382

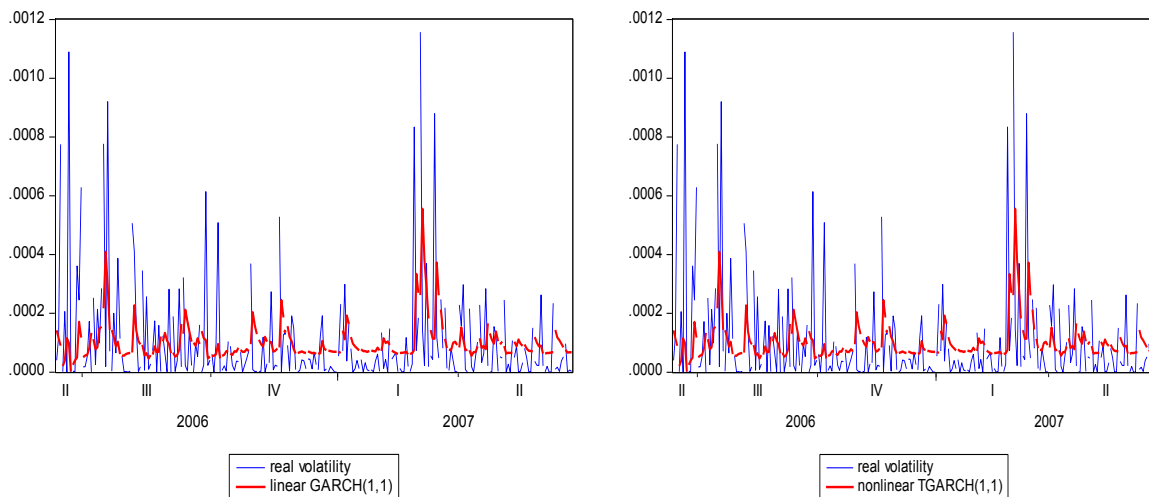Figure 4.8: Model forecasting, Japanese market, pre-crisis period

Figure 4.8 shows that both linear and non-linear models can play as good representatives of real situation in volatility in Japanese stock market under pre-crisis time period. High volatility for Japanese market occurred at around the year 2005.

In the summer of 2004, Japan has suffered from natural disasters like typhoon and earthquake, which has slowed the pace of construction investment and also influenced the

equipment investment. Since the second half of 2004, Japan's export slowdown due to the increasing of crude oil prices and the appreciation of yen against the dollar, while imports continue to increase. This led to a fall in net exports and a drag on the pace of the Japanese economy growth.

Figure 4.9: Model forecasting, Japanese market, crisis period
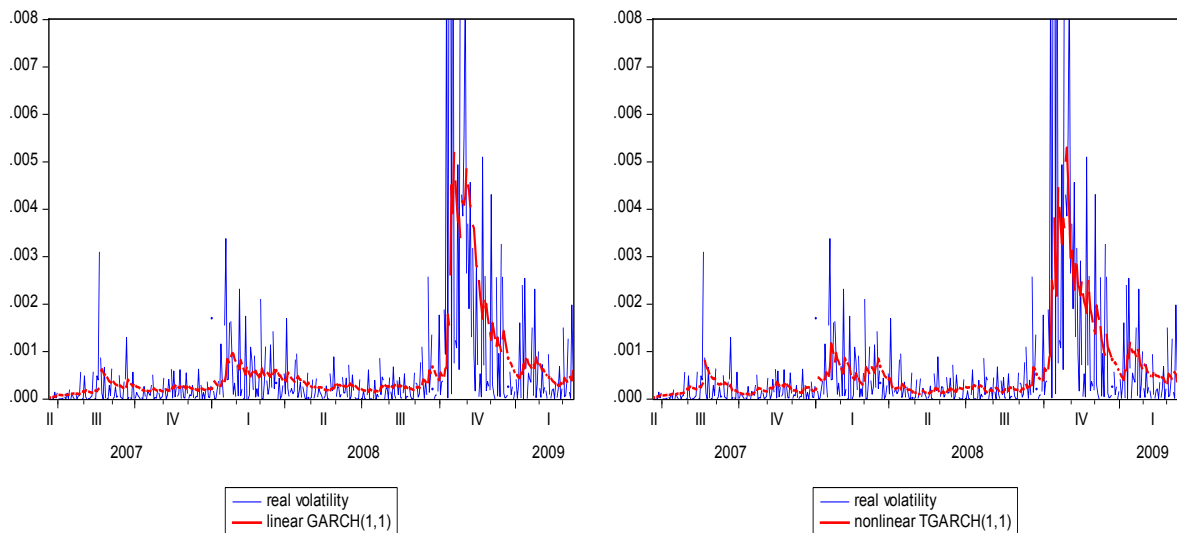
From Figure 4.9, we can see that even though the models established in crisis period have weak prediction power than the other two periods within Japanese market, these two models are on the trend of almost the same pace as the real situation.

To combine Figure 4.6 and Figure 4.9 together, we can see that the estimated models for Japanese market have much stronger prediction power than that of Chinese stock market during crisis period of time. What is more, the attack on volatility of financial crisis on Japanese market is more significant than that of Chinese stock market. Outside of crisis period, the volatility is not stable as well at Chinese stock market, while the volatility keeps at a relatively peaceful pace at Japanese market beyond the crisis period, which indicates that the a better developed stock market in Japan than China.

Consequences derive from Figure 4.6 and Figure 4.9 are also consent to the conclusion from sub-subchapter 4.5.1 and 4.5.2 that during crisis period, we cannot find suitable models for Chinese market while we can still find suitable models for Japanese market.

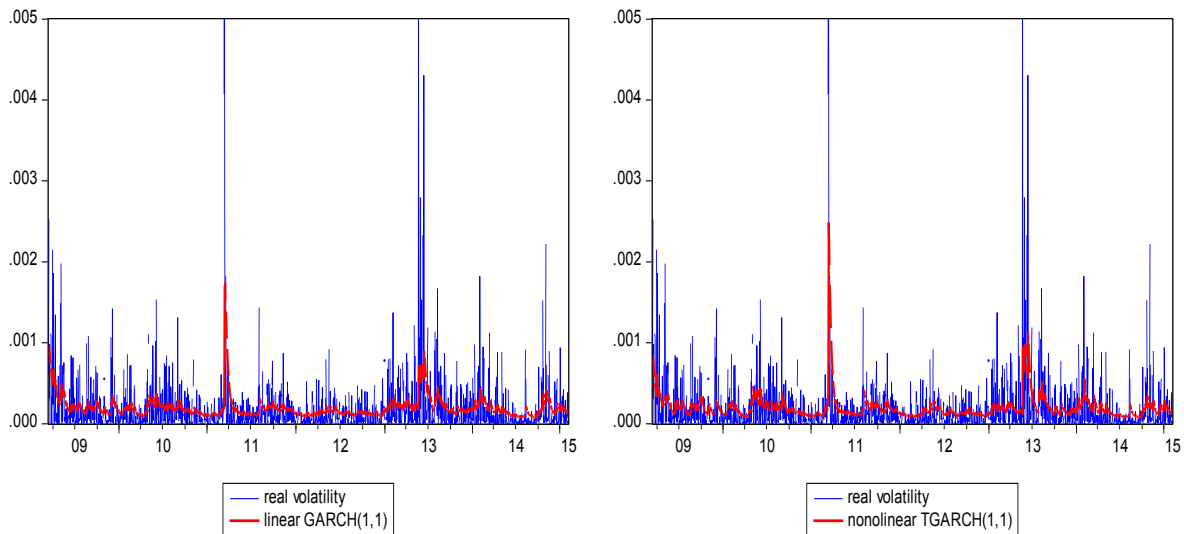Figure 4.10: Model forecasting, Japanese market, post-crisis period

Figure 4.10 shows high volatility for Japanese market under post-crisis period occurred at around 2013. The prosperous of recovery in Japanese market is mainly due to the achievements gained by the so called "Abenomics", which refers to the three main reformations took by Japanese premier Abe. These three tools include: 1. monetary policy, quantitative easing; 2. expansionary fiscal policy; 3. structure reform. These methods have helped Japan to get rid of deflation, increase the liquidity of financial market, and stimulate export, etc.

To sum up, when we compare the forecasting power of estimated models for Chinese stock market and Japanese stock market, it seems that during pre-crisis period, non-linear model is better for Chinese market while linear model is better for Japanese market; the crisis period has lowest forecasting power than the other two periods for both markets, however, models for Japanese market are better; during post-crisis period, non-linear models are more suitable for both markets.

5. Summary

Chapter 5 is mainly aimed at making a summary on chapter 4, which is the most important part among the whole thesis. Chapter 4 is the practical part and it puts the theory which has been described in chapter 3 into practice. Tables in chapter 5 are derived from results of chapter 4 by own calculation.

As what has been mentioned in chapter 1, the main goal of this thesis was to model effect of global financial crisis on volatility of stock market using conditional volatility models. The objected markets were Chinese stock market and Japanese stock market. The reason why these two markets were chosen laid on the fact that both of them were Asia stock markets; what's more, there existed many similarities on culture traditions from historical point of view. However, China and Japan is developing country and developed country respectively. The choice of methods on country development and present situations on macroeconomics for these two countries are not the same. These features make it interesting on comparing the results in model choosing process. The two sub-goals which were used to support the main goal included: first, measurement of whether the linear or non-linear model was more suitable for the objected market under a certain period of time; second, investigation of potential existence of leverage effect for both markets.

For the selection of length on financial time series, the total time period that was chosen for Chinese stock market was from 3/1/2006 to 3/1/2015. On the basis of different trending on stock price, the whole time period was further divided into three sub-periods: pre-crisis period from 1/3/2006 to 15/10/2007, crisis period from 15/10/2007 to 26/10/2008 and post-crisis period from 26/10/2008 to 3/1/2015. The total time period that was chosen for Japanese stock market was from 14/6/2006 to 8/2/2015. On the basis of differences in price trend, the whole time period was further divided into three sub-periods: pre-crisis period from 14/6/2006 to 21/6/2007, crisis period from 21/6/2007 to 11/3/2009 and post-crisis period from 11/3/2009 to 8/2/2015.

The first sub-chapter of chapter 4 made a general description of fundamental situations for

both Chinese and Japanese stock markets. The components, features and history of stock indexes for both markets were mentioned as well.

Sub-chapter 4.2 was about the sample data description for both Shanghai composite stock index and Nikkei 225 stock index. The trends of daily price for both indexes were plotted into figures. Figure 4.1 and Figure 4.2 provided us with intuitive idea on how to make sub-periods divisions.

Sub-chapter 4.3 turned daily data into logarithmic returns because the altering was one of the solutions to change non-stationary data into stationary data so that the estimated models could be more accurate.

Sub-chapter 4.4 summarized the features of data by using descriptive statistic. As what has been presented by Table 4.1, the influence of financial crisis on stock markets was mainly reflected on two aspects: first, the mean values for both markets were negative during this period; second, the standard deviations for both markets were much higher than the other two periods. Both aspects signaled negative effects derived from financial crisis.

We entered into empirical analysis on sub-chapter 4.5. First of all, linear and non-linear models were established for both Chinese and Japanese stock markets for all three periods. We used p-value to test whether the parameters were statistically significant. Parameter γ was compared with 0 to see whether the non-linear models could measure leverage effect. The comparison of linear and non-linear model for a certain market under an objected period of time was done according to AIC.

Table 5.1: Comparison of significance of parameters

	Chinese stock market		
	pre-crisis	crisis	post-crisis
GARCH(1,1)	OK	NOT OK	OK
EGARCH(1,1)	OK	NOT OK	OK
	Japanese stock market		
	pre-crisis	crisis	post-crisis
GARCH(1,1)	OK	OK	OK
TGARCH(1,1)	OK	OK	OK

Table 5.1 shows the results of significant test for models. We can see that for Chinese stock market, the parameters are not statistically significant under crisis period of time. So that we cannot use this kind of models for modeling the volatility at Chinese stock market. However, for Japanese stock market, we have no reason to reject the models according to the result of significant test.

Table 5.2: Comparison of leverage effect

Chinese stock market			
		p-value	γ
EGARCH(1,1)	pre-crisis	0.0000	0.0862
	crisis	0.1024	0.1068
	post-crisis	0.805	0.0015
Japanese stock market			
		p-value	γ
TGARCH(1,1)	pre-crisis	0.0001	0.3305
	crisis	0.0000	0.2368
	post-crisis	0.0000	0.0888

As what has shown in Table 5.2, the non-linear model EGARCH(1,1) failed on the test of leverage effect for Chinese stock market, leverage parameter γ is not statistically significant or not in harmony with theoretical expectations. On Japanese stock market, we cannot reject the null hypothesis of leverage effect even in crisis period.

Sub-chapter 4.6 was about diagnostic tests, which were used to test whether these models were qualified to meet certain assumptions. Results from diagnostic tests were as follows:

Table 5.3: Comparison of diagnostic tests

Chinese stock market						
Periods	GARCH(1,1)			EGARCH(1,1)		
	Normality	Het.	AC	Normality	Het.	AC
pre-crisis	No	No	No	No	No	No
crisis	No	No	No	No	No	No
post-crisis	No	No	No	No	No	No
Japanese stock market						
Periods	GARCH(1,1)			TGARCH(1,1)		
	Normality	Het.	AC	Normality	Het.	AC
pre-crisis	No	No	No	No	No	No
crisis	No	No	No	Yes	No	No
post-crisis	No	No	No	No	No	No

On Table 5.3, we can see that by making normality test, we found almost all the established models had the problem with normality, except the non-linear model for Japanese market under crisis period. By making heteroskedasticity test, the result showed that the assumptions of no heteroskedasticity for all of these models failed to be rejected. By making autocorrelation test, it seemed that all the models avoided the problem of autocorrelation.

The last sub-chapter in Chapter 4 was in-sample forecasting to estimated models. We used loss functions RMSE, MAE and Theil's inequality coefficient to indentify the quality of estimated models, based on the logic that the lower was the value of loss functions, the higher was the predictive ability of the estimated model. The comparison of results for Chinese and Japanese stock markets is stated as follows:

Table 5.4: Comparison of in-sample forecasting

	pre-crisis	crisis	post-crisis
Chinese stock market	non-linear	no models	non-linear
Japanese stock market	linear	non-linear	non-linear

Table 5.4 summarizes the results from Table 4.28 and Table 4.29. With the help of loss functions, we got the results that during pre-crisis period, non-linear model was more suitable for Chinese stock market while the linear model was more suitable for Japanese stock market. During crisis period, we failed to find suitable models for Chinese stock market while the non-linear model was preferred for Japanese stock market. During post-crisis period, non-linear model was better for both Chinese and Japanese stock market in in-sample forecasting. Global financial crisis led significant impact on forecasting performance of efficient models since values of loss functions reached highest results when comparing with pre-crisis period and post-crisis period.

6. Conclusion

The main goal of this diploma thesis was to test the effect of global financial crisis on volatility of specified stock markets, namely, Chinese stock market and Japanese stock market by using conditional volatility models. To fulfill the main goal, two sub-goals were set up, one of which was decision on whether linear or non-linear model could be better match of volatility for given market under certain period of time; the other one was investigation on the existence of possible leverage effect for both markets.

The whole thesis was divided into 6 chapters totally, including the first chapter: introduction and the last chapter: conclusion.

The introduction chapter briefly stated the focus of whole thesis and summarized main content for each chapter.

Chapter 2 and chapter 3 belonged to theoretical and methodological parts. Chapter 2 led us to a quick view on the fundamental knowledge about financial market and one of its assignable components, stock market. We also got information about financial crisis and related examples, financial time series and their characteristics in chapter 2.

Chapter 3 introduced the theoretical and equations of models that would be used in chapter 4.With the help of plotted figures, basic imagine on volatility and its consequences formed. Then linear models like ARCH, GARCH and non-linear models like EGARCH and TGARCH together with responded equations were presented. Furthermore, to meet the requirements of conditional volatility models, certain assumptions should be achieved, which led to the analysis on diagnostic tests. The selection of models with better forecasting power was tested against loss functions, which brought into the conception of RMSE, MAE and Theil's coefficient.

Chapter 4 was the most important part among the whole thesis, because chapter 4 specified the detailed analysis procedures. Data used were time series of daily price for both Shanghai Composite Stock Index and Nikkei 225 Stock Index. The chosen period for both Chinese stock market and Japanese stock market began roughly at the beginning of 2006 till the

March of 2015. According to different trending on daily stock price, the whole time period was divided into three sub-periods for both markets. On the basis of objected market and specified time period, linear and non-linear models were established. The estimated models went into diagnostic test to see whether they were qualified or not and the loss functions were used for testing in-sample forecasting ability of estimated models.

Chapter 5 made a brief summary for chapter 4 and made comparisons between Chinese stock market and Japanese stock market on estimated models. Differences of influence on these two markets derived from global financial crisis were measured as well.

As a whole, the main goal of this thesis is fulfilled. The effect of financial crisis on Chinese stock market and Japanese stock market is quit distinguishing. It is still possible to find suitable models for Japanese market under crisis period while the conditional volatility models cannot be used for Chinese market during crisis period. Even though models under crisis period seem to have weaker in-sample forecasting power for both markets, fitting ability of Japanese market is better than that of Chinese market if we go through a horizontal comparison.

When it comes to sub-goals, there is no universal answer to the first sub-goal, namely, whether linear or non-liner model can better match the actual volatility of stock markets under different time periods. If we use the results of significant test, AIC and parameter γ as the basis on choice, we can conclude that for Chinese stock market, there are no suitable models during crisis period while non-linear model takes a little advantage over linear model during pre-crisis period and linear model fits post-crisis period better. For Japanese stock market, it is suggested that non-linear model is better choice because it is not only statistically significant, but also it can measure leverage effect. However, If we use results of loss function as foundation for choice, we can conclude that for Chinese stock market, there are no suitable models for crisis period while non-linear model is better than linear model for both pre-crisis period and post-crisis period. For Japanese stock market, linear model is preferred for pre-crisis period while non-linear model is preferred for crisis and post-crisis period.

For the second sub-goal, we can draw the conclusion that for Chinese stock market, the leverage effect is either not statistically significant or in harmony with theoretical expectations, which lead to the rejection of assumption on possible leverage effect at Chinese stock market during whole period. For Japanese stock market, we fail to reject the null hypothesis of leverage effect even during crisis period, which reflects the possibility of existence of leverage effect for Japanese stock market during whole period.

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Extent and terms of a thesis are specified in directions for its elaboration that are opened to the public on the web sites of the faculty.

List of Abbreviations

Cov: Covariance

Corr: Correlation

OLS: Ordinary Least Squares

ARCH: Autoregressive Conditional Heteroskedasticity Model

GARCH: Generalized Autoregressive Conditional Heteroskedasticity Model

EGARCH: Exponential Generalized Autoregressive Conditional Heteroskedasticity Model

TGARCH: Threshold Autoregressive Conditional Heteroskedasticity Model

AIC: Akaike Information Criterion

RMSE: Root-Mean-Square Error

MAE: Mean Absolute Error

JB: Jarque-Bera statistical test

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Ostrava dated 20th April, 2015

YAXIN GUO

List of Annexes

Annex 1: Constituent of Shanghai Composite Stock Index

Annex 2: Constituent of Nikkei 225 Stock Index

Annex 3: Daily Values of Shanghai Composite Stock Index

Annex 4: Daily Values of Nikkei 225 Stock Index

Annex 5: Logarithmic Daily Returns of Shanghai Composite Stock Index

Annex 6: Logarithmic Daily Returns of Nikkei 225 Stock Index