

**DYNAMIC CORRELATION BETWEEN SELECTED WORLD MAJOR  
STOCK MARKETS AND COMMODITY MARKETS**

by

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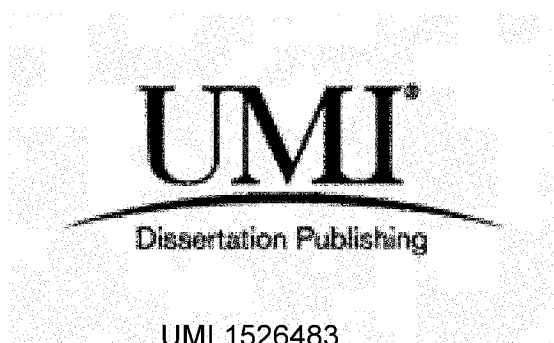
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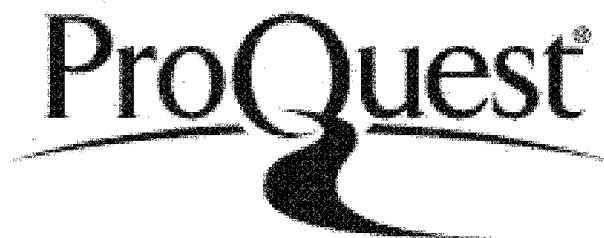


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## ABSTRACT

This thesis studies the dynamic correlation between price variation of bulk international commodities and major stock markets. Dynamic conditional correlation (DCC) multivariate GARCH model is used to analyze the volatility spillover effect between world major indexes and bulk commodities prices from January 1st, 2003 to December 31st, 2012, for petroleum, copper, and aluminum, and China (SSE), USA (S&P 500), Russia (RTS), Australia (S&P/ASX 200), and Canada (S&P/TSX). Moreover, this study investigates whether the 2007 global financial crisis has strengthened or weakened the dynamic correlations between stock markets and commodity markets. The results show that the dynamic correlations between selected world major stock indexes and commodity prices after the financial crisis have increased than that before the crisis, and the trend of integration of world economic volatility is further verified.

*Keywords:* Stock market, Commodity market, Financial crisis, Volatility, Dynamic correlation, DCC-GARCH model

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## **Chapter 1: Introduction**

### **1.1 Research Background and Significance**

#### **1.1.1 Research Background**

With the trends of financial liberalization and globalization since the 1980s, the information transmission and interaction mechanism between stock markets and commodity markets may have been further strengthened. The outbreak of the 2007 global financial crisis has promoted financial regulators to improve the supervision mechanism of financial markets. In addition the global financial crisis has significantly impacted investors' trading strategies and investment expectations. Thus, the dynamic correlations between different capital markets may have changed dramatically after the 2007 global financial crisis. At the same period, after several large-scale finance crises, the correlations between different capital markets have become the focus of attention to many investors and researchers, due to the demands of risk prevention and asset diversification. This thesis analyzes the dynamic correlations between international commodity markets and world major stock markets.

Market comovement has been one of the important topics in international finance that attract the interests of both international investors and policymakers. Understanding the level of market integration allows investors to improve their portfolio performance through diversification with less correlated assets, as well as

promotes the enactment of policies to help capital markets in the event of global economic and financial crisis. Many studies on stock market comovement have been carried out. Kasman (2009) analyzes sudden changes of volatility in the stock markets of the BRIC countries (Brazil, Russia, India and China) using the iterated cumulative sums of squares algorithm for the period 1990 to 2007 along with their impacts on the persistence of volatility. The results show that the estimated persistence in return volatility is reduced significantly in every return series when endogenously determined sudden shifts in variance are taken into account in the GARCH model. Phylaktis and Xia (2009) use an asset pricing perspective to investigate the equity market comovement and contagion at the sector level across the regions of Europe, Asia, and Latin America during the period 1990-2004. Their results confirm the sector heterogeneity of contagion. Modi et al. (2010) study various alternative techniques for recognizing comovement resulting among India (Bombay Stock Exchange Sensitive Index (SENSEX)), Hong Kong (HANGSENG Index (HSI)), Mexico (Mexican Stock Exchange (MXX)), Russia (Russian Trading System (RTS)), Brazil (Bovespa Index (BVSP)), UK (UK Index Series 100 (FTSE-100)) and US (Dow Jones Industrial Average (DJIA) and NASDAQ Stock Exchanges (NASDAQ)). Their results suggest that there is a high correlation between the DJIA and NASDAQ and a low correlation between SENSEX and NASDAQ.

Most of the research and investigation revolves around stock markets and their historical and potential future development. However, commodities came to the foreground recently and they are playing a much bigger role. During the last decade,

commodity prices experienced an exceeding volatility, with simultaneous and alternating phases of rising and falling trends. For example, the international crude oil price went up from \$52/barrel in early 2007 to the highest of \$147/barrel in June 2008, then fell rapidly to \$40/barrel after the first quarter of 2009. After the 2007 financial crisis, the comovement between stock markets and commodity markets has become more important to investors as commodities enter into many investment portfolios along with the traditional stock classes. So far the literature focuses on the correlations between oil and stock markets. Chen (2010) investigates whether a higher oil price pushes the stock market into bear territory, by using time-varying transition-probability Markov-switching models. The empirical evidence from monthly returns on the Standard & Poor's 500 (S&P 500) price index suggests that an increase in oil prices leads to a higher probability of a bear market emerging. Awartani and Maghyreh (2013) investigate the dynamic spillover of return and volatility between oil and equities in the Gulf Cooperation Council Countries (GCCC) during the period 2004 to 2012. Their results indicate that return and volatility transmissions are bi-directional, albeit asymmetric. In particular, the oil market gives other markets more than it receives in terms of both return and volatility.

#### **1.1.1.1 Financial Crisis of 2007**

The 2007 Financial Crisis, also known as the 2007-2008 Financial Crisis or the credit crunch of 2007-2008. This crisis is considered the most substantial financial

crisis since the Great Depression of 1930s in the United States and the banking crises prior to the First World War (Dungey, 2009). The 2007 Financial Crisis contributed to the bankruptcy of many banks, such as Lehman Brothers Holdings Inc., the bailout of many large financial institutions by the federal government of the United States, such as Bear Stearns Companies Inc. and American International Group Inc., and the collapse of many stock markets around the world. The crisis of 2007-2008 had a huge impact in many key businesses. The declines in consumer wealth is estimated in trillions of U.S. dollars, and a downturn in economic activity led to the 2008–2012 global recession and contributed to the European sovereign-debt crisis (Williams, 2012; Elliott & Baily, 2009). Economies worldwide slowed during this period as credit crunched and international trade declined (World Economic Outlook, 2009).

### **1.1.2 Research Significance**

This thesis focuses on the links between selected world major stock markets and international commodity markets. More specifically, it studies on the dynamic correlation effect between both markets. Extra attention is paid to the 2007 Financial Crisis by investigating whether it has strengthened or weakened the relationships between stock and commodity markets. In order to acquire the dynamic correlation coefficients between bulk commodities and various major stock markets, the dynamic conditional correlation (DCC) multivariate GARCH model of Engle (2002) is selected as the research method. The volatility spillover effect is analyzed between three

commodities (petroleum, copper, and aluminum) and five international stock markets (China's Shanghai Stock Exchange (SSE), US's Standard and Poor's 500 (S&P 500), Russia's Russian Trading System (RTS), Australia's Standard and Poor's / Australian Securities Exchange 200 (S&P/ASX 200), and Canada's Standard and Poor's / Toronto Stock Exchange (S&P/TSX)) from January 1, 2003 to December 31, 2012. Our results suggest that the dynamic correlations between stock indexes of various countries and prices of bulk commodities after the 2007 financial crisis are greater than that before the crisis, and the trend of integration of world economic volatility is further verified.

The remainder of this thesis is organized as follows. Chapter 2 presents the theoretical foundations, literature review of markets comovements, and hypotheses. Chapter 3 discusses the methodology and data source. Empirical results are displayed in Chapter 4, and Chapter 5 concludes the thesis.

## **Chapter 2: Theoretical Foundations, Literature Review and Hypothesis**

Along with the rapid development of information technology, the liberalization of capital flows and the globalization of economics and finance, the relationship between asset markets becomes increasingly closer. The alleged “comovement” covers the interaction between earnings and fluctuation, and the dynamic characteristics of correlation. These relationships exist not only between stock markets in different countries and areas, for example, the Canadian stock markets might be influenced by fluctuations in the American stock markets, but also between different asset markets, for example, there might be interaction among stock markets, foreign currency markets, bond markets and commodity markets. This thesis aims to compare systematically the comovements between different commodity markets and stock markets in different regions, giving priority to the underlying foundation for comovements between these markets, then empirically investigating and illustrating the differences between comovements among various markets and their dynamic characteristics.

Theoretically speaking, comovements exist between stock markets and commodity markets for the following three main reasons. Firstly, there is homogeneous information in these two markets. In other words, information transfer between these markets generates comovement features, corresponding to the efficient market theory. Secondly, irrational behavior of heterogeneous investors brings about

uncertainty of comovement between the stock market and commodity market, corresponding to behavioral finance theory. Thirdly, the financial attributes of the commodity market gives rise to the fact that an increasing number of investment institutions configure financial derivatives of commodity market and stocks simultaneously, resulting in possible influence of cross-market capital flow to the comovement between two markets.

## **2.1 Efficient Market Theory and Information Transmission Mechanism**

### **2.1.1 Efficient Market Theory**

Modern financial theory states that the current asset price is the discounted present value of investors' expectation in the future earnings of the asset. The fundamental reason of asset price fluctuations is that the information which affects the future value of the asset is changing constantly. Therefore, the underlying fundamental factor of the capital market is the information market. Investors trade assets based on the information they obtained. The process of asset trading is actually the process of information flow, reflecting investors' understanding and reactions about market information.

The theoretical basis for the price reflecting promptly to information is the efficient market hypothesis (EMH). Fama (1970) proposes the EMH, affirming that financial markets are "informationally efficient". Therefore, stocks are always traded at their true value on stock exchanges so nobody can consistently achieve returns in

excess of average market returns on a risk-adjusted basis, given the information available at the time the investment is made. There are three major forms of the hypothesis: 1) weak form, 2) semi-strong form, and 3) strong form. The weak form of the EMH states that prices on traded assets only reflect all past publicly available information. The semi-strong form of the EMH states that prices reflect all publicly available information and that prices instantly change to reflect new public information. The strong form of the EMH claims that prices instantly reflect all of the information, including both publicly available information and inside information. No matter in which form of market, prices would react fully and accurately to the received available information.

EMH reflects an ideal competitive equilibrium, with two important premises: complete publicity of information and complete rationality of investors. The former refers to the fact that all information in the market are real, with no false information; and that the flow of information is rapid and smooth, during which process there is no cost, with information fairly distributed among investors.

The nature of comovement between different markets is the process of information flow and transmission. Engle (1994) puts forward that there are two categories of information in some capital markets, i.e., local information and global information. The former merely influences local markets, whereas the latter influences both local and other capital markets. Global information reflects the phenomenon of information flow among different markets, the transmission of which brings about interplay among different markets. On the one hand, under efficient



market conditions, the global information of a certain market would be immediately informed by investors and revealed by the price fluctuation of this market. On the other hand, due to the flow effect of this information, which is rapidly transferred to another market, investors alter their expectations as to the market value accordingly and adjust their trade strategies. Because the market is efficient, there is no leakage or distortion of information during the transmission process. Investors could take in the information completely and thereby expect the resulting variation of asset value, which is revealed quickly by the asset price. Hence, the mechanism of information transmission should be explicit, and the market comovement should be estimable.

### **2.1.2 Information Transmission Mechanism of Stock Market and Commodity Market**

This section aims to analyze proper mechanism of information transmission in stock market and commodity market under efficient market conditions. When the price fluctuates in the commodity market, information flows to the stock market. However, information flows from the stock market to the commodity market mainly refers to the fact that its function of reflecting macroeconomic expectation would impact commodity demand. The respective mechanism of information transmission between stock market and two commodities, namely petroleum and metal, will be discussed in the following part.

As the pillar industry of the world, petroleum earns an incomparable strategic position in many countries' economy. When the price of petroleum rises, those oil and gas companies in the upstream of the industry, which engage with oil and gas exploration and exploitation would obtain higher profits; whereas in order to keep their own profits, those petrochemical enterprises in the downstream of the industry, which engage with crude oil refining and processing would shift the burden of rising prices to oil consumption enterprises. These enterprises would face adverse impact, for example, businesses on mining, nonferrous metals, heavy chemicals, industrial products, transportation, residential construction, household appliance producer, aviation, tourism and leisure industries (Jin & Jin, 2010). In addition, since cars and petroleum are complement goods to each other, the rise of petroleum price would demonstrate adverse impact on cars and auto parts industry. Since coal, electricity and petroleum are substitute goods, the rise of petroleum prices would have a positive effect on coal and electricity industry. From the viewpoint of the overall stock market, the rise of petroleum prices would lead to increased costs for many enterprises and the increase of burden on consumers. This would trigger the reduction of production and consumption and increase price inflation. In order to curb inflation, government might raise the interest rates, adding to a further decline of expected economic growth and a drop in the stock market. If the market is efficient, this information would be transmitted rapidly to the stock market. Hence, the comovement would grow between petroleum price and the stock price.

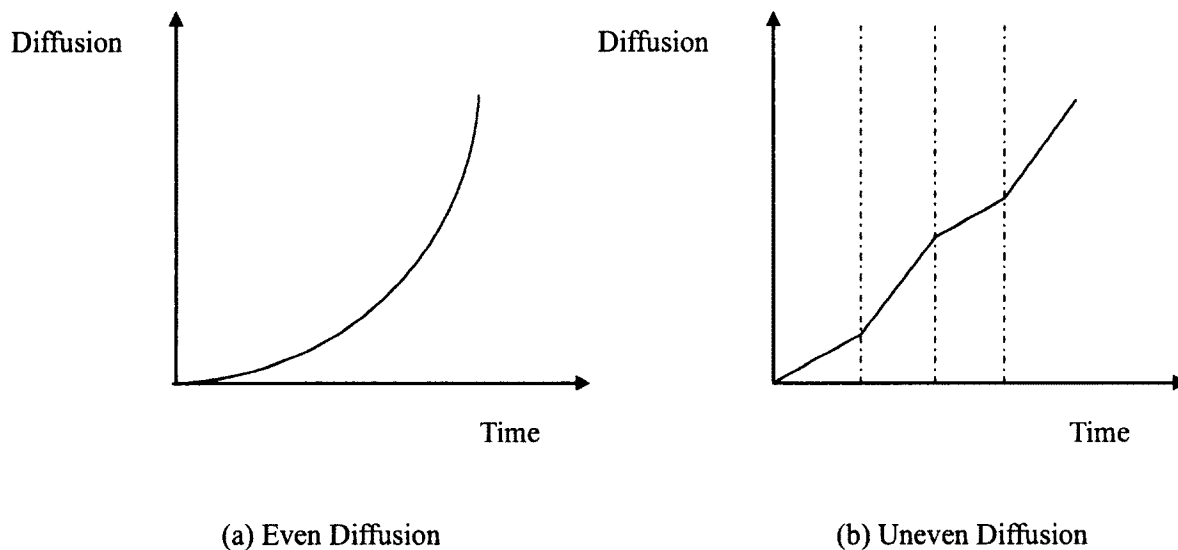
Metal is an important raw material of industrial production, which plays a significant role in the economy of many countries. When the price of metal rises, profits of mining enterprises will go up, whereas enterprises with metals as raw materials will face a profit decline. For example, companies in machinery manufacturing, construction, electronics, aerospace and nuclear power, etc (Li, 1998). This gives rise to comovements between metal prices and relevant stock prices. The same is true for other commodities. Some stock markets are more heavily weighted towards certain commodities and their commensurate returns.

## **2.2 The Uncertainty of Market Comovement**

The efficient market theory is founded on the basis of rational investor and complete information. However, there is almost no such perfect market in the real world. There is a considerable amount of empirical research findings that contradict the efficient market hypothesis. In order to explain the phenomenon of market fluctuations, scholars attempt to study relevant financial issues from the perspective of irrationality and information asymmetry, i.e., behavioral finance theory.

According to efficient market theory, information flows rapidly and completely inside the market and between different markets. There is no leakage or distortion during the process of transmission. Therefore, information is fully reflected in the market price. However, according to behavioral finance theory, information may not flow rapidly and completely, but correlated by the minority and then spread to more

investors and other markets. The transmission of information could be illustrated by information space raised by Boisot (1995). Generally speaking, certain information is merely acquired by a small number of people and then spread to more. The speed of information spreading grows exponentially, assuming that all investors are heterogeneous and the information is transmitted steadily, then the information diffusion curve could be illustrated as figure 1 (a). Taking into consideration the transmission in different markets and the fact that different markets correspond with different investors and different trading behaviors, each market is divided into sub-sphere with its own internal property and sphere distribution. In this way, information starts from one market, transmits steadily inside this market, but breaks over in another market which makes the curve turning, as shown in figure 1 (b). Differences on the nature of markets correspond to a different changing path of information curve, showing a unique comovement in different markets. If there is a leakage of information during transmission between markets, the turning point in figure 1 (b) would further become discontinuous points, high on the right and low on the left, rendering non-precise estimation of information transmission in different markets.

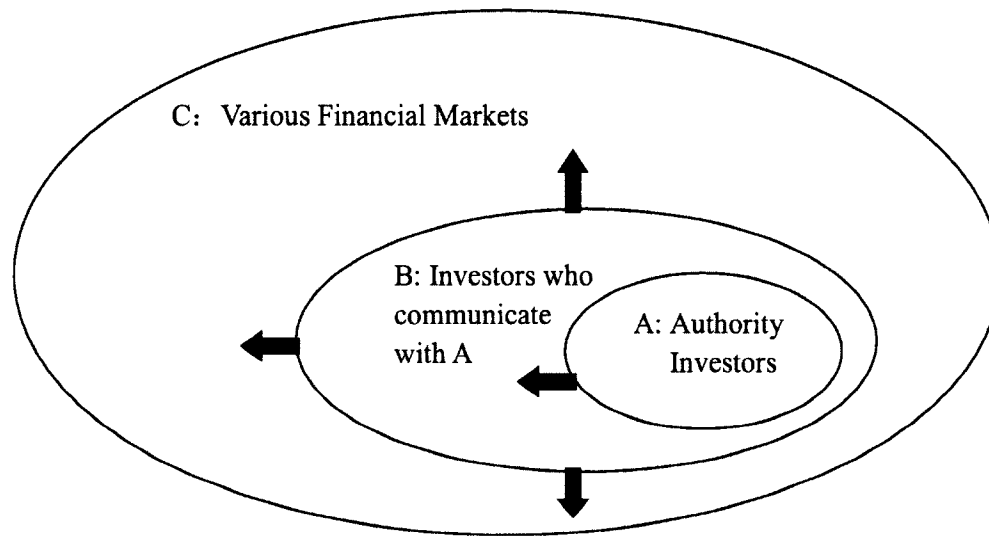


**Figure 1: Information Diffusion Curves**

Adapted from *Information Space: A Framework for Learning in Organizations Institutions and Cultures*, by M. H. Boisot, 1995, London: Routledge.

Any fluctuation of price should be generated by trade, and any reflection of information should be demonstrated by trade. Comovement between different markets is realized eventually through investors' trading behavior. In the real market, investors' understanding and reflection to information differ with one another. On the other side, investors are partly rational. Besides, information is asymmetric and insufficient. In order to obtain excess earnings, investors tend to adapt irrational investing strategies. These cause information transmission in different markets to deviate from the theoretical path and consequently make the comovement uncertain.

Research shows that the irrational investing behaviors tend to perform a sheep-flock effect or herd behavior (Banerjee, 1992). Herd behavior is where in an asymmetric market investors who lack of information would speculate on information other investors may have and therefore generate trade behavior such as imitating others and relying on public opinions. Whereas those who possess partial information would assume that other investors may have more internal information and thereby give up their own judgments to follow the mainstream investment direction. Generally speaking, sheep-flock effect represents the market trend as guided by authority investors and gradually spread to other markets. Authority investors own a relatively comprehensive information set and analysis technology. When they carry on transactions, other investors may follow. As this is reflected in asset price fluctuation, more investors in the same market would follow their investment moves. When investors in other markets observe such fluctuation in price, they would gradually follow the same transactions path, and thus brings about comovement between different markets. The contagious path of sheep-flock effect is shown in figure 2. Sheep-flock effect may minimize the effect of true information in the market, while false information is exaggerated. Eventually this makes market comovement irrational and unpredictable



**Figure 2: The Contagious Path of Sheep-Flock Effect**

## **2.3 The Financial Attributes of Commodity Markets and the Cross-Market Capital Flow**

### **2.3.1 The Financial Attributes of Commodity Markets**

Commodity market usually consists of two attributes. The commodity attribute is the influence of the change of supply-demand relation of commodity itself on the commodity price trend. The financial attribute is utilizing financial leverage to speculate and thus divorce commodity price from supply-demand relation. The main reasons for the commodity market to have the financial attribute is stated as follows: first, some commodities become the preference in warehouse receipt transactions and inventory financing due to their natural attribute and hedging function. While many financial institutions conduct warehouse receipt transactions directly or indirectly, large merchants utilize commodities to conduct financing operations, resulting in the

fact that these commodities carry higher values than their actual values by becoming a risk management tool and investment. Second, some commodities constitute as an component of the whole financial market by developing financial derivatives such as futures, et cetera. These financial derivatives attract a large amount of investment capital utilizing financial leverage to participate in the transaction, which reflects the “pan-financial attribute” of commodity market. Third, some important natural resources are considered as “hard assets” corresponding with “paper assets” which refer to stocks and bonds, et cetera. They have become important investments or substitutes by possessing a similar investment function with financial assets.

Compared with other commodities, oil and metals have two prominent functions as: first, hedge against US dollar devaluation, and second, hedge against inflation. Moreover, oil, copper and aluminum are important raw materials in the construction industry due to their favorable natural attribute. The important position of oil, copper and aluminum in the economy enlarges their financial attribute, with the gradual perfection of corresponding futures markets further enhancing this attribute. Since 1970, the annual return of the Goldman Sachs Commodity Index has reached 12% on average, slightly above that of major stocks and bonds index between 8.5% and 11% in the corresponding period.



### **2.3.2 The Cross-Market Capital Flow and Market Comovement**

The intensifying of innovation in capital market gradually highlights the financial attribute of the commodity market, which gains the favor of investors due to the non-physical delivery feature of commodity derivatives, and progressively becomes an investment place keeping pace with the stock market. The cross-market capital flow, caused by investors' portfolio investment among different markets and assets, has become a key issue of modern finance.

The cross-market capital flow may influence the comovement between corresponding markets. Barberis (2003) finds that investors tend to distinguish their investable assets from certain features, based on how they distribute capital among different assets and carry out portfolio investment. The behavior of capital transfer in portfolio investment will influence corresponding asset prices. When a certain asset market fluctuates, investors will promptly adjust the portfolio proportion in order to maximize profit, which causes capital transfer and corresponding variation of asset prices in another market, i.e. comovement among markets.

The main factor to influence capital distribution in portfolio investment is the correlation between assets. Markowitz (1952) puts forward the theory of portfolio diversification, which assumes that portfolio diversification could reduce effectively non-systemic risks. When there exists negatively correlated or uncorrelated assets in an investment portfolio, there is an opportunity to include other highly positive correlated and high risk investments. As the number of investments increase in the

portfolio the total risk is dominated by correlation effect among investments rather than the variance of individual assets.

## **2.4 Literature Review**

Previous literature has been taken as important reference to the current study, which is divided into two groups. The first group of studies is about stock market comovement. The second group-is about comovement between stock market and commodity.

### **2.4.1 Literature of Stock Markets Comovement**

Schwert (1989) analyzes the relation of stock volatility with real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity using monthly data from 1857 to 1987. He finds that aggregate leverage is significantly and positively correlated with volatility, it explains a relatively small part of the movements in stock volatility. He believes that the amplitude of the fluctuations in aggregate stock volatility is difficult to explain using simple models of stock valuation, especially during the Great Depression from 1929-1939.

Hamao et al. (1990) study the short-run interdependence of prices and price volatility across three major international stock markets (Tokyo, London, and New York). They utilizes the autoregressive conditionally heteroskedastic (ARCH) family

of statistical models to explore the pricing relationships between these stock markets. They find the evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London, but they do not find any price volatility spillover effects in other directions for the pre-October 1987 period.

Pindyck and Rotemberg (1993) test whether comovements of individual stock prices can be justified by economic fundamentals. This is a test of the present value model of security valuation with the constraint that changes in discount rates depend only on changes in macroeconomic variables. Then, stock prices of companies in unrelated lines of business should move together only in response to changes in current or expected future macroeconomic conditions. Using a latent variable model to capture unobserved expectations, they find excess comovement of returns. They believe that this excess co-movement can be explained in part by company size and degree of institutional ownership suggesting market segmentation.

King et al (1994) study the time-variation in the covariances between stock markets and the extent of capital market integration of 16 national stock markets. They estimate a multivariate factor model in which the volatility of returns is induced by changing volatility in the factors. Unanticipated returns are assumed to depend both on innovations in observable economic variables and on unobservable factors. The risk premium on an asset is a linear combination of the risk premium associated with the factors. Their findings suggest that idiosyncratic risk is significantly priced, and that the price of risk is not common across countries. This either can be interpreted as evidence against the hypothesis of integrated capital markets or could

reflect the failure of some other maintained assumptions. Another empirical finding is that only a small proportion of the covariances between national stock markets and their time-variation can be accounted for by observable economic variables. Changes in correlations between markets are driven primarily by movements in unobservable variables.

Bekaert and Harvey (1995) propose a measure of capital market integration arising from a conditional regime-switching model to study the equity markets of 21 developed and 12 emerging countries and regions. They find that a number of emerging markets exhibit time-varying integration. Some markets appear more integrated than one might expect based on prior knowledge of investment restrictions. Other markets appear segmented even though foreigners have relatively free access to their capital markets.

Karolyi and Stulz (1996) present the fundamental factors that affect cross-country stock return correlations by using transactions data from 1988 to 1992. In the results, they find that U.S. macroeconomic announcements, shocks to the Yen/Dollar foreign exchange rate and Treasury bill returns and industry effects have no measurable influence on U.S. and Japanese return correlations.

Tuluca (2001) investigates the comovement of daily returns from 13 Asian and non-Asian markets before and after the advent of the Asian crisis in July 1997. His results show a seven-fold increase in feedback relations for individual pairs of markets. They find a reduction in the number of common factors that generate returns for the markets as a group. He also analyzes six three-month sub-periods surrounding

the crisis since the post-crisis period including the collapse of the Russian market and attack on the Brazilian real. His results show that the perceived increase in comovement during the post-crisis interval was the result of sub-period transitory shocks.

Longin and Solnik (2001) test the hypothesis that international equity market correlation increases in volatile times is a difficult exercise and misleading results have often been reported in the past because of a spurious relationship between correlation and volatility. They derive the distribution of extreme correlation for a wide class of return distributions by using the extreme value theory to model the multivariate distribution tails. Their results suggest that correlation is not related to market volatility per se but to the market trend. Also, correlation increases in bear markets, but not in bull markets.

Forbes and Roberto (2002) use the heteroskedasticity biases test for contagion based on correlation coefficients between world major stock markets. Their results indicate that correlation coefficients are conditional on market volatility. Under certain assumptions, it is possible to adjust for this bias. Using this adjustment, there was virtually no increase in unconditional correlation coefficients (i.e., no contagion) during the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. stock market crash.

Fisman and Inessa (2004) use a new methodology based on industry comovement to examine the role of financial market development in intersectoral allocation for 37 different industries in 42 countries. They find that countries have more highly

correlated growth rates across sectors when both countries have well-developed financial markets.

Brooks and Negro (2004) explore if the rise in comovement across national stock markets since the mid-1990s is driven by global integration and therefore likely to be permanent, or if it is a temporary phenomenon associated with the stock market bubble. Their results suggest that diversifying across countries may therefore still be effective in reducing portfolio risk in the aftermath of the bubble.

Baele (2005) studies the magnitude and time-varying nature of volatility spillovers from the aggregate European (EU) and U.S. market to 13 local European equity markets. He uses a regime-switching model to allow the shock sensitivities to change over time to account for time-varying integration. The results show that regime switches to be both statistically and economically important. Both the EU and U.S. shock spillover intensity increased substantially over the 1980s and 1990s, though the rise is more pronounced for EU spillovers. Shock spillover intensities increased most strongly in the second half of the 1980s and the first half of the 1990s. He also finds evidence for contagion from the U.S. market to a number of local European equity markets during periods of high world market volatility.

Barberis et al. (2005) use additions to the S&P 500 to distinguish two views of return comovement: the traditional view, which attributes it to comovement to news about fundamental value, and an alternative view, in which frictions or sentiment delink it from fundamentals. After inclusion, a stock's beta with the S&P goes up. In bivariate regressions which control for the return of non-S&P stocks, the increase in

S&P beta is even larger. These results are generally stronger in more recent data.

They provide new evidence in support of the alternative friction- or sentiment-based view.

Kizys and Christian (2006) study the linkage between international monthly equity correlations and the comovement of business-cycle fluctuations in seven major countries over the period 1970 to 2004. Their results show that the linkage between international equity correlations and the comovement of business-cycle fluctuations is in general statistically not significant.

Boyer et al. (2006) find empirical evidence that stock market crises are spread globally through asset holdings of international investors. By separating emerging market stocks into two categories, namely, those that are eligible for purchase by foreigners (accessible) and those that are not (inaccessible). They estimate and compare the degree to which accessible and inaccessible stock index returns comove with crisis country index returns. Their results show greater comovement during high volatility periods especially for accessible stock index returns. This finding suggests that crises spread through the asset holdings of international investors rather than through changes in fundamentals.

Lucey and Voronkova (2008) examine the relationships between Russian and other equity markets over the period of 1995–2004. They find that the Russian equity market remained isolated from the influence of international markets in the long run and that while a structural break might have occurred in August 1998 this did not alter the nature of the long-run relationships.

Kallberg and Pasquariello (2008) study the excess comovement among 82 industry indexes in the U.S. stock market between January 5, 1976 and December 31, 2001. They use sector groupings and the three Fama-French factors for their analysis. Their methodology included estimating residuals of joint rolling regressions on industry returns. After computing the excess comovement as the mean of square unconditional, statistically significant correlations of these residuals, they find that excess co-movement is high, statistically significant, and represents an economically significant portion of the average gross square return correlation. Excess comovement is also uniformly significant across industries over time and only weakly asymmetric.

Bekaert et al. (2009) examine the international stock return co-movements using country-industry and country-style portfolios as the base portfolios. They find that, first of all, there is no evidence for an upward trend in return correlations except for the European stock markets. Second, the increasing importance of industry factors relative to country factors is a short-lived phenomenon. Third, large growth stocks are more correlated across countries than small value stocks and the difference has increased over time.

Chittedi (2010) empirically investigates the long run equilibrium relationship between the BRIC stock markets and the stock market indexes of three major developed countries using the multivariate cointegration. The results suggests that India and the developed country markets of USA, UK, Japan, and BRIC markets were highly cointegrated during the period from January 1998 to August 2009.



Wang (2010) studies the dynamic relationship between the variables of oil price, stock price, and real economic activity in Russia, China and Japan. The results of the cointegration analysis suggest that a long-run equilibrium relationship exists among the real economic activity, stock price and oil price in Russia. However, this relationship among the three variables is not found in China and Japan.

Ullah and Long (2008) study the conditional volatility and correlation predictability of four emerging BRIC stock markets (Brazil, Russia, India and China), and addresses the issue whether investors could exploit this predictability to earn excess returns from the minimum variance portfolio of index component stocks. Their results suggest that economic gains exceeded a conservatively high transaction cost across the selected countries. They also find that semiparametric modeling falls in a grey area of profitability - sometimes attractive whilst sometimes not attractive.

Naranjo and Porter (2010) examine the sources of cross-country comovement of momentum returns over the period of 1975–2004 by using data on more than 17,000 individual firms across 100 industries from 40 countries. They find that country-neutral momentum returns are significantly correlated across countries, the correlation is time-varying, and that comovement among industries cannot explain the comovement of country-neutral momentum returns.

Wälti (2011) uses a panel specification to explain bilateral stock market return correlations between fifteen developed economies over the period 1975–2006. He finds that monetary integration leads to stronger stock market synchronization, both through the elimination of exchange rate volatility and through the common monetary

policy and the convergence of inflation expectations. Trade and financial integration also contribute to higher stock market return comovements.

Choe et al. (2012) test financial contagion on heteroskedastic asset returns in time-varying conditional correlation. They find that out of the countries reporting contagion evidence under the constant correlation test, none of the countries exhibits contagion evidence from the 1997 Asian crisis. They believe that a high level of cross-market correlation during a crisis reported as contagion evidence under the standard constant correlation test is mostly due to the high level of cross-market comovement resulting from the intertemporal risk-return adjustment.

#### **2.4.2 Literature of Comovement between Commodities and Stock Markets**

Jones and Gautam (1996) test whether the reaction of international stock markets to oil shocks can be justified by current and future changes in real cash flows or changes in expected returns or both. Their results suggest that in the postwar period, the reaction of American and Canadian stock prices to oil shocks can be completely accounted for by the impact of these shocks on real cash flows alone. In contrast, in both the United Kingdom and Japan, oil prices shocks appear to cause larger changes in stock prices than can be justified by subsequent changes in real cash flows or by changing expected returns.

Basher and Sadorsky (2006) study the impact of oil price changes on a large set of emerging stock market returns. They find strong evidence that oil price risk

impacts stock price returns in emerging markets.

Cong et al. (2008) study the interactive relationships between oil price shocks and the Chinese stock market using multivariate vector auto-regression. Their results suggest that oil price shocks do not show statistically significant impact on the real stock returns of most Chinese stock market indexes, except for manufacturing index and some oil companies. Some important oil price shocks depress oil company stock prices. Increases in oil price volatility may increase the speculation in the mining index and petrochemicals index, which raise their stock returns. Both the world oil price shocks and China oil price shocks can explain much more than interest rates for the manufacturing index, which means that oil price shocks are a significant source of monthly volatility in its stock returns, the relative importance of oil price shocks and interest rates varies across different indices and oil company stock prices in Chinese stock market.

Chiou and Lee (2009) examine the asymmetric effects of oil prices on stock returns of daily data on S&P 500 and West Texas Intermediate (WTI) oil transactions covering the period from January 1992 to November 2006. They incorporate the expected, unexpected and negative unexpected oil price fluctuations with stock returns into the ARJI (Autoregressive Conditional Jump Intensity) model. Their findings suggest that high fluctuations in oil prices have asymmetric unexpected impacts on S&P 500 returns.

Aloui and Jammazi (2009) use a two regime Markov-Switching EGARCH model to examine the relationship between crude oil price shocks and stock markets of UK,

France and Japan over the sample period from January 1989 to December 2007. They detect two episodes of series behavior one relative to low mean/high variance regime and the other to high mean/low variance regime. Also, they find evidence that recessions coincide with the low mean/high variance regime. They allow both real stock returns and probability of transitions from one regime to another to depend on the net oil price increase variable. In addition, their results show that increases in oil prices have a significant role in determining both the volatility of stock returns and the probability of transition across regimes.

Imarhiagbe (2010) analyzes the impact of oil prices on stock prices of selected major oil producing and consuming countries with nominal exchange rates as an additional determinant. He finds one long-run relationship (Mexico inconclusive) in Saudi Arabia, India, China and the US while Russia exhibits two long-run relationships. The results from the long-run exclusion test suggest all three variables cannot be eliminated from cointegrating space in all countries (except Mexico). The weak exogeneity test reveals all variables to be responsive to deviation from long-run relationships (except China).

Chen (2010) investigates whether a higher oil price pushes the stock market into bear territory, by using time-varying transition-probability Markov-switching models. The empirical evidence from monthly returns on the S&P 500 stock index suggests that an increase in oil prices leads to a higher probability of a bear market emerging.

Gogineni (2010) studies the impact of daily oil price changes on the stock returns of a wide array of industries. His results suggest that in addition to the stock returns of

industries that depend heavily on oil, stock returns of some industries that use little oil also are sensitive to oil prices perhaps because their main customers are impacted by oil price changes.

Cifarelli and Paladino (2010) investigate the relationship between oil prices, stock prices and US dollar exchange rate from October 1992 to June 2008 using a behavioral Intertemporal Capital Asset Pricing Model (ICAPM) approach where noise traders are allowed to influence asset demands. They find strong evidence that the serial correlation of oil returns is influenced by the conditional covariances between Dow Jones Industrial index return and the US dollar exchange rate change. Moreover, the feedback of the conditional covariance between stock returns and oil returns is important for the feedback traders in the equity markets. Their results suggest that traders hedge their portfolio considering oil as a component of their wealth allocation strategy, and this may have some policy implications.

Ono (2011) examines the impact of oil prices on real stock returns for the BRIC countries over the period of Jan 1999 to Sep 2009 using VAR models. He finds that real stock returns positively respond to some of the oil price indicators with statistical significance for China, India and Russia, whereas those of Brazil do not show any significant responses. In addition, statistically significant asymmetric effects of oil price increases and decreases are observed in India.

Filis et al. (2011) investigate the time-varying correlation between stock market prices and oil prices for oil-importing and oil-exporting countries. Their results show that oil prices exercise a negative effect in all stock markets, regardless of the origin

of the oil price shock. The only exception is the 2008 global financial crisis where the lagged oil prices exhibit a positive correlation with stock markets.

Mohanty and Nandha (2011) study the relation between oil price movements and stock returns in US transportation companies. Their results suggest that oil price exposures of firms in the US transportation sector vary across firms and over time. The varying effects of oil price shocks on stock returns may be attributed to several factors such as differences among firms' cost structure, financial policies, diversification activities, and hedging strategies.

Broadstock et al. (2012) use time varying conditional correlation and asset pricing models to discover how the dynamics of international oil prices affect energy related stock returns in China. Their results show a much stronger relation following the 2008 financial crisis.

Aloui et al. (2012) focus on the effects of oil price shocks on stock market returns in emerging countries. Their results suggest that oil price risk is significantly priced in emerging markets, and that the oil impact is asymmetric with respect to market phases. Multivariate GARCH models are used to model conditional correlations and to analyze the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. His results show that the stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices. On average, a \$1 long position in clean energy companies can be hedged for 20 cents with a short position in the crude oil futures market.

Lee et al. (2012) examine sector stock prices and oil prices in January 1991 to May 2009 for the G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States). They find that stock price changes lead oil price changes in 8 of 9 sectors in Germany, most in the G7 countries followed by the UK, Italy, France, Canada and the US. However, such causal relationship is found for Japan. With respect to specific sectors, stock price changes in consumer staples and materials sectors were impacted most significantly by oil price changes followed by transportation, financial, energy, health care, industrials, utilities, information technology and telecommunication sectors with the exception of consumer discretionary sector. In addition, short term stock price changes are found to lead positively oil price changes.

Li et al. (2012) investigate the relationship between oil prices and the Chinese stock market at the sector level. In a panel cointegration and Granger causality framework, the major sectors in China are studied using data collected from July 2001 to December 2010. Their results indicate that there is some evidence of structural breaks in the interaction between oil prices and Chinese sectoral stocks. The long-run estimates suggest that the real oil price has a positive effect on sectoral stocks in the long run.

Wen et al. (2012) apply time-varying copulas to investigate whether a contagion effect existed between energy and stock markets during the recent financial crisis. Their findings suggest that there is a significantly increasing dependence between crude oil and stock markets after the failure of Lehman Brothers, thus supporting the

existence of contagion in the sense of Forbes and Rigobon's (2002) definition.

Moreover, increased tail dependence and symmetry characterize all the paired markets.

Creti et al. (2013) study the links between price returns for 25 commodities and stocks over the period from January 2001 to November 2011. They find a speculation phenomenon is highlighted for oil, coffee and cocoa, while the safe-haven role of gold is evidenced at the idiosyncratic level.

Awartani and Maghyreh (2013) focus on the dynamic spillover of return and volatility between oil and equities in the Gulf Cooperation Council Countries during the period 2004 to 2012. Their results indicate that return and volatility transmissions are bi-directional, albeit asymmetric. In particular, the oil market gives other markets more than it receives in terms of both returns and volatilities.

In review of the literature, most of the studies on correlation between stock markets and commodity markets only focus on the correlation of oil prices and stock markets. Therefore, there is a research gap on correlation between stock markets and different kind of commodities. In order to fill this gap, our study extends the previous literature by taking copper and aluminum into consideration.

## **2.5 Hypotheses**

Based on the theoretical foundations and literature review, this study tries to answer two related questions:



1. Do dynamic correlations exist between selected world major stock markets and commodity markets?
2. Has the 2007 global financial crisis strengthened or weakened the relationships between selected stock markets and commodity markets?

Thus, hypothesis 1 is:

H1: Dynamic correlations exist between selected world major stock markets and commodity markets.

And hypothesis 2 is:

H2: The 2007 global financial crisis has strengthened the dynamic correlations between selected stock markets and commodity markets.

## Chapter 3: Data and Methodology

### 3.1 Data Selection and Descriptive Statistics

This thesis selects the daily spot prices of bulk commodities, including Organization of the Petroleum Exporting Countries (OPEC) petroleum, London Metal Exchange (LME) copper, and LME aluminum from January 1, 2003 to December 31, 2012, and daily closing prices of China (SSE), U.S. (S&P500), Russia (RTS), Australia (S&P/ASX 200), and Canada (S&P/TSX) of the same period. All of the data are from Yahoo Finance, OPEC, and LME. All of the commodity prices are quoted in US dollars. Data during holidays are excluded when merged, and 2,293 trading days of each series are acquired. All of the computations are conducted using STATA 12 software.

Return of series at time  $t$  is represented as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right). \quad (1)$$

Where  $P_t$  represents the index price or commodity price at time  $t$ .

Some basic descriptive statistics of converted data are shown in Table 1, with descriptions to various parameters therein given as follows.

Skewness represents the third central moment of variables. Kurtosis measures concentration of distribution.

Jarque-Bera statistic of normal distribution is a statistic integrating skewness and kurtosis, satisfying two-dimensional Chi-squared distribution. Through comparison with corresponding critical value, it can be determined whether the samples are in normal distribution. Conclusions could be drawn from the JB value of Table 1 that all data of time series do not satisfy the assumption of normal distribution, but present the characteristics of financial data, with typical sharp peak and thick tails.

Q (lags) statistic of Ljung Box is used to verify the autocorrelation degree of series. The data in brackets is the number of lag intervals which is originally assumed as correlation coefficient (0). It can be concluded from the data in Table 1 that at the significance level of 5% are significantly autocorrelated.

In order to verify data stationarity, we conduct the DF test, ADF test with 10 lagged intervals, and Pilips Perron test. In all tests, the stationarity becomes significant at the significance level of 1%. This indicates that all series are stationary and thereby Autoregressive Integrated Moving Average model (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity model (GARCH) operations are feasible.

The ARCH LM test represents the Lagrange test of Autoregressive Conditional Heteroskedasticity (ARCH) effect of data. For each series, its own lag terms are used

to carry out ordinary least squares regression and then take the regression residual for the LM test. It can be concluded that at the condition when the data lags 5 intervals, ARCH test values of all series are at the significance level of 1%. This indicates that heteroscedasticity exists in each series and supports the reasonableness of selecting GARCH model to analyze the data.

**Table 1: Basic Statistical Information of Stock Indexes and Commodities Price Returns**

	SSE	SP500	ASX	RTS	TSX	Oil	Copper	Aluminum
Mean value	0.0002271	0.0001875	0.0001933	0.0006260	0.0002606	0.000553	0.000705	0.000192
Standard deviation	0.0174720	0.0133724	0.0111238	0.0232590	0.0119740	0.018442	0.021034	0.016417
Skewness	-0.2651558	-0.4919415	-0.5014732	-0.6027275	-0.7752254	0.670811	-0.130313	-0.290078
Kurtosis	7.4439758	11.0814200	10.3348756	14.3249248	11.5893067	23.007510	6.494144	5.045439
Mean value	0.0002532	0.0007395	0.0006033	0.001745193	0.0007200	0.001449	0.000768	0.000498
Max.	0.0903426	0.0924066	0.07369715	-0.2119942	0.0700405	0.263790	0.118539	0.069149
Min.	-0.1276357	-0.0946951	-0.1048740	0.2020392	-0.0978785	-0.100288	-0.117981	-0.083877
Ljung-Box Q (5 lags)	10.918**	64.243***	8.2422	38.354***	19.329***	86.764***	16.844***	11.682**
Ljung-Box Q (10 lags)	30.186***	77.168***	16.805*	42.242***	24.716***	102.74***	25.909***	15.178
Ljung-Box Q (20 lags)	42.573***	129.12***	42.839***	69.097***	81.803***	136.53***	38.168***	24
Unit root DF test	-49.1480***	-56.0400***	-49.9710***	-42.7620***	-49.7340***	-40.1420***	-50.9140***	-50.7970***
Unit root ADF (10 lags) test	-13.1430***	-13.3920***	-8.308***	-13.9960***	-13.1670***	-13.7560***	-11.9640***	-13.9310***
Philips perron test	-49.1550***	-56.4230***	-50.0050***	-42.6860***	-49.9960***	-40.0810***	-50.8310***	-50.7420***
Arch test (5 lags)	127.384***	535.601***	243.583***	423.31***	610.533***	212.277***	199.585***	69.207***

Note: table shows the descriptive statistics for period (01/01/2003-31/12/2012). \*\*\*, \*\* and \* indicate the significance level at 1%, 5%, 10% respectively.

### 3.2 ARCH and GARCH Model

The ARCH model Engle (1982), is mainly used to describe volatility clustering phenomenon occurring in financial time series. Engle used the autoregressive conditional heteroscedasticity, namely, ARCH model, which is capable of describing the volatility clustering phenomenon in a better way, with the model given as follows.

Linear regression model considering k variables is

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_k X_{kt} + u_t$$

(1)

Provided the available information of the previous period, namely t-1 period, is the condition, where  $Y_t$  is the dependent variable,  $X_{1t}$  is the independent variable, the error terms conform to the distribution  $u_t \sim N(0, (\alpha_0 + \alpha_1 u_{t-1}^2))$ .

That is to say, the variance of error terms satisfies ARCH (1) process. If

$$Var(u_t) = \sigma^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_p u_{t-p}^2, \quad (2)$$

the variance of error terms satisfies ARCH (p) process. Where  $u_{t-1}$  is the previous residuals.

Because  $\sigma^2$  is unobservable and is generally replaced by  $\hat{u}_t^2$ , the regression

$$\hat{u}_t^2 = \alpha_0 + \alpha_1 \hat{u}_{t-1}^2 + \alpha_2 \hat{u}_{t-2}^2 + \dots \alpha_p \hat{u}_{t-p}^2 \quad (3)$$

can be made for verification.  $\hat{u}_t$  refers to residual acquired from the regression.

In order to increase the applicability of the model, Bollerslev (1992) put forward the generalized autoregressive conditional heteroskedasticity, in which  $\sigma_{t-1}^2$  is used to replace  $\hat{u}_{t-1}^2$  of the former model, and the conditional variance of error terms is changed into

$$Var(u_t) = \sigma^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2. \quad (4)$$

This is the form of GARCH (1, 1) model. In the formula, where  $\alpha_0$  is the constant,  $\alpha_1$  is the coefficient of previous residuals quadratic term and  $\beta_1$  is the coefficient of conditional variance quadratic term.  $\alpha_1 u_{t-1}^2$  is also called the ARCH term, and  $\beta_1 \sigma_{t-1}^2$  term is also called the GARCH term. The formula:

$$Var(u_t) = \sigma^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \dots + \alpha_p u_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_q \sigma_{t-q}^2 \quad (5)$$

is more general, indicating the form of GARCH (p, q) model.

Variance of error terms is the data measuring volatility of time series. In order to study the mutual impact of volatility of several time series, GARCH model has gradually evolved into multivariate generalized autoregressive conditional heteroskedasticity. In consideration of general situation of MGARCH, the conditional variance of univariate GARCH model,

$$Var(u_t) = \sigma^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \dots + \alpha_p u_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_q \sigma_{t-q}^2, \quad (6)$$

has to be represented by using conditional covariance matrix which is indicated by  $H$ .

Considering  $H_t$  is more suitable to be used to represent the dynamic nature, the

two-dimensional GARCH (1, 1) model is selected in this thesis. The dynamic

conditional covariance matrix is represented as

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} = \begin{pmatrix} \alpha_{01} \\ \alpha_{02} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \begin{pmatrix} u_{1,t-1} \\ u_{2,t-1} \end{pmatrix} \begin{pmatrix} u_{1,t-1} \\ u_{2,t-1} \end{pmatrix}' + \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix}. \quad (7)$$

In the calculation result  $\begin{pmatrix} u_{1,t-1}^2 & u_{1,t-1} \cdot u_{2,t-1} \\ u_{2,t-1} \cdot u_{1,t-1} & u_{2,t-1}^2 \end{pmatrix}$  of  $\begin{pmatrix} u_{1,t-1} \\ u_{2,t-1} \end{pmatrix} \begin{pmatrix} u_{1,t-1} \\ u_{2,t-1} \end{pmatrix}'$ , elements

on the secondary diagonal are the same, so in order to simplify the operation, the

triangle part is extended into a three-dimensional vector, namely,

$$\begin{pmatrix} u_{1,t-1}^2 & u_{1,t-1} \cdot u_{2,t-1} \\ u_{2,t-1} \cdot u_{1,t-1} & u_{2,t-1}^2 \end{pmatrix} \Rightarrow \begin{pmatrix} u_{1,t-1}^2 \\ u_{2,t-1} \cdot u_{1,t-1} \\ u_{2,t-1}^2 \end{pmatrix}. \quad (8)$$

Accordingly, the coefficient matrixes of  $\alpha$  and  $\beta$  are changed into three-dimensional

situations, and the overall conditional covariance matrix is changed into



$$H_t = \begin{pmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{pmatrix} = \begin{pmatrix} \alpha_{01} \\ \alpha_{02} \\ \alpha_{03} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{pmatrix} \begin{pmatrix} u_{1,t-1}^2 \\ u_{2,t-1} \cdot u_{1,t-1} \\ u_{2,t-1}^2 \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix} \quad (9)$$

It can be concluded after calculation by adopting

$$h_{11,t} = \alpha_{01} + \alpha_{11}u_{1,t-1}^2 + \alpha_{12}u_{2,t-1} \cdot u_{1,t-1} + \alpha_{13}u_{2,t-1}^2 + \beta_{11}h_{11,t-1} + \beta_{12}h_{12,t-1} + \beta_{13}h_{22,t-1} \quad (10)$$

that the conditional variance of error terms of time series 1 is impacted not only by its  $u_{1,t-1}^2$  and  $\beta_{11}h_{11,t-1}$ , but also by  $u_{2,t-1}^2$  and  $h_{22,t-1}$  of time series 2. Meanwhile, it is synchronously impacted by  $u_{2,t-1} \cdot u_{1,t-1}$  and  $\beta_{12}h_{12,t-1}$  involved in the two time series. The impact degree under each condition depends on the coefficient before each term.

Generally, we can use  $h_{11,t}$  to describe the volatility of series at period t. It can be concluded from the operational formula for conditional variance  $h_{11,t}$  of the aforesaid time series 1 that:

1. Volatility  $h_{11,t}$  of series 1 at period t is impacted by its own ARCH terms and GARCH terms, as well as ARCH terms and GARCH terms of series 2;
2. the synergetic impact between the two series will also pose simultaneous impact on volatility  $h_{11,t}$  of series 1 at period t and volatility  $h_{22,t}$  of series

2 at period  $t$ ;

3. if we estimate the data of coefficient matrixes  $\alpha$  and  $\beta$ , we will be able to analyze the degree of mutual impact between the two series, and this situation can be extended to the N-dimensional situation.

Based on the three reasons as aforesaid, MGARCH model is widely used to analyze the volatility of time series, or the transmission among the series.

### 3.3 DCC-GARCH Model

In order to study the dynamic correlations between the stock markets and commodities, this study relies on the dynamic conditional correlation DCC-GARCH models introduced by Engle (2002).

Assumed that time series is

$$Y_t = E(Y_t | I_{t-1}) + \varepsilon_t. \quad (11)$$

Wherein,  $I_{t-1}$  refers to the information collection of period  $t-1$  and

$$\varepsilon_t = H_t^{1/2} v_t. \quad (12)$$

Where  $H_t$  is the conditional covariance matrix,  $v_t$  is the error-term vector.

The corresponding conditional covariance matrix is represented as

$$H_t = D_t^{1/2} R_t D_t^{1/2}. \quad (13)$$

$$\text{Wherein, } D_t = \text{diag}(\sqrt{h_{11,t}}, \dots, \sqrt{h_{nn,t}}) \quad (14)$$

is a diagonal matrix of time-varying standard deviations issued from the estimation of univariate GARCH (1, 1) model.  $h_{11,t}$  is the volatility.

$$\text{and } R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2} \quad (15)$$

is the dynamic conditional correlation coefficient matrix,

$$\text{while } Q_t = (1 - \lambda_1 - \lambda_2) \bar{Q} + \lambda_1 u_{t-1} u'_{t-1} + \lambda_2 Q_{t-1} \quad (16)$$

$Q_t$  is the covariance matrix and  $\bar{Q}$  is the unconditional variance matrix of  $n \times n$  dimension ( $u_t$ ). Its value can be estimated or directly set as empirical value to make the estimation easier.  $\lambda_1$  and  $\lambda_2$  are non-negative vector parameters, called coefficients of DCC-GARCH model, satisfying:

$$\lambda_1 + \lambda_2 \leq 1 \quad (17)$$

Therefore, in the matrix,

$$q_{ij,t} = (1 - \lambda_1 - \lambda_2) \bar{q}_{ij} + \lambda_1 u_{i,t-1} u'_{j,t-1} + \lambda_2 q_{ij,t-1}. \quad (18)$$

The aforesaid contents are the representation form of DCC (1, 1) model. If it is DCC (p, q) model, the representation form shall be

$$q_{ij,t} = (1 - \lambda_1 - \lambda_2) \bar{q}_{ij} + \lambda_1 \sum_{i=1}^p u_{i,t-i} u'_{j,t-i} + \lambda_2 \sum_{j=1}^q q_{ij,t-j} \quad (19)$$

In the process of studying correlation, the most important thing is to acquire the dynamic conditional correlation coefficient  $r_{ij,t}$  in correlation matrix through operation of matrix  $Q_t$ , with

$$r_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} = \frac{(1 - \lambda_1 - \lambda_2) \bar{q}_{ij} + \lambda_1 \sum_{m=1}^p u_{i,t-m} u'_{j,t-m} + \lambda_2 \sum_{n=1}^q q_{ij,t-n}}{\sqrt{\left[ (1 - \lambda_1 - \lambda_2) \bar{q}_{ii} + \lambda_1 \sum_{m=1}^p u_{i,t-m}^2 + \lambda_2 \sum_{n=1}^q q_{ii,t-n} \right] \left[ (1 - \lambda_1 - \lambda_2) \bar{q}_{jj} + \lambda_1 \sum_{m=1}^p u_{j,t-m}^2 + \lambda_2 \sum_{n=1}^q q_{jj,t-n} \right]}} \quad (20)$$

In DCC (1, 1) model, the aforesaid formula can be simplified as

$$r_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} = \frac{(1 - \lambda_1 - \lambda_2) \bar{q}_{ij} + \lambda_1 u_{i,t-1} u'_{j,t-1} + \lambda_2 q_{ij,t-1}}{\sqrt{\left[ (1 - \lambda_1 - \lambda_2) \bar{q}_{ii} + \lambda_1 u_{i,t-1}^2 + \lambda_2 q_{ii,t-1} \right] \left[ (1 - \lambda_1 - \lambda_2) \bar{q}_{jj} + \lambda_1 u_{j,t-1}^2 + \lambda_2 q_{jj,t-1} \right]}} \quad (21)$$

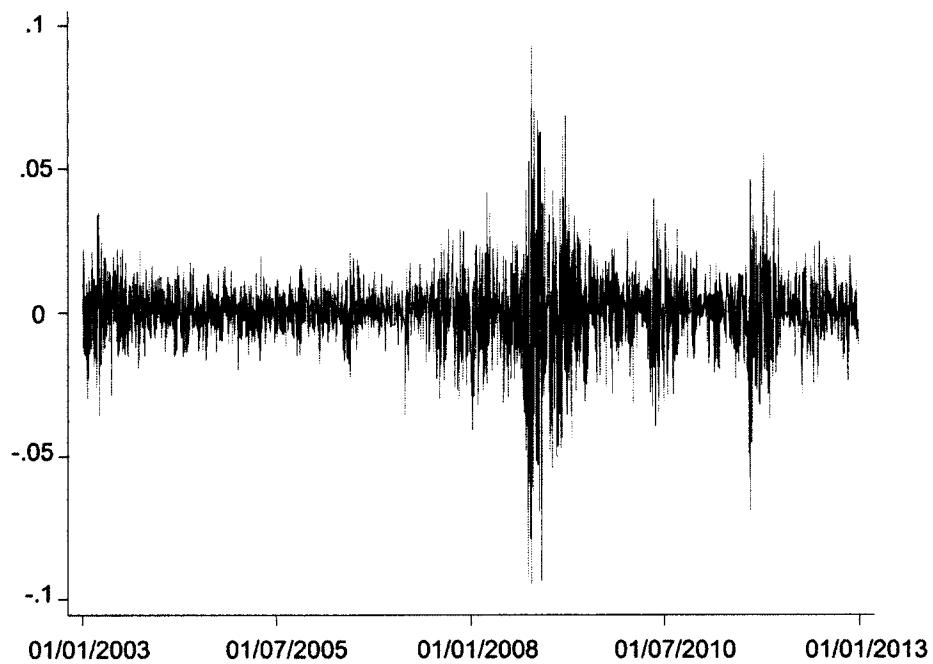
The DCC-GARCH model is generally divided into two steps for estimation: first, estimate the univariate GARCH model of each series, calculate its residual and conditional variance, divide the square root of conditional variance by the residual, and acquire the standardized residual; second, use the calculated standardized residual for regression and acquire the dynamic conditional correlation coefficient.

## Chapter 4: Results

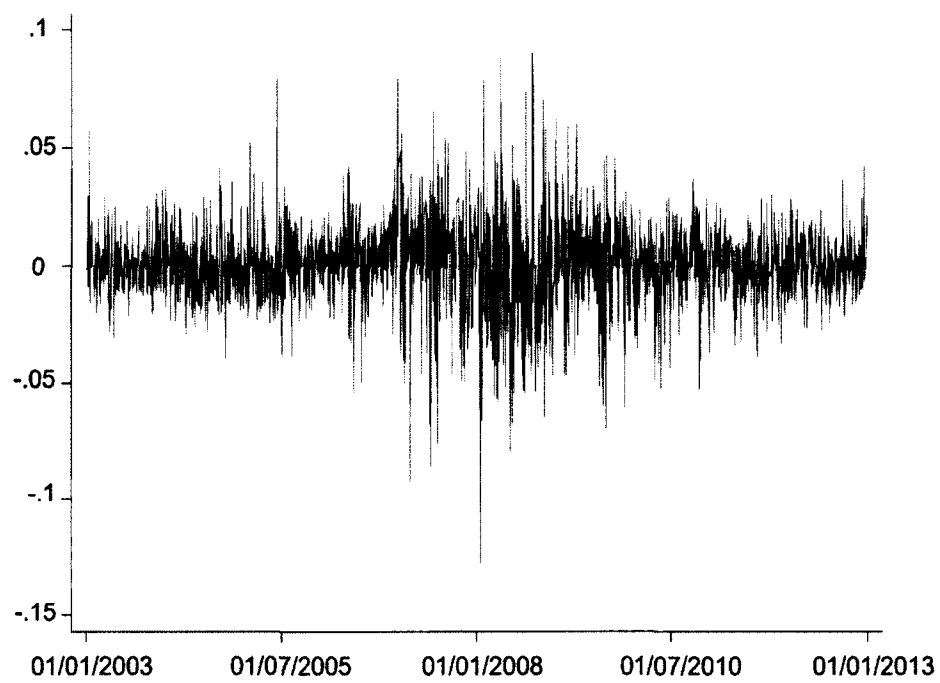
### 4.1 Empirical Results

Figure 3.1 to 3.8 present the changes of various stock indexes and price returns from January 1, 2003 to December 31, 2012. Obvious volatility clustering phenomenon can be observed in the second half of 2008 to the first half of 2009.

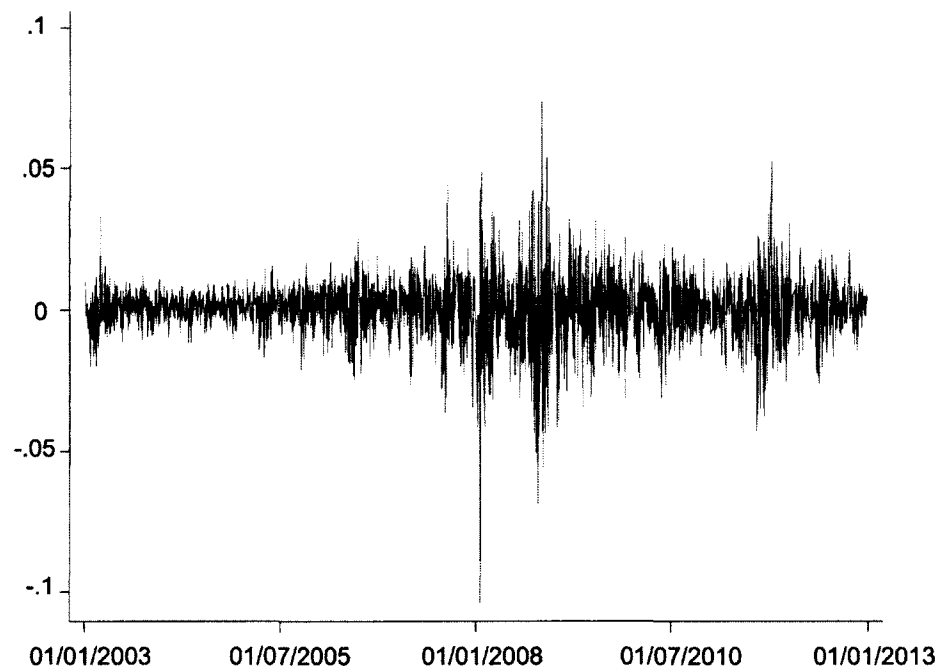
**Figure (3.1 to 3.8): Volatility of Stock Indexes and Commodities Price**



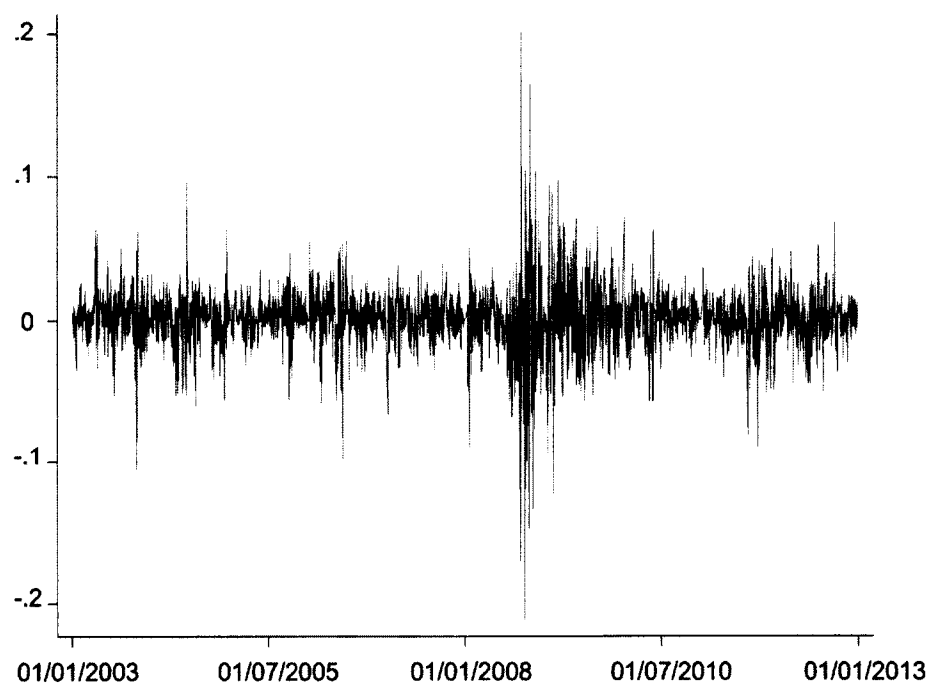
**Figure 3.1: S&P 500**



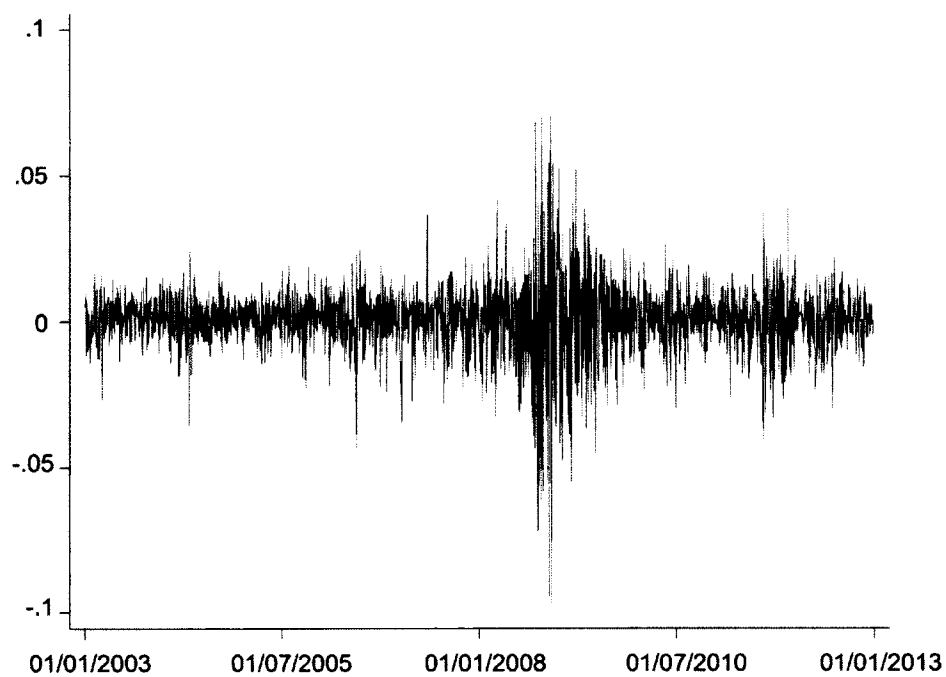
**Figure 3.2: SSE**



**Figure 3.3: ASX 200**

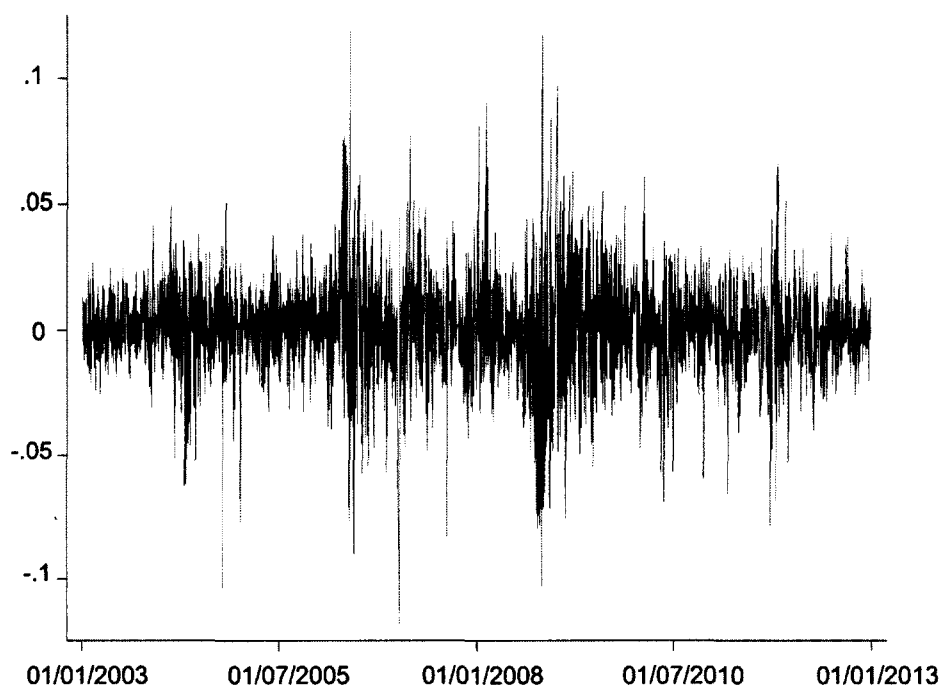


**Figure 3.4: RTS**

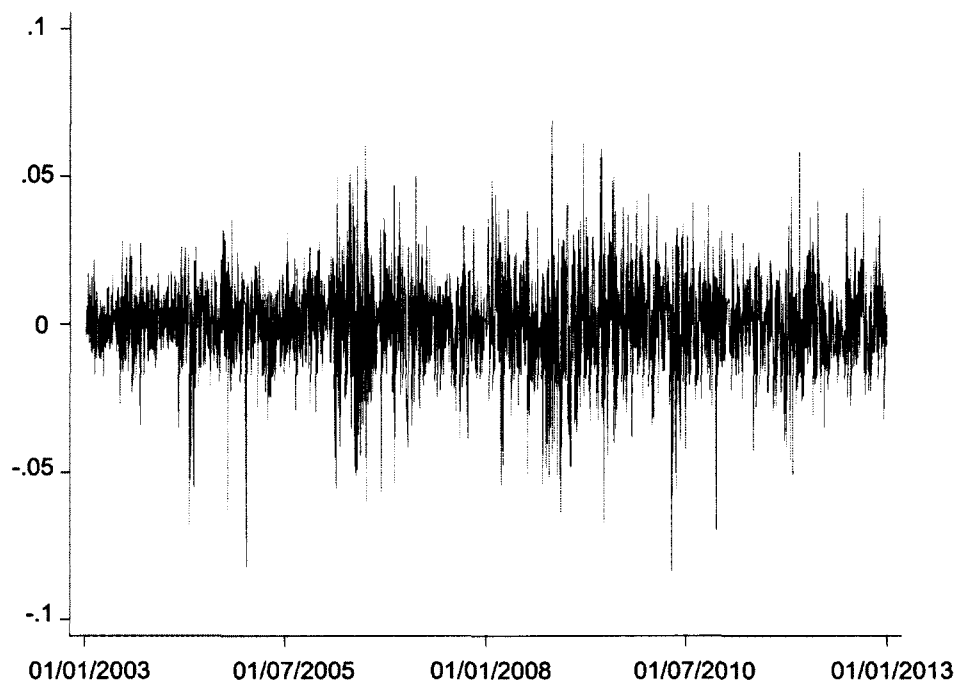


**Figure 3.5: TSX**

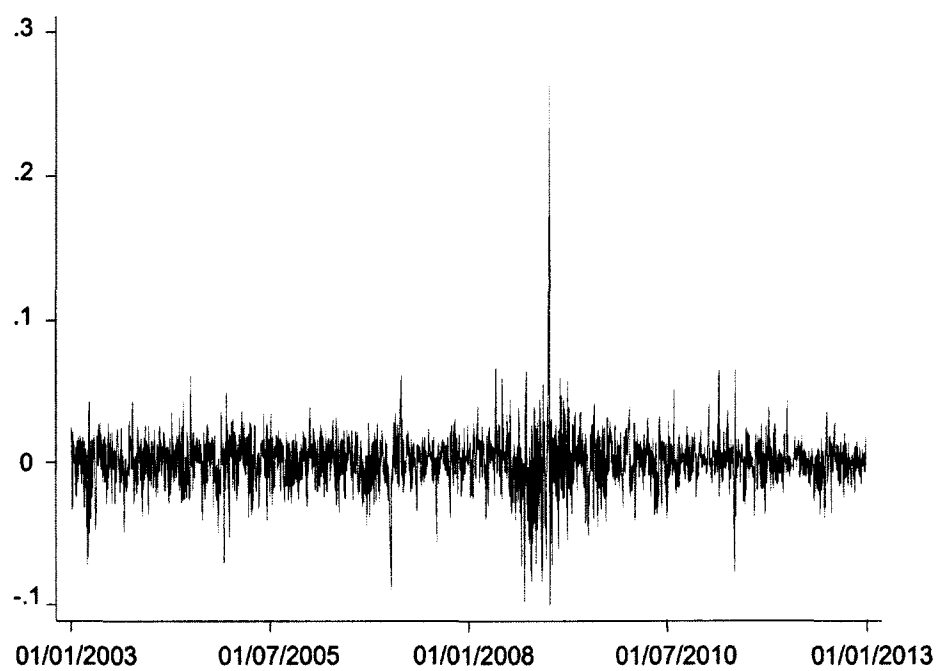




**Figure 3.6: Copper**



**Figure 3.7: Aluminum**



**Figure 3.8: Oil**

Based on the ARCH test to each time series data, it is reasonable to confirm these data fit the GARCH model. After using GARCH (1, 1) model to respectively estimate each time series, we acquire the GARCH (1, 1) estimators of all-time series as shown in Table 2 (a & b). Wherein,  $\omega$ ,  $\alpha$ ,  $\beta$  respectively represent coefficient of constant term, ARCH (1) term, and GARCH (1) term. It can be concluded that the coefficient of all ARCH terms and GARCH terms is significant at the significance level of 1%.  $\alpha$  represents the coefficient concerning the influence of market impact of previous trading day on the volatility of the current period;  $\beta$  represents the influence of previous volatility variance to current volatility variance; while  $\alpha+\beta$  represents the duration degree of the whole market volatility. If all  $\alpha+\beta$  values approach 1, it indicates that the market volatility has a long duration, which is also accordant to actual market situations.

**Table 2 (a): Estimated Parameters of Stock Indexes and Commodities Price  
Returns Based on GARCH (1, 1) Model**

Coefficient		SSE	SP500	ASX	RTS
$\omega$	Estimate	2.10E-06	1.40E-06	4.25E-07	1.29E-05
	Standard error	4.81E-07	2.60E-07	1.49E-07	1.56E-06
	t statistics (significant level)	4.37***	5.37***	2.68***	8.29***
$\alpha$	Estimate	0.0468452	0.0750043	0.0860872	0.1119939
	Standard error	0.0053315	0.0073804	0.0080137	0.0093697
	t statistics (significant level)	8.79***	10.16***	10.74***	11.95***
$\beta$	Estimate	0.9463950	0.9139929	0.9138546	0.8609338
	Standard error	0.0057834	0.0082856	0.0082701	0.0112244
	t statistics (significant level)	163.64***	110.31***	110.50***	76.70***
$\alpha+\beta$		0.993240	0.988997	0.999942	0.972928

Note: \*\*\*, \*\* and \* indicate the significance level at 1%, 5%, 10% respectively.

**Table 2 (b): Estimated Parameters of Stock Indexes and Commodities Price Returns Based on GARCH (1, 1) Model**

Coefficient		TSX	Oil	Copper	Aluminum
$\omega$	Estimate	1.22E-06	4.70E-06	7.49E-06	2.54E-06
	Standard error	3.40E-07	8.16E-07	2.09E-06	9.23E-07
	t statistics (significant level)	3.60***	5.75***	3.589***	2.75***
$\alpha$	Estimate	0.0773466	0.0496354	0.090118	0.055038
	Standard error	0.0086656	0.0060602	0.010072	0.007405
	t statistics (significant level)	8.93***	8.19***	8.95***	7.43***
$\beta$	Estimate	0.9120209	0.9346573	0.894850	0.934607
	Standard error	0.0100588	0.0077422	0.011479	0.008487
	t statistics (significant level)	90.67***	120.72***	77.96***	110.12***
$\alpha+\beta$		0.989368	0.984293	0.984969	0.989645

Note: \*\*\*, \*\* and \* indicate the significance level at 1%, 5%, 10% respectively.

It can be concluded from the estimated parameters of the GARCH (1, 1) model from Table (a & b) that the 8 time series' coefficients of the ARCH terms and the GARCH terms of all models are significant at the significance level at 1%, which supports the conjecture that that volatility clustering effect exists in the time series. That is to say, volatility clustering effect exists. In addition, except Russia's RTS, all other  $\alpha$  estimators are lower than 0.1, which indicates that volatility of previous trading day has not much impact on the volatility of current period, but the volatility of duration has much impact on that of the current period. All  $\beta$  estimators are larger than 0.9 (except RTS and Copper), which provides further support to the high impact

of previous trading day's volatility duration on that of the current period.

All  $\alpha+\beta$  values are very close to 1, which indicates that the market volatility has a long duration, and the attenuation speed of volatility is very slow. The situation can also be observed from the linear graph concerning stock indexes and commodity price returns of recent 10 years in Figure 3.1 to 3.8.

In order to acquire the dynamic conditional correlation between prices and stock indexes, prices of three commodities and returns of five stock indexes are used to respectively establish the DCC-GARCH (1, 1) model, acquiring the estimated parameters shown in Table 3 (a to c).

In Table 3 (a to c),  $\bar{\rho}_{12}$  represents estimator of average correlation coefficient. Except that the  $\bar{\rho}_{12}$  values of Copper/SSE and Copper/TSX are not significant, Copper/ASX is significant at the significance level of 5%, and Aluminum/SSE and Copper/SP500 are significant at the significance level of 10%. The correlation coefficients of Oil/SSE, Oil/SP500, Oil/ASX, Oil/RTS, Oil/TSX, Copper/ASX, Copper/RTS, Aluminum/SP500, Aluminum/ASX, Aluminum/RTS and Aluminum/TSX are all significant at the significance level of 1%, which indicates the existence of volatility correlation. In addition, when estimators of dynamic correlation coefficients between returns of SSE and the three kinds of commodities are compared with other stock indexes, correlation coefficients of Oil/SSE and Aluminum/SSE are much lower than those between other stock indexes and the three commodities.

**Table 3 (a): Estimated Parameters of Stock Indexes and Commodities Price Returns Based on DCC-GARCH (1, 1) Model**

		Oil/SSE	Oil/SP500	Oil/ASX	Oil/RTS	Oil/TSX
$\lambda_1$	Estimate	0.018519	0.020917	0.033414	0.035019	0.023267
	Standard error	0.006833	0.003919	0.007423	0.006536	0.006429
	t statistic	2.71***	5.34***	4.59***	5.36***	3.62***
$\lambda_2$	Estimate	0.967146	0.975029	0.952326	0.952865	0.951001
	Standard error	0.015327	0.004731	0.011951	0.009427	0.014202
	t statistic	63.1***	206.1***	79.69***	101.08***	66.96***
$\bar{\rho}_{12}$	Estimate	0.137425	0.245529	0.275441	0.423131	0.297871
	Standard error	0.050819	0.119947	0.061464	0.063666	0.037012
	t statistic	2.7***	2.05***	4.48***	6.65***	8.05***

Note: \*\*\*, \*\* and \* indicate the significance level at 1%, 5%, 10% respectively.

**Table 3 (b): Estimated Parameters of Stock Indexes and Commodities Price  
Returns Based on DCC-GARCH (1, 1) Model**

		Copper/SSE	Copper/SP500	Copper/ASX	Copper/RTS	Copper/TSX
$\lambda_1$	Estimate	0.012443	0.016687	0.0021275	0.028239	0.012807
	Standard error	0.003065	0.003215	0.0028	0.005572	0.002616
	t statistic	4.06***	5.19***	0.76	5.07***	4.9***
$\lambda_2$	Estimate	0.985228	0.981547	0.995803	0.957407	0.986564
	Standard error	0.003532	0.003581	0.001325	0.008536	0.003328
	t statistic	278.98***	274.09***	751.53***	112.16***	296.46***
$\bar{\rho}_{12}$	Estimate	0.254112	0.351147	0.442768	0.425704	0.642139
	Standard error	0.156811	0.199489	0.208309	0.052171	0.567119
	t statistic	1.62	1.76*	2.13**	8.16***	1.13

Note: \*\*\*, \*\* and \* indicate the significance level at 1%, 5%, 10% respectively.



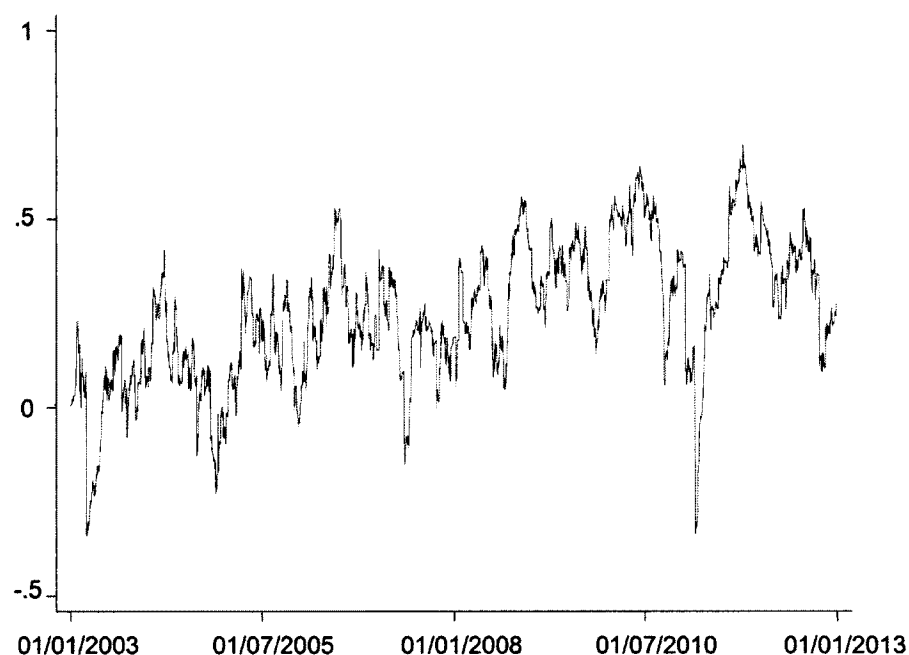
**Table 3 (c): Estimated Parameters of Stock Indexes and Commodities Price Returns Based on DCC-GARCH (1, 1) Model**

		Aluminum/SSE	Aluminum/SP500	Aluminum/ASX	Aluminum/RTS	Aluminum/TSX
$\lambda_1$	Estimate	0.009643	0.015815	0.024994	0.021165	0.017574
	Standard error	0.003528	0.005314	0.017107	0.005722	0.005333
	t statistic	2.73***	2.98***	1.46	3.7***	3.3***
$\lambda_2$	Estimate	0.984898	0.980000	0.810409	0.956890	0.965546
	Standard error	0.005555	0.008145	0.160910	0.012265	0.010320
	t statistic	177.3***	120.19***	5.04***	78.02***	93.56***
$\bar{\rho}_{12}$	Estimate	0.114036	0.266125	0.181784	0.327057	0.351866
	Standard error	0.068539	0.082456	0.023859	0.038015	0.038423
	t statistic	1.66*	3.23***	7.62***	8.6***	9.16***

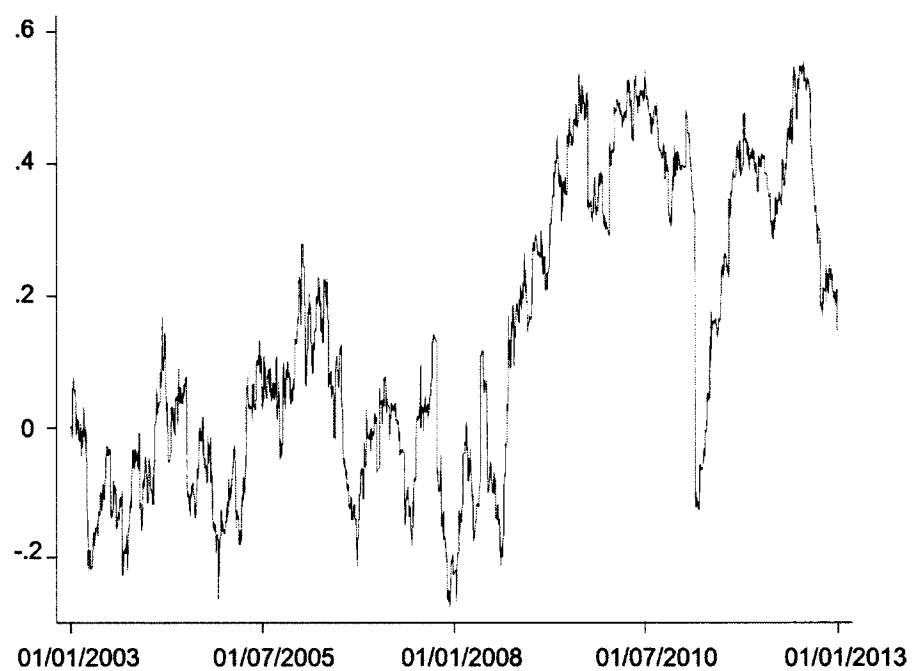
Note: \*\*\*, \*\* and \* indicate the significance level at 1%, 5%, 10% respectively.

Figure 4.1 to 4.15 outline in detail the changes of dynamic correlation of the price returns between selected commodities and stock indexes from January 1, 2003 to December 31, 2012. It could be observed that the correlation is a process of volatility, but all correlation coefficients have a rising trend in volatility. It is more dramatic that the dynamic correlation coefficients of S&P 500 to the three kinds of commodities had a sharp rise after the financial crisis in 2007, and simultaneously declined from 2011 to the end of 2012. The aforesaid characteristics are also embodied in other figures concerning dynamic correlation coefficients, but less obvious than those of SP500.

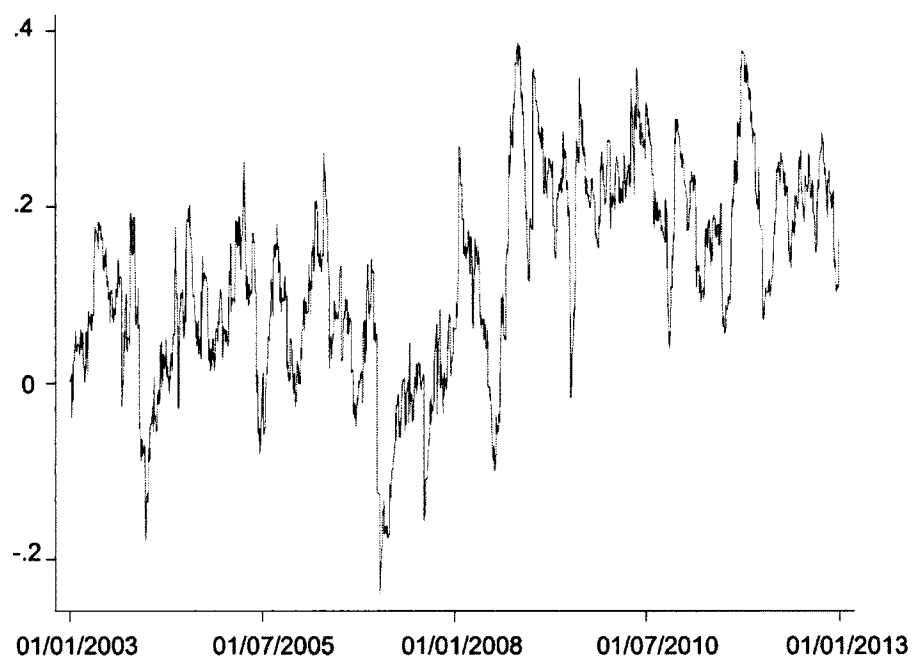
**Figure (4.1 to 4.15): Dynamic Conditional Correlation between Commodities Prices and Stock Indexes Returns**



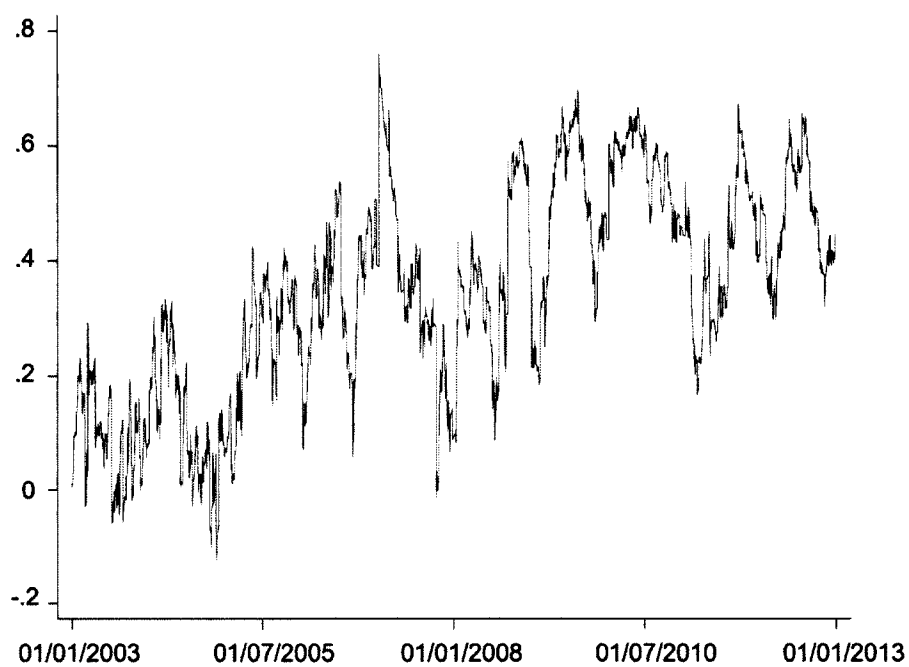
**Figure 4.1: Oil / ASX 200**



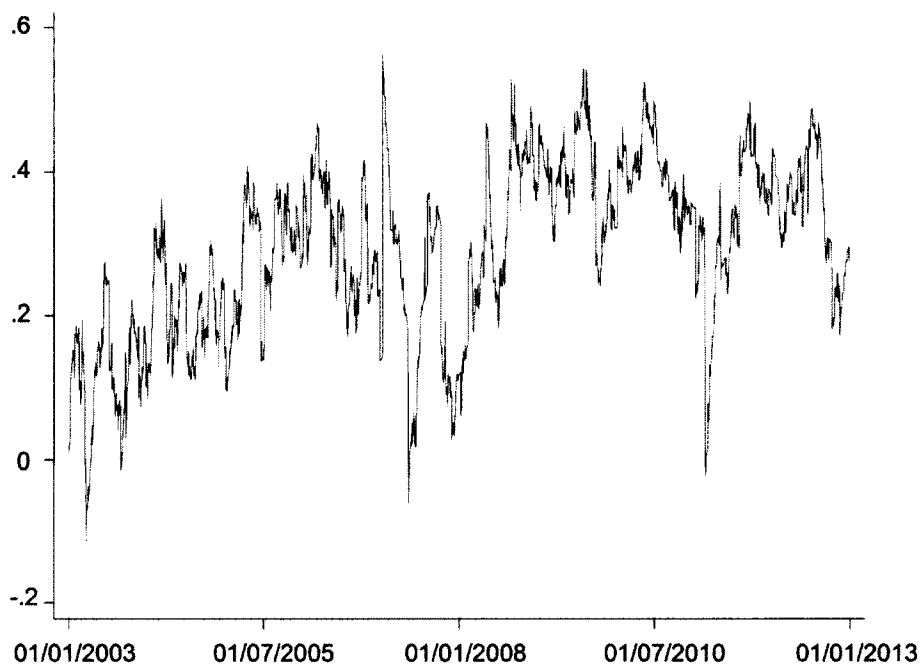
**Figure 4.2: Oil / S&P 500**



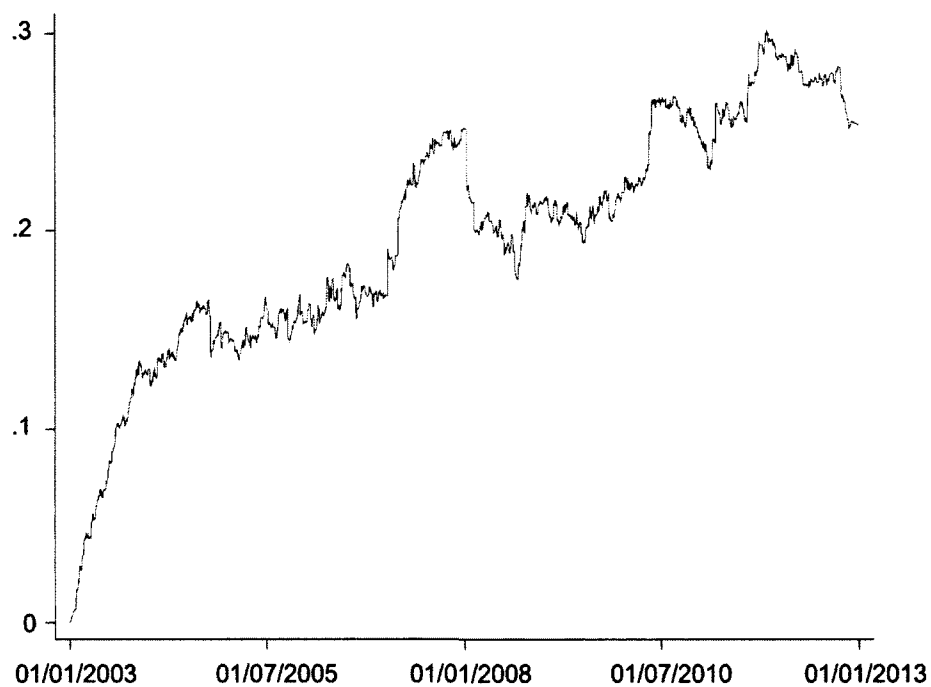
**Figure 4.3: Oil / SSE**



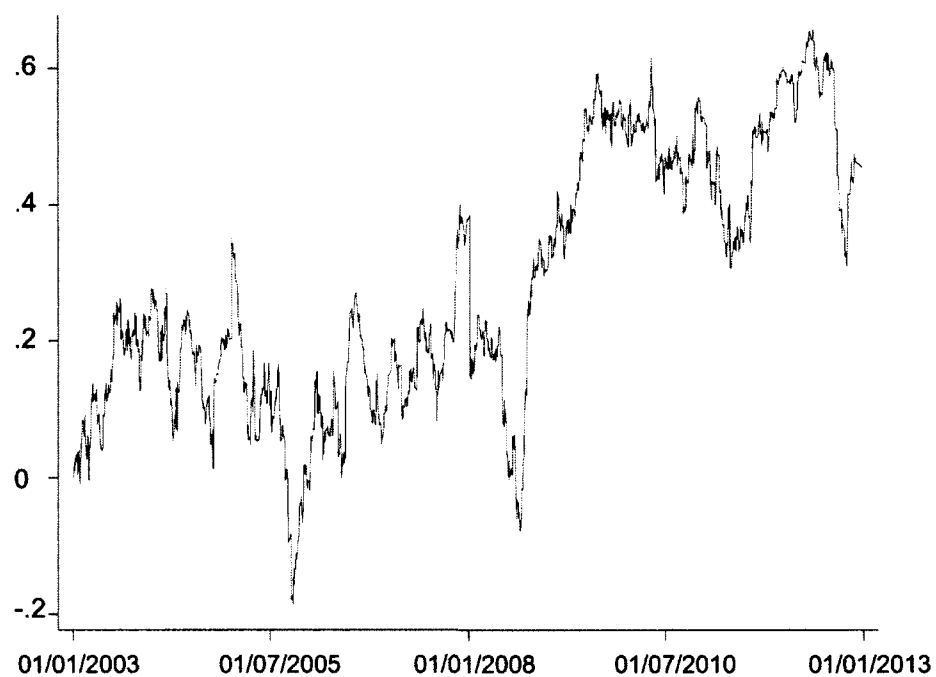
**Figure 4.4: Oil / RTS**



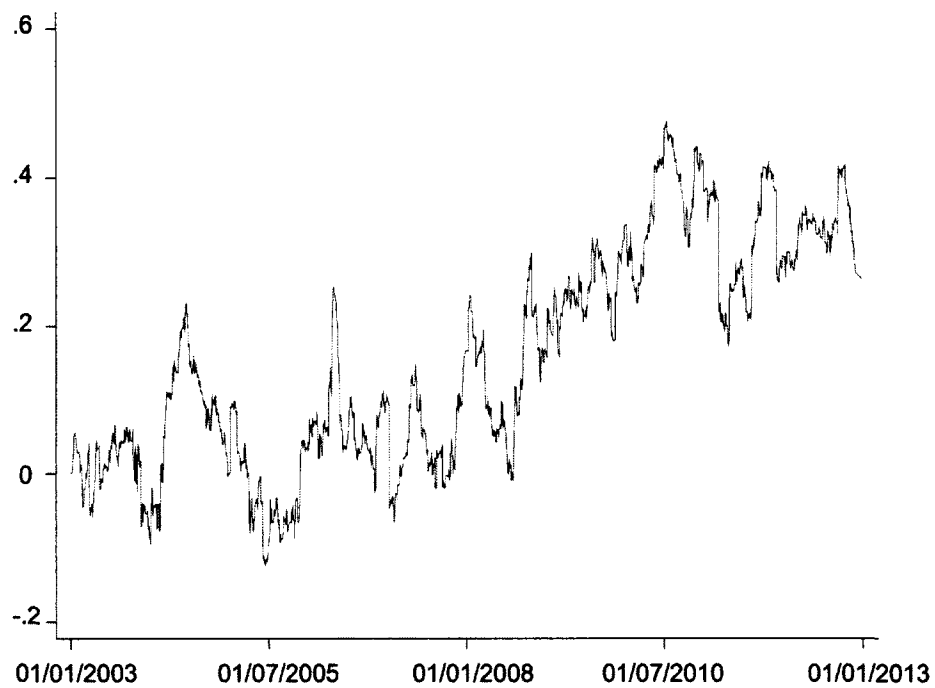
**Figure 4.5: Oil / TSX**



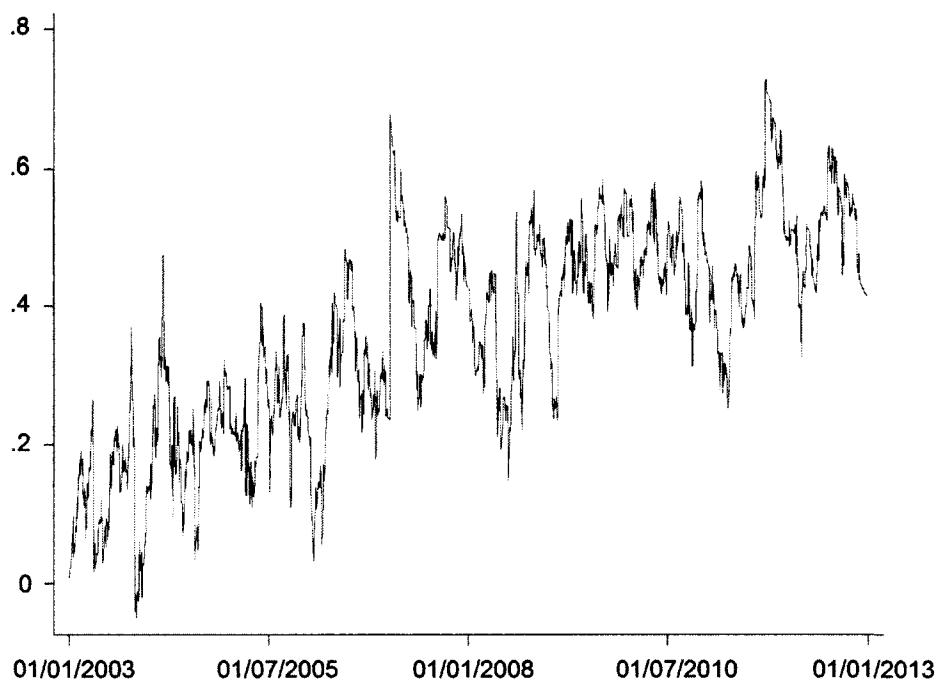
**Figure 4.6: Copper / ASX 200**



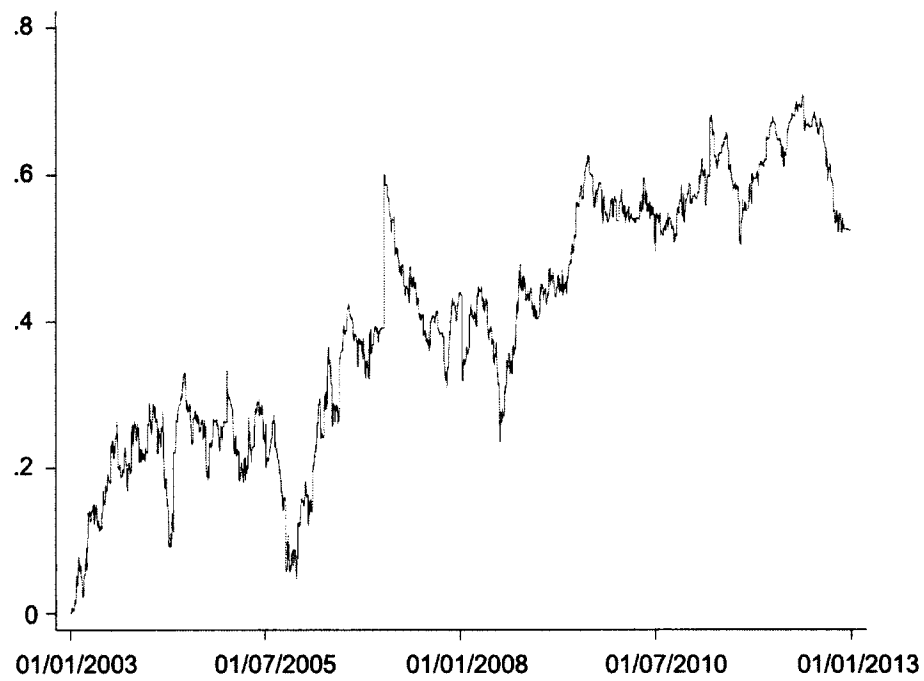
**Figure 4.7: Copper / S&P 500**



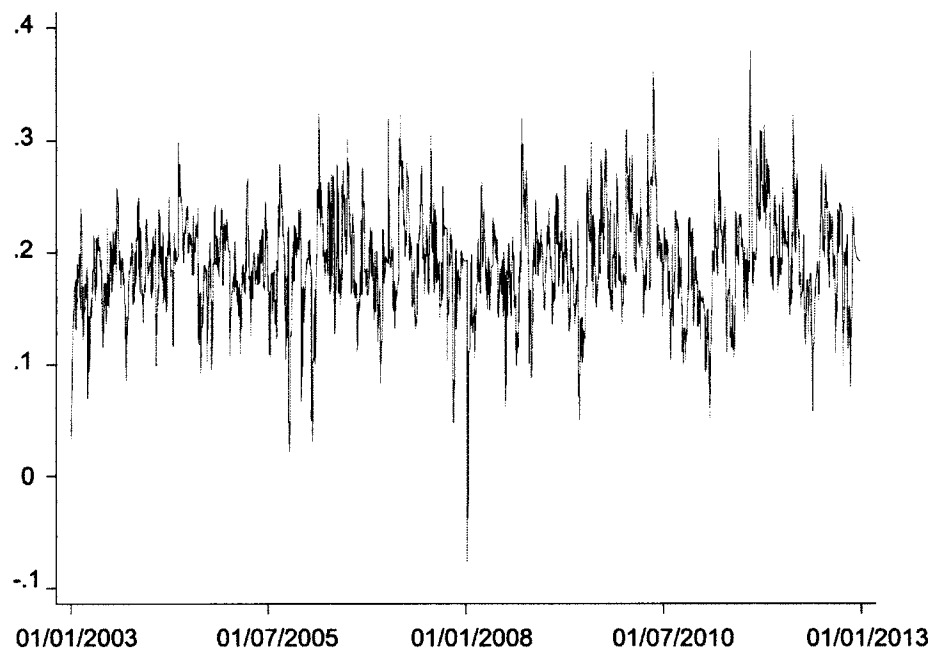
**Figure 4.8: Copper / SSE**



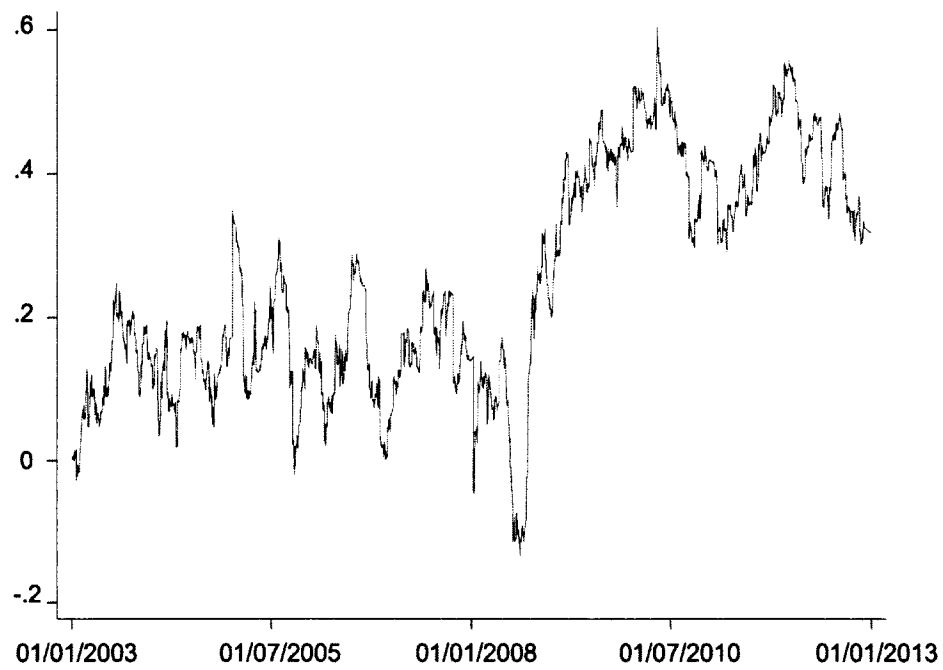
**Figure 4.9: Copper / RTS**



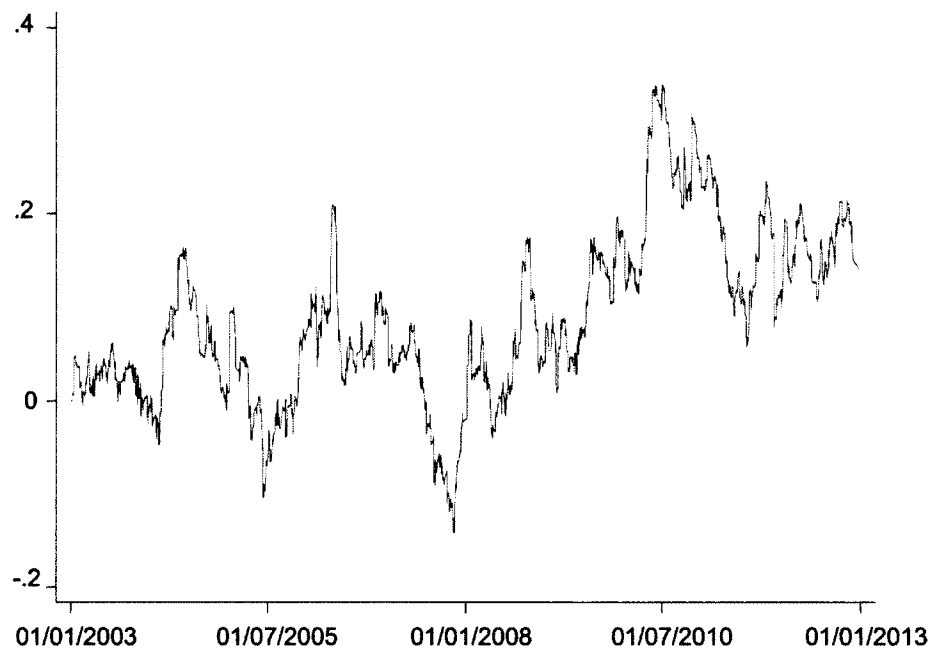
**Figure 4.10: Copper / TSX**



**Figure 4.11: Aluminum / ASX 200**

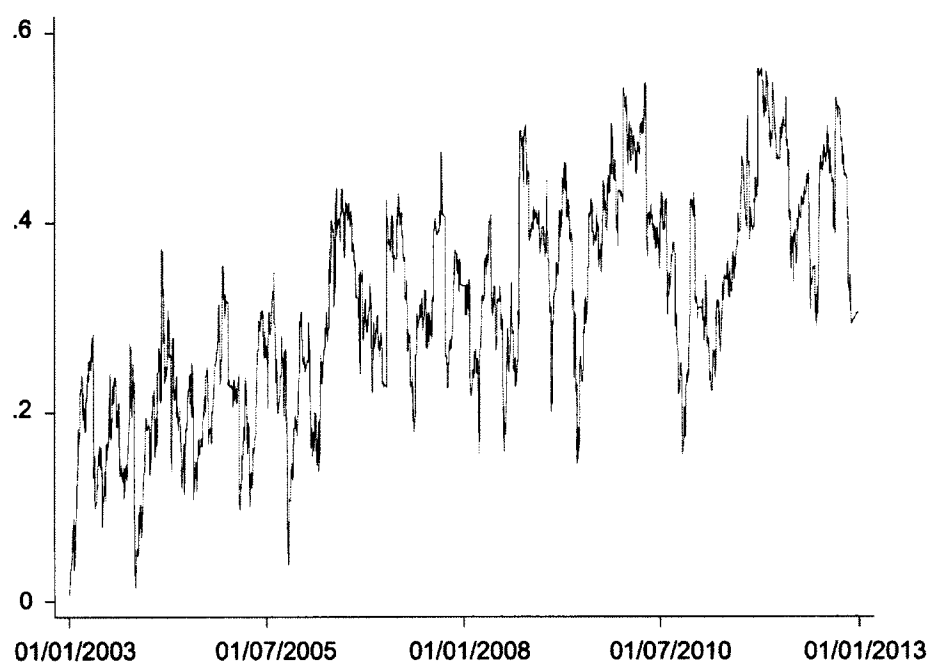


**Figure 4.12: Aluminum / S&P 500**

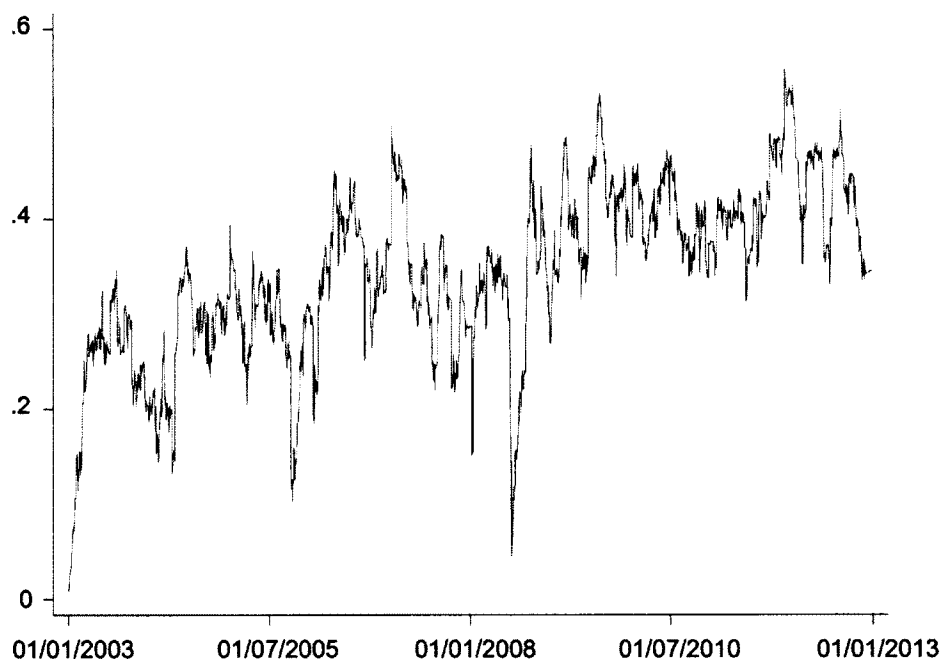


**Figure 4.13: Aluminum / SSE**





**Figure 4.14: Aluminum / RTS**



**Figure 4.15: Aluminum / TSX**

In order to compare the changes of dynamic correlations before the financial crisis with those after, this thesis takes July 17, 2007 as the date of occurrence of financial crisis and compares the correlation by dividing it into two parts, with the results shown in Table 4. The reason for taking this date is supported by Dungey (2009) who used July 17, 2007 as the starting date of the 2007 Global Financial Crisis in her study. She observed that the crisis gave the first signal on July 17, 2007, when Bear Stearns announced its failing hedge funds.

It can be concluded from Table 4 (a to c) that the dynamic correlation coefficients between price changes of the three kinds of commodities, including petroleum, copper, and aluminum, and stock indexes of various countries after the financial crisis have changed from those before; the mean value, maximum value, and minimum value have increased by at least 0.1. Using China's SSE as an example, the mean value of its dynamic correlation coefficients between SSE and prices of the three commodities before the financial crisis are 0.056548, 0.035666, and 0.042759 respectively, less than 0.1, which suggests that the correlations are very low. However, after the financial crisis, the values are respectively increased to 0.180363, 0.256244, and 0.124297 respectively. Further, the dynamic correlation coefficients between SSE and the three kinds of commodities are obviously lower than those between the other four stock indexes and corresponding commodities.

**Table 4 (a to c): Comparison of Statistical Data Concerning Dynamic Conditional Correlation Coefficients before and after the 2007 Financial Crisis**

Tale 4 (a): Comparison of Dynamic Conditional Correlation Coefficients between Price Returns of Petroleum and Stock Index before and after the 2007 Financial Crisis

	<b>Oil/SSE</b>		<b>Oil/SP500</b>		<b>Oil/ASX</b>		<b>Oil/RTS</b>		<b>Oil/TSX</b>	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mean value	0.056548	0.180363	-0.018630	0.261203	0.140825	0.340598	0.231917	0.439522	0.230825	0.343352
Standard deviation	0.082789	0.102624	0.106574	0.216813	0.153355	0.160070	0.166556	0.145708	0.112290	0.104236
Min.	-0.241159	-0.157357	-0.265154	-0.276160	-0.342130	-0.337979	-0.123457	-0.016957	-0.117995	-0.022355
Max.	0.260972	0.386709	0.279197	0.553493	0.531424	0.697110	0.760062	0.697545	0.562518	0.543050

Note: before crisis period is from 01/01/2003 to 16/07/2007. After crisis period is from 17/07/2007 to 31/12/2012.

Tale 4 (b): Comparison of Dynamic Conditional Correlation Coefficients between Price Returns of Copper and Stock Index before and after the 2007 Financial Crisis

	<b>Copper/SSE</b>		<b>Copper/SP500</b>		<b>Copper/ASX</b>		<b>Copper/RTS</b>		<b>Copper/TSX</b>	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mean value	0.035666	0.256244	0.129524	0.406963	0.143324	0.240604	0.241702	0.458031	0.255913	0.525547
Standard deviation	0.071335	0.118186	0.087984	0.159145	0.045457	0.031385	0.127056	0.095659	0.117426	0.101915
Min.	-0.124288	-0.020086	-0.187439	-0.078276	0.000457	0.175142	-0.051017	0.148841	0.000272	0.235761
Max.	0.251757	0.475140	0.351993	0.654468	0.239414	0.301425	0.679440	0.729155	0.601759	0.709273

Note: before crisis period is from 01/01/2003 to 16/07/2007. After crisis period is from 17/07/2007 to 31/12/2012.

Tale 4 (c): Comparison of Dynamic Conditional Correlation Coefficients between Price Returns of Aluminum and Stock Index before and after the 2007 Financial Crisis

	<b>Aluminum/SSE</b>		<b>Aluminum/SP500</b>		<b>Aluminum/ASX</b>		<b>Aluminum/RTS</b>		<b>Aluminum/TSX</b>	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mean value	0.042759	0.124297	0.140872	0.339197	0.186995	0.192052	0.235379	0.376392	0.292613	0.386859
Standard deviation	0.049480	0.098967	0.070994	0.156221	0.041955	0.048145	0.089602	0.088570	0.079113	0.076653
Min.	-0.102866	-0.141891	-0.027543	-0.135223	0.021703	-0.076288	0.007233	0.144386	0.006062	0.044720
Max.	0.209048	0.339157	0.348799	0.603558	0.323896	0.378978	0.437281	0.563591	0.498049	0.558973

Note: before crisis period is from 01/01/2003 to 16/07/2007. After crisis period is from 17/07/2007 to 31/12/2012.

## Chapter 5: Conclusions

### 5.1 Conclusions

This thesis focuses on the dynamic conditional correlation between prices of three kinds of bulk commodities and five selected stock indexes based on the DCC-GARCH model. Based on the empirical results, it can be concluded as follows:

First of all, dynamic correlations exist between prices of bulk international commodities and world major stock indexes. Except the estimators of average correlation coefficient of Copper/SSE and Copper/TSX are not significant, Copper/ASX is significant at the significance level of 5%, and Aluminum/SSE and Copper/SP500 are significant at the significance level of 10%. The estimators of average correlation coefficient of Oil/SSE, Oil/SP500, Oil/ASX, Oil/RTS, Oil/TSX, Copper/ASX, Copper/RTS, Aluminum/SP500, Aluminum/ASX, Aluminum/RTS and Aluminum/TSX are all significant at the significance level of 1%. Especially USA (S&P 500), Australia (S&P/ASX 200), and Russia (RTS) have very significant correlations to three commodities prices, which indicates that important raw materials market and crude oil market are correlated to selected stock indexes. Moreover, the estimators of average correlation coefficient of Oil/SSE and Aluminum/SSE are much lower than those between other stock indexes and the three commodities.

Second, after comparing correlation coefficients between SSE and the three kinds of commodities with those between other stock indexes and commodities, it can be

observed that the dynamic correlation coefficients between SSE and the three kinds of commodities are always far lower than corresponding dynamic correlation coefficients of other stock indexes both before and after the financial crisis, especially when they are compared with S&P 500, RTS, and TSX. However, at the same time, China is the main importer of raw materials. With constant development of in industries such as real estate, automobile, and mechanical manufacturing, China's demand for copper is increasing rapidly. Even as the second largest copper producer in the world, with the output of copper currently ranking only second to Chile, the gap in supply of copper, especially refined copper, always exists in China. In addition, in terms of petroleum, China is the second largest importer in the world, only ranking second to America, having higher foreign-trade dependence. However, the two aforesaid aspects have not been manifested in corresponding dynamic correlation, which indicates that there is a certain gap between opening degree of stock markets in China and those in other countries.

Third, changes can be observed from the comparison of dynamic correlation coefficient between China's stock indexes and prices of the three kinds of bulk commodities before and after the crisis. The mean value of correlation coefficient (Oil/SSE) between return of SSE and that of petroleum price changes from 0.056548 before the financial crisis to 0.180363 after; mean value of correlation coefficient (Copper/SSE) between return of SSE and that of copper price changes from 0.035666 before the financial crisis to 0.256244 after; mean value of correlation coefficient (Aluminum/SSE) between return of SSE and that of aluminum price changes from

0.042759 before the financial crisis to 0.124297 after.

Finally, not only have the dynamic correlation coefficients between China's stock indexes and prices of the three kinds of bulk commodities after the financial crisis increased compared with those after the crisis, but also the same trend is embodied in stock indexes of other countries. The largest change occurs with the S&P500 index, whose dynamic correlation coefficients with selected commodities sharply rise after 2007 and approaches the maximum value (0.6). Then, in the middle of 2011 and at the end of 2012, the three correlation coefficients simultaneously declined, while just in the above two periods the American stock markets and other world major stock markets showed a recovery trend. Therefore, it may be taken into consideration that the correlation among various markets during financial crisis is strong because the general panic emotion during financial crisis leads to large volatility of various markets simultaneously, and causes instant enhancement of correlation. Such situation is also embodied in corresponding correlation coefficients of other countries, but not as significant as that in USA (S&P 500). In addition, after comparing mean values of correlation coefficients between stock indexes of various countries and prices of commodities before the financial crisis with those after the financial crisis, it is observed that some data grows significantly, which indicates that after the financial crisis the correlation between commodities prices and stock indexes has been further strengthened and the integration of global economy is escalating.

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