ERASMUS UNIVERSITY ROTTERDAM

FACULTY OF SCHOOL OF ECONOMICS

Exploring Volatility Spillovers and Dynamic Conditional Correlations among MSCI, NIKKEI 400, S&P 500 and CSI 300 using Multivariate DCC-GARCH models

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Contents

ABSTRACT

The aim of this thesis was to investigate whether volatility spillover effects of MSCI on the NIKKEI 400, S&P 500 and CSI 300 exist, using the DCC-GARCH model and the respective dynamic conditional correlations. For the purposes of the study, day-to-day data was collected for a period that encompassed growth, crisis decline and re-growth, i.e. the period between 25th November 2007 and 12th May 2016. Based on the empirical findings of the research, MSCI has a statistically significant positive effect on the investment returns enjoyed in the equity markets that were examined at a level of significance $\alpha=0.05$, with conditional covariance between MSCI and equity markets being positive and extremely volatile. Further, the results of the empirical analysis that was held with the trivariate DCC-GARCH model indicated that spillover effects are indeed evident between the three major stock markets that were reviewed and compared ($p<0.05$). As far as the analysis of DCCs is concerned, research findings revealed that major contagion effects exist among the markets across the years of the review period, with the corresponding trend lines being more or less straight over the period, indicating a more or less stable equity markets' performance over the review period. From an investors' perspective, research findings indicate that they have to be careful with investing in markets that are subject to contagion effects, while they also have to always quantify the risk of investing in different markets, being flexible in managing their investments in equity markets. Research findings provide important implications for policymakers as well, who shall ensure that spillovers in markets are allowed, especially in the case of future crises that markets may face.

1. INTRODUCTION

Political condition and financial performance have always been two very interconnected terms, with political instability being considered as a factor having a strong impact on financial performance. Based on the findings of Chau et al. (2014), who conducted research to identify the consequence of economic uncertainty in major stock markets in the Middle East, a rise in the number and value of Islamic markets has been observed in period of political uncertainty. In the same context, after examining how the Australian federal election has led to economic uncertainty, Smales (2014) has reached the conclusion that overall economic uncertainty is correlated with uncertainty in financial markets. Antonakakis et al. (2013) have found that economic ambiguity and stock markets are two negatively associated areas, with the only positive connection between them having been evident during the global economic crisis and particularly in the year 2018. In their research, Boubakri et al. (2011) have found that governmental bond yields are highly associated with the political environment and the policies that governments develop in a national context. The above connection between governmental policies and bond yields is generally mirrored in the spillover effects and the overall performance of financial markets. In periods of financial crises, volatility in the performance of financial markets is mostly observed, while investment risks in these markets are also higher (Vortelinos & Saha, 2016).

The most major determinant of the financial performance of organizations, both in present and future, is their share price. Current share prices are highly determined by forecasts about their future prices and the future nature of the factors that determine them. It follows from the above that any estimations about cash flows, as well as estimations about discount rates, are likely to influence share prices at present (Chang et al., 2015). Regarding the degree to which stock returns are explained by patterns in expected cash flows, cash flow expectations are often reported next to dividend yields, the dividend-to-price ratio, and earnings variables, such as the earnings-to-price ratio and the dividend-to-earnings ratio. Based on the analysis provided by Fama (1990), the variance of stock returns could be described and measured in terms of shocks in future cash flows. The analysis of Campbell (1990) is also important in analyzing how unplanned stock returns and changes in future dividends are associated. Based on the exploration of US stocks over the review period 1927-1988, the researcher has found that 30% of variance in future dividends shall be explained by unplanned stock returns. Further to the above, based on the literature review conducted by Hecht and Vuolteenaho (2005), unlike unplanned current stock returns, future stock returns are negatively correlated with future dividends. More specifically, there are certain factors that stock returns are correlated with, namely prevailing earnings growth, dividend growth and future real activity, also accompanied by other factors and variables that have an impact on organization's cash flows. The findings of Hirshleifer et al. (2009) are somewhat different, when they reveal that cumulative accruals are positively correlated with stocks, whereas cash flows are negatively correlated with stocks. Based on the findings of the same research, innovations and cash flows returns are positively correlated, while at the same time also influencing corporate profitability. In a more recent study, the one conducted by Maio and Santa-Clara (2015), it was found that dividend yield is a very powerful factor in predicting future stock prices. The time difference of the price-dividend ratio is closely related to the time variation of future returns and future dividends. It follows from the above that a major question to be answered is whether it is possible to predict stock and dividends, taking into consideration that the response to this question is crucial for addressing and explaining the risk-return relationship (Koijen and Van Nieuwerburgh 2011).

Of course, there are also studies that correlate stock prices with the other factors that can pose risk to them, namely business cycles and fluctuations in various key macroeconomic factors. For example, Fama and French (1989) demonstrate that future stock prices and future bonds include an insurance period which is has a clear business cycle model. In addition, expected returns with premium associated with long-term business circles. Over time, the premium can be very strong. More interestingly, premium can affect stock markets more than it would affect the bond market. Another very indicative empirical study in the above context is the one conducted by Kandir (2008). The researcher reviewed the period 1997-2005 with respect to the development of various macroeconomic indicators, namely GDP growth rate, industrial production index, consumer price index, money supply, exchange rates, interest rates, international crude oil prices and the MSCI World Equity Index performance, taking Turkish stock returns as a case study. Based on the findings of the research, interest rates and MSCI World Equity Index influence portfolio returns, while the corresponding impact of inflation was found to be slightly significant.

In contrast, industrial production, money supply and oil prices were not found to have a statistically significant effect on stocks (Kandir, 2008). In a similar context, Osamwonyi and Evbayiro-Osagie (2012) conducted empirical research in Nigeria for the period 1975-2005 to identify whether correlation exists between certain macroeconomic variables (interest rates, inflation fiscal deficit, GDP and money supply) with capital market index. The researchers came to the conclusion that the development of robust macroeconomic policies is crucial for the development of capital markets.

Oil prices were mentioned before as one of the macroeconomic variables that have been found to influence stock returns. Based on the analysis provided by Kang & Ratti (2013) for the case of the United States, unexpected changes in macroeconomic policy can have a significant effect on stock returns. In the same context, taking oil prices into consideration, increased demand for oil leads to concerns about the adequacy of future oil supply. These concerns in turn lead to strengthening economic policy for oil production, causing uncertainty that negatively affects stock returns. It is worth noting that uncertainty, combined with strong economic policies and rise in oil demand, represents 19% and 12% of long-term stock returns respectively, an effect that is mainly met in countries with high oil-exporting activity. As far as the research of Pradhan et al. (2015) is concerned, this examined how economic growth, real exchange rates, inflation and real interest rates, together with oil prices, can have an impact on stock returns, taking as a case study the G-20 countries for the review period 1961-2012. Based on research findings, a strong correlation has been identified between economic growth and all other macroeconomic variables under investigation. Indeed, in the long-run, economic growth has been found to be vulnerable and responsive to any changes observed in the macroeconomic variables under discussion.

One more factor that has been found to influence stock market performance has been terrorism, at least based on the findings of Nikkinen and Vähämaa (2010). The researchers conducted research to examine the relationship between terrorism and global stock market performance, placing emphasis on expected density probability of the effects of terrorism on FTSE 100 index. Based on their findings, a statistically significant negative correlation was found between

terrorism and FTSE 100 index, with terrorism attacks having been found to cause a significant drop in the particular index, while at the same time also increasing overall market uncertainty.
In particular, the terrorist attacks undoubtedly cause a sharp drop in the FTSE 100 index price and a significant increase in market uncertainty. Moreover, the researchers conclude that expected density probability of the FTSE 100 became significantly more negative and decreased by the passage of time immediately after the terrorist acts. The rationale behind conducting studies like those outlined above is that investors are active players in stock markets, so they are based on both the actual real situations in the market and combine them with previous research studies to take their investment decisions.

Taking the brief theoretical framework outlined above into consideration, the aim of this thesis is to explore the potential volatility spillover effects and the potential dynamic conditional correlations between four major global equity indexes, namely the national equity markets of China, Japan and USA, as well as the MSCI global index, i.e. a major global index market. Different multivariate GARCH models will be used, which have never been explored before, thereby indicating the rationale and importance of conducting this research. For the purposes of the thesis, quantitative analysis will be conducted, collecting secondary quantitative data on the four major national and global equity indexes mentioned before. The findings of the research will be presented in the form of tables and diagrams, the analysis of which shall lead to producing meaningful conclusions about the subject under investigation. Apart from the above, dynamic conditional correlation analysis shall also be held.

Chapter 2 is the literature review chapter, which provides an extensive review on the existing academic theory and previous research findings regarding the subject under research. Chapter 3 outlines the methodology followed for the study, justifying the selection of research methods that were followed and the data that was collected. Chapter 4 presents and analyzes the findings of the research. Finally, Chapter 5 provides a summary of research findings, while also presenting the most important and key conclusions drawn on them.

2. LITERATURE REVIEW

The relationship between organizations' type of industrial activity and the performance of their stocks in stock markets is a well-documented one. In other words, there are industrial sectors with a very strong influence in the total capitalization of the global stock market. As such, the magnitude of such industrial sectors is higher, as far as the performance of organizational stocks and the overall stock market are concerned. Apart from the type of industrial activity, the evaluation of the performance of organizations' stocks is also influenced by the type of data that is collected for empirical analysis every time.

One of the previous studies that have explored the influence of the type of industrial sector in stock performance is that of Furman (2000). The researcher conducted research with respect to corporations in Australia, Canada, the United Kingdom and the United States. What makes this research study special is that apart from type of industrial sector and company, the researcher evaluated stock performance also on the basis of companies' geographical location. Data in this research was collected through the international Worldscope for the review period 1992-1996. In order to allow for country-based comparisons, data was separated into industries based on 4-digit SIC codes. Based on the findings of the research, the type of industrial sector was found to strongly influence stock performance in all countries under comparison. It is also worth noting that both type of industry and type of parent company were found to have an influence – though not so significant – in the profitability of the companies that were reviewed. The year of evaluation of stock performance was not found to have a significant effect on research results.

Next to type of industrial sector and type of data collected, interrelationships have also been identified in the performance between different national stock markets. The above has been the main conclusion of the research conducted by Huang, Yang and Hu (2000), who conducted research, in order to identify the causality and co-integration among stock markets of the USA, Japan, and the Southern China Development Triangle region. After conducting root tests between October 1992 and June 1997, the researchers found that there is indeed co-integration between different stock markets, which in the case of this study, though, was evident only in the case between the Shanghai and the Shenzhen stock markets. Also, the Granger causality method that was followed revealed that US stock prices influence those of South China Growth triangle markets to a bigger extent than they influence those of Japan. The researchers reached the conclusion that such research findings are very important, given that someone could observe U.S. stock prices on one day, in order to predict stock prices in Hong Kong and Taiwan the next day.

Another similar research was conducted by Masih and Masih (2001). The researchers' aim was to investigate the interactions among nine major stock markets of the world, namely Australia, Germany, United Kingdom, USA, Japan, South Korea, Singapore, Taiwan and Hong Kong. Based on their findings, the researchers found that a significant interrelationship exists mainly between the UK and the US stock markets, while also predicting the leading role of the Japanese stock markets for the years that would follow.

Martens and Poon (2001) studied the timing of returns and the daily correlation dynamics between international stock markets. They predicted the use of near-close returns underestimates the affection of returns because international stock markets have different trading hours. The rise of daily correlation is only evident under extremely adverse conditions and especially when a large negative return has been recorded previously. By studying the distributions of returns and using daily data, Panas (2001) concluded that there is a long-run dependence in the past returns of the Athens Stock Exchange. In their research, Serletis and Shintani (2003) examined the behavior of the USA stocks through random walk and chaos theory. The researchers reached the conclusion that there is against low-dimensional chaos but also demonstrated the importance of using stochastic models and statistical inference in stock market modeling.

Voronkova (2004) conducted research, in order to identify the long-term interrelationships between Central Europe, American and overall Europe stock markets. The researcher found that Central Europe's stock markets performed better than they did in the past. Also, the same stock markets were found to have become more mature than in the past, while also having established their influence in the performance of stock markets of other regions. However, Timmermann and Granger (2004) investigating the presence of the market hypothesis examined forecasting models and showed that these models cannot be efficient at all.

Another country-comparison research was the one conducted by Papathanasiou, Kouravelos, and Bourletidis (2005). The researchers conducted research, in order to examine interrelationships with respect to stock-market performance between five European stock markets, namely FTSE 100 (England), CAC 40 (France), SMI (Switzerland), DAX 30 (Germany) and the General Index (Greece). They reviewed the period January 1991 - December 2004. Their empirical findings empirical findings showed that indices carried out through the cointegration technique rejected proof of an efficient market in its weak form, whereas positive results to prove the existence of Granger causality among European indicators. Last but not least, research findings also revealed that a strong relationship between the review stock markets exists, a phenomenon that shall also be attributed to globalization and the unification of national borders with respect to trade transactions and financial transactions. Toth and Kertesz (2006) analyzed temporal differences in the cross-correlations of NYSE returns. Empirical evidence reveals the growing efficiency of the market.

Cross-country comparisons were also made by Egert and Kocenda (2007), who examined the interrelationships of the transactions between three major European stock market, namely the stock markets of France, Germany and the UK, which they compared with three emerging European stock markets, namely the stock markets of Czech Republic, Hungary and Poland. The review period for this research was June 2003 - January 2006. Research findings indicated that a strong correlation was observed between the German and French stock markets, as well as a correlation between the two abovementioned markets and that of the UK. In contrast, a slight and insignificant correlation was found between the three major European stock markets and the three emerging stock markets under discussion.

Hou and Robinson (2006) conducted research, as a means of exploring the relationship between industry and average stock returns. This research was held, as a means of filling in the research gap with respect to the hypothesis whether sectoral organization and asset pricing are related with each other. In principle, there are companies finding it difficult to enter some industrial markets, due to the higher barriers that these markets are subject to. In these markets, companies are subject to lower average returns, mainly because of the fact that the average price of failure risk is lower in these markets as well. At the same time, there is also the general opinion that companies operating in larger industries and overall market sectors are also more likely to have lower average returns, given that companies in these markets are more secure against fluctuations in demand. The sample considered includes all NYSE, AMEX, and NASDAQ stocks listed under stock codes 10 or 11 entailed in CRPS Monthly Return File and Compustat Annual Database from July 1963 through December 2001. Before in January 1973 the number of industries was thinner since the CRPS included firms from only the 62 NYSE and AMEX. Stocks are categorized into industries, which are based on a three-digit SIC code. Industry concentration is quantified with the use of the Herfindahl index. The findings of the researchers indicated that asset valuation has an important impact on industry market structure. More specifically, market fundamentals and stock returns were found to be subject to a statistically significant relationship. The positive correlation coefficient identified with respect to the above relationship indicates that when the company has a large value compared to the rest of the markets, then the concentration of the industry increases. It follows from the above that organizations listed in small stock markets may be subject to unexpected returns. Of course, it is also important to control other factors that may influence stock prices, such as the size of the industry, the timing when stock transactions take place and book-to-market price, among others. It is worth noting that the above conclusion is valid both at the sector and the enterprise levels.

Elder and Serletis (2007), following up on research by Serletis and Shintani, (2003), re-examined existing evidence from the literature for the existence of the random walk effect in the USA stock market, using daily observations of the Dow Jones Industrial Average. Their findings indicated that the above-mentioned relationship indeed exists.

Gallagher R. D. and Ignatieva K. (2010) argue that additionally to classic factors affecting Australian stock returns, the structure is very important of the product market. More specifically, differences in stock returns based on market structure are observed for small firms, where increasing industry concentration rises average stock returns while for large firms it tends to decrease them. The sample data was drawn from The Australian school of business share price & price relative (SPPR) database and time examined was from 1993 to 2007. It was historical data for Australian stock market.

Mukherjee, Sen, and Sarkar (2011) tried to detect the possibility of long-run dependence in Indian stock market returns. Net returns showed no long-term dependence unlike absolute and squared returns.

Wang, Podobnik, Horvatic, and Stanley (2011) studied the correlation of time lags in 48 global indices in 48 different countries. Research has proved a strong relation in returns of absolute values of returns that quantify risk. The gravity of the correlations reveals the risk of the portfolios is not reduced through diversification but decays very slowly.

Degiannakis, Filis and Floros (2013) aimed at exploring the relationship between oil prices and stock returns, paying particular attention to the interaction of stock returns with oil prices mainly during periods of oil price shocks. Based on their findings, in mid-2008, when the global economic crisis had started to develop and expand across countries of the world, diversification opportunities emerged for investors in the crude oil market.

Christopoulos, Papathanasiou, Kalantonis et al. (2014) undertook their own research, also as a means of comparing stock performance in various stock markets across Europe and particularly the PIIGS countries, namely Portugal, Italy, Ireland, Greece and Spain. After reviewing stock-market performance in these markets over the period January 2005-January 2011 through following the cointegration method, the researchers concluded in that the hypothesis of efficient market in these countries over the abovementioned review period shall be rejected.

Xiao-lin Li, Mehmet Balcilar, Rangan Gupta and Tsangyao Chang (2015) wanted to explore the correlation among the economic uncertainty index and stocks. The data which was downloaded by the analysts was monthly for the decade 2003-2013 and concerned China and India. They used Granger testing and checked the sample for stability due the structural changes that happened. in it. The empirical results revealed that in the two specific emerging countries the correlation of the under investigation variables is weak. Moreover, I underline that a two-way relationship was delivered among the economic uncertainty index and stock returns for several sub-periods.

The research of Tsung-Pao Wu, Shu-Bing Liu & Shun-Jen Hsueh (2016) is one more research that has investigated the relationship between economic uncertainty and stock market performance. Monthly panel data was collected for the years 2004 and 2005 for nine countries, namely Italy, Spain, England, Germany, France, China, Canada, India and the USA. The empirical findings of the research indicated that dependence should be taken into consideration as well, in order to examine the relationship between economic uncertainty index (EPU) and stock prices. As part of the research methodology, checks were done regarding endogeneity, where its existence is not supported, and the Granger causality test was employed, from which it was resulted that not all stock index prices are correlated with financial uncertainty index. The particular conclusion was exported from the analyses held for India, Spain and Italy, which are countries were economic uncertainty does not have a strong influence on stock markets. Last but not least, it is important to note that the Granger causality tests that were conducted yielded different results and insights for different countries, thereby not leaving room for the generation of generalized conclusions, as derived from mainstream economic theories.

Last but not least, the study by Shirafkan, Masoomzadeh and Sayareh (2017) aims to explore the potential correlation of stock returns in Iran and the time is set from May 2009 until February 2016. Again, in this research, the type of industrial sector was examined as a factor influence stock returns. The findings of this research indicated that the stock returns of credit institutions, industrials, mining, chemicals, nuclear fuel and cement converge in average returns. It was worth noting that the corresponding coefficients were significant at a 10% level. In contrast, companies in other sectors, such as base metals, telecommunications, materials and construction, pharmaceuticals, transportation, communication, and related activities were not found to converge on average returns over the review period.

3. METHODOLOGY

3.1 GARCH MODEL

Firstly, the logarithmic returns are calculated as follows:

$$y_t = \mu + \varepsilon_t, \text{ with } t = 1,\ldots,T \tag{1}$$

where μ is constant and ε_t is standardized residuals defined as follows:

$$\varepsilon_t = \sqrt{h_t} u_t, \text{ where } \varepsilon_t \sim N(0, H_t) \text{ and } u_t \text{ are i.i.d.} \tag{2}$$

where u_t is standardized errors and h_t is conditional variance depending on h_t and ε_t for each market lagged one period, generated by the univariate GARCH (1,1) model (Bollerslev 1986):

$$h_t = \omega + a\varepsilon_{t-1}^2 + bh_{t-1} \tag{3}$$

where ω is constant, a and b are ARCH and GARCH effects.

3.2 GJR GARCH MODEL

This popular model is proposed by Glosten, Jagannathan, and Runkle (1993). Its generalized version is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{4}$$

where S_t^- is a dummy variable that take the value 1 when γ_i is negative and 0 when it is positive. In this model, it is assumed that the impact of ε_t^2 on the conditional variance σ_t^2 is different when ε_t is positive or negative.

3.3 DCC MODEL

In the second stage, the Engle (2002) representation of the multivariate GARCH model is employed in order to estimate the bivariate conditional variance matrix (H_t is N x N matrix, with N the number of markets, i = 1,…,N) as follows:

$$H_t = D_t R_t D_t \tag{5}$$

D_t is the conditional variance matrix given by:

$$D_t = \text{diag}\left(h_{11t}^{\frac{1}{2}} \ldots h_{NNt}^{\frac{1}{2}}\right) \tag{6}$$

R_t is the condition correlation matrix of N x N dimension, and is defined as follows:

$$R_t = (\rho_{iit}) = \text{diag}(q_{11,t}^{-\frac{1}{2}} \ldots q_{NN,t}^{-\frac{1}{2}}) Q_t \text{diag}(q_{11,t}^{-\frac{1}{2}} \ldots q_{NN,t}^{-\frac{1}{2}}) \tag{7}$$

where the N x N symmetric positive definite matrix $Q_t = (q_{ii,t})$ is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \tag{8}$$

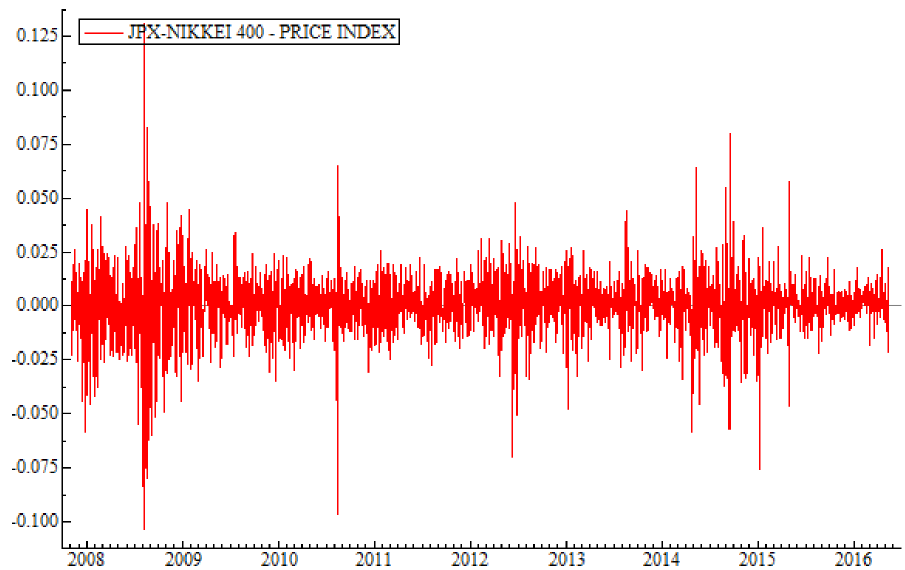
$\bar{Q}$ is the N x N unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.

3.4 DATA CHARACTERISTICS

For the purposes of this research, data on a daily basis was collected for major global and national equity indexes. More specifically, the research sample comprised of data collected from three major stock markets, namely Japan, China and the U.S.A. Data was collected for the period November 2007 to May 2016. The rationale behind choosing this period was that it encompasses the period just before, during and after the global economic crisis, which consequences were evident for at least 6 years after its global outburst in the second half of 2008 and especially within 2009. As such, effects on stock returns were observed and analyzed during a period of high growth (before 2008), during a period of significant economic crisis, as well as the following period of uncertainty, as it was gradually substituted with some economic certainty and confidence again. In short, the review period was selected, as a means of encompassing all those factors that were found in the literature review and previous research findings to have an impact on stock prices, stock market performance and stock returns. Market logarithmic returns were calculated using the following equation $r_t = log\ (p_t) - log(p_{t-1})$, where p_t is the price of the market on day *t* and p_{t-1} the price of the market on day *t-1*.

Figure 1 illustrates that data for the actual series of calculated returns for JPX-NIKKEI 400 - PRICE INDEX. As observed in Figure 1, the review period was subject to significant peaks and troughs. At the same time, volatility in logarithmic returns was also identified, showing the heteroscedasticity phenomenon and rationalizing us to employ a DCC-GARCH model.

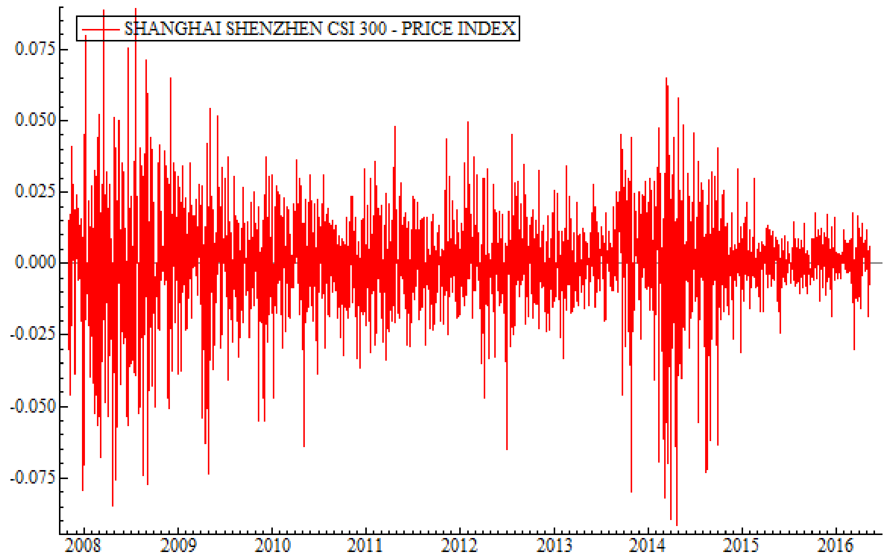
Figure 1. Actual series of the logarithmic returns of the JPX-NIKKEI 400 - PRICE INDEX



Source: Datastream Database

Figure 2 illustrates the actual series of logarithmic returns for SHANGHAI SHENZHEN CSI 300 - PRICE INDEX. Peaks and troughs also become evident in terms of this stock market as well over the review period, together with extreme volatility for the logarithmic returns, again showing the heteroscedasticity phenomenon.

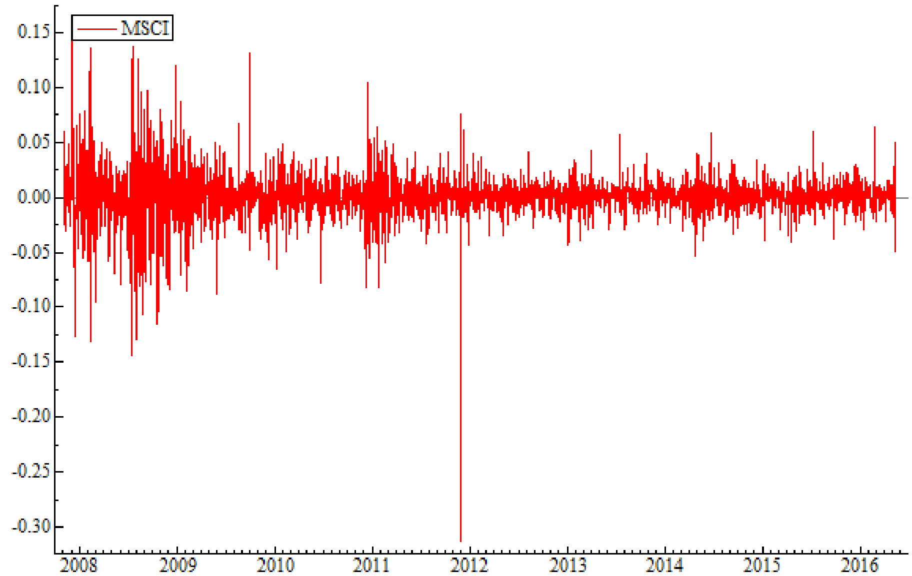
Figure 2. Actual series of the logarithmic returns of the SHANGHAI SHENZHEN CSI 300 - PRICE INDEX



Source: Datastream Database

Figure 3 presents the series of logarithmic returns of MSCI. As shown in the corresponding figure, logarithmic returns for MSCI are overt. Furthermore, in Figure 3 the actual series of calculated returns of MSCI are overt. It is also observed that there are significant peaks and troughs during the whole period, while the volatility identified in returns could be characterized here as extreme. Once again, heteroscedasticity becomes evident, which once again provides the rationale for employing a DCC-GARCH model.

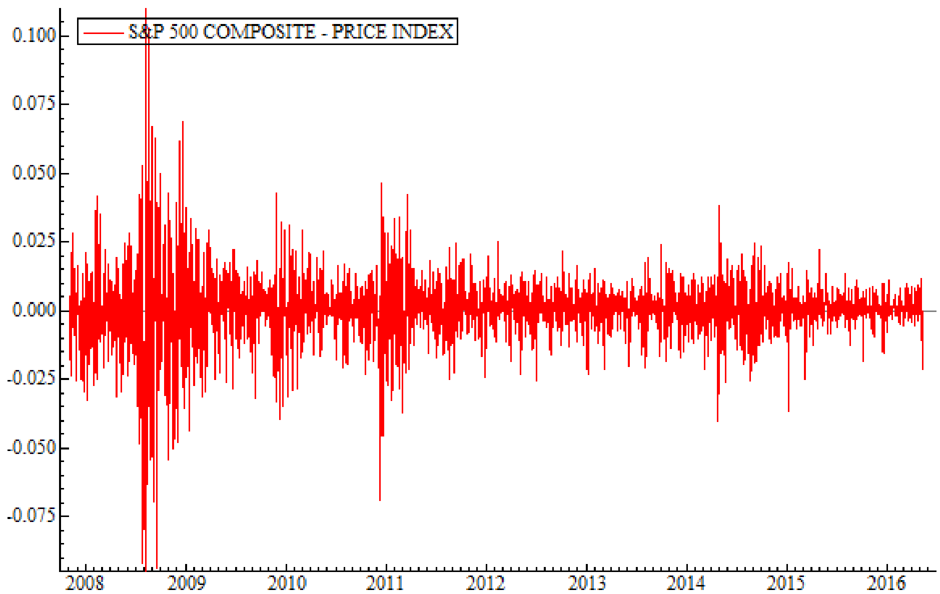
Figure 3. Actual series of the logarithmic returns of the MSCI



Source: Datastream Database

Figure 4 shows the actual series of calculated returns for S&P 500 COMPOSITE - PRICE INDEX. Further, significant peaks and troughs are noticed during the under investigation time. In this case, extreme volatility in calculated returns is also identified. The profound phenomenon of heteroscedasticity led to employing a DCC-GARCH model.

Figure 4. Actual series of the logarithmic returns of the S&P 500 COMPOSITE - PRICE INDEX



Source: Datastream Database

4. EMPIRICAL RESULTS

4.1 DCC-GARCH MODEL

The results chapter comprises of seven subsections, one for each of the statistical tests that were held, as part of the statistical analysis. More particularly, Section 1 presents the results of the univariate GARCH (1,1) model. Section 2 presents the results of the normality rest of univariate GARCH (1,1) model that was employed. Section 3 presents results of the Diagnostic Tests and Information Criteria of Univariate GARCH (1,1) model. Section 4 presents the estimates of the bivariate DCC-GARCH (1,1) model, degrees of freedom, as well as log-likelihood. Section 5 presents the estimates of the Average Correlations for DCC-GARCH (1,1) model. Section 6 presents the results of the diagnostic Tests, Hypothesis Testing and Information Criteria of the four variate DCC-GARCH (1,1) model. Finally, Section 7 presents the results for the Analysis of Dynamic Conditional Correlation Coefficients that was held.

4.1.1 Estimates of the univariate GARCH (1,1) model

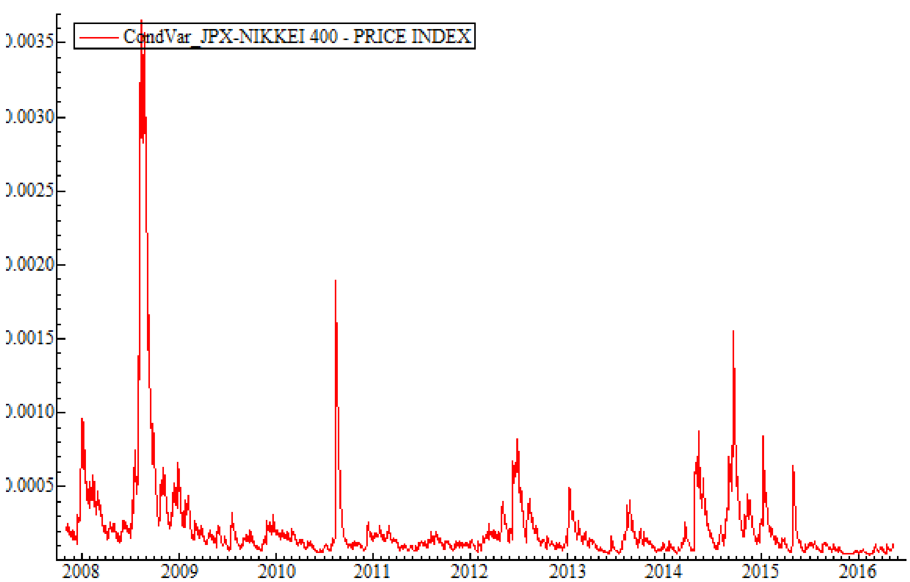
The values for mean equation and univariate GARCH(1,1) model regarding JPX-NIKKEI 400 - PRICE INDEX, SHANGHAI SHENZHEN CSI 300 - PRICE INDEX, MSCI and S&P 500 COMPOSITE - PRICE INDEX are presented at Table 1. The mean equation presents significant μ value for all markets. Moreover, variance equation demonstrates significant ω of the four under investigation markets. ARCH (a) and GARCH (b) terms are highly significant. Figures 5 to 8 illustrates the calculated conditional variances.

Table 1. Estimates of univariate GARCH (1,1) model

	JPX-NIKKEI 400 - PRICE INDEX	SHANGHAI SHENZHEN CSI 300 - PRICE INDEX	MSCI	S&P 500 COMPOSITE - PRICE INDEX
constant (*μ*)	0,000827***	0,000658***	0,001285***	0,000739***
t-Statistic	4,217	3,121	5,351	5,690
p-Value	0,0000	0,0018	0,0000	0,0000
constant (ω)	0,034215**	0,010629**	0,037313**	0,015762***
t-Statistic	2,677	2,372	2,913	3,345
p-Value	0,0075	0,0178	0,0036	0,0008
ARCH (*Alpha*1)	0,107433***	0,055621***	0,055546***	0,089087***
t-Statistic	5,224	5,259	4,548	5,723
p-Value	0,0000	0,0000	0,0000	0,0000
GARCH (*Beta1*)	0,884479***	0,943787***	0,929940***	0,898287***
t-Statistic	39,91	93,51	62,77	52,25
p-Value	0,0000	0,0000	0,0000	0,0000

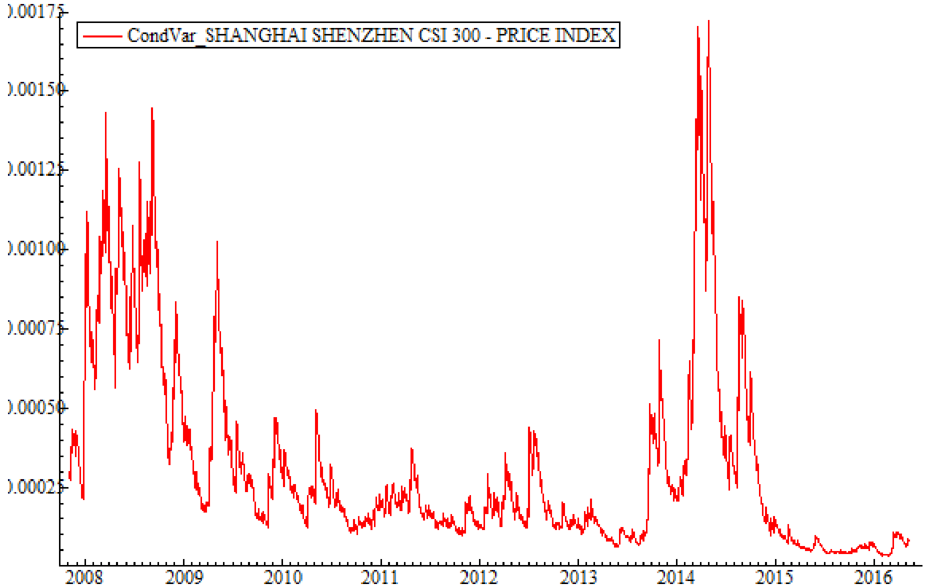
Source: Datastream Database

Figure 5. Conditional variance for the JPX-NIKKEI 400 - PRICE INDEX of the univariate GARCH (1,1) model



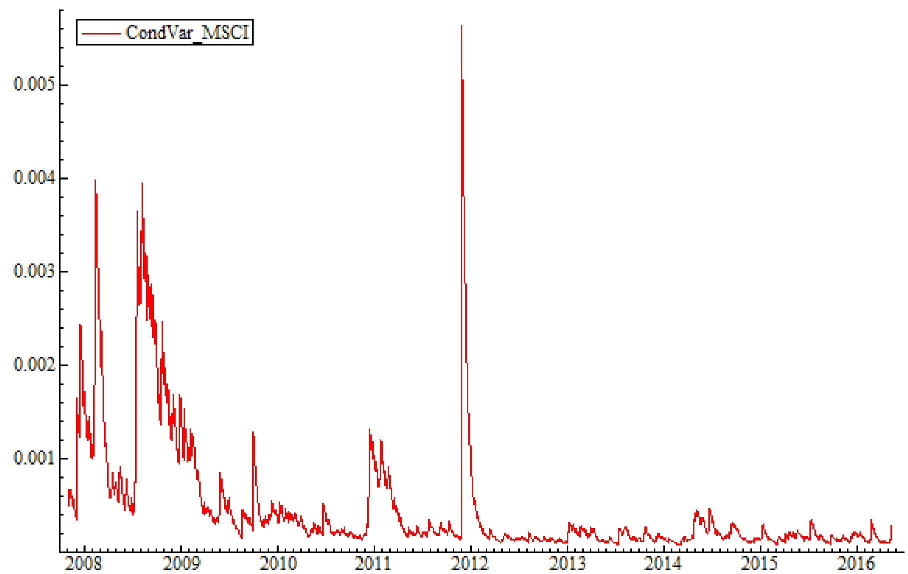
Source: Datastream Database

Figure 6. Conditional variance for the SHANGHAI SHENZHEN CSI 300 - PRICE INDEX of the univariate GARCH (1,1) model



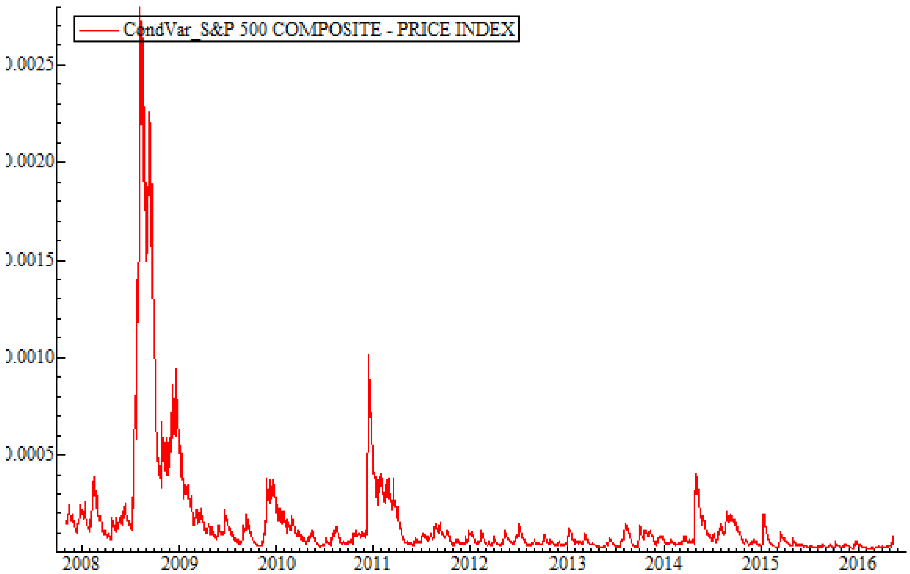
Source: Datastream Database

Figure 7. Conditional variance for the MSCI of the univariate GARCH (1,1) model



Source: Datastream Database

Figure 8. Conditional variance for the S&P 500 COMPOSITE - PRICE INDEX of the univariate GARCH (1,1) model



Source: Datastream Database

4.1.2 Normality Test of univariate GARCH (1,1) model

Table 2 shows the normality test results of univariate GARCH (1,1) model for JPX-NIKKEI 400 - PRICE INDEX, SHANGHAI SHENZHEN CSI 300 - PRICE INDEX, MSCI and S&P 500 COMPOSITE - PRICE INDEX. Results indicate a non-normal distribution for the three markets regarding the statistically highly significant skewness, Excess Kurtosis and the Jarque-Bera test statistics.

Table 2. Normality Test of univariate GARCH (1,1) model

	JPX-NIKKEI 400 - PRICE INDEX	SHANGHAI SHENZHEN CSI 300 - PRICE INDEX	MSCI	S&P 500 COMPOSITE - PRICE INDEX
Skewness	-0,38405***	-0,30908***	-5,2973***	0,55470***
t-Statistic	8,1015	6,5200	111,75	11,701
p-Value	5,4305e-016	7,0320e-011	0,0000	1,2531e-031
Excess Kurtosis	2,0407***	2,0399***	139,53***	13,605***
t-Statistic	21,532	21,5200	1472,2	143,55
p-Value	7,7461e-103	9,2059e-103	0,0000	0,0000
Jarque-Bera	528,34**	504,89**	2,1758e+006**	20704**
p-Value	1,8762e-115	2,3096e-110	0,0000	0,0000

Source: Datastream Database

4.1.3 Diagnostic Tests and Information Criteria of univariate GARCH (1,1) model

In table 3, the diagnostic tests of the univariate GARCH (1,1) model for JPX-NIKKEI 400 - PRICE INDEX, SHANGHAI SHENZHEN CSI 300 - PRICE INDEX, MSCI and S&P are presented.

Table 3. Diagnostic tests of the univariate GARCH (1,1) model

	JPX-NIKKEI 400 - PRICE INDEX	SHANGHAI SHENZHEN CSI 300 - PRICE INDEX	MSCI	S&P 500 COMPOSITE - PRICE INDEX
Box/Pierce^2 (50)	48,7948	48,6613	0,782059	20,0326
p-Value	0,5217856	0,5271887	0,9999625	0,9999518

Source: Datastream Database

4.1.4 Estimates of the bivariate DCC-GARCH (1,1) model, degrees of freedom, log-likelihood

In Table 4, the calculated fourvariate DCC is presented for the pair of markets JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX. DCC model results indicate statistically significant α and β, showing significant ARCH and GARCH effects for JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX, suggesting that the markets are integrated. Additionally, the estimated degrees of freedom (v) and the log-likelihood are stated.

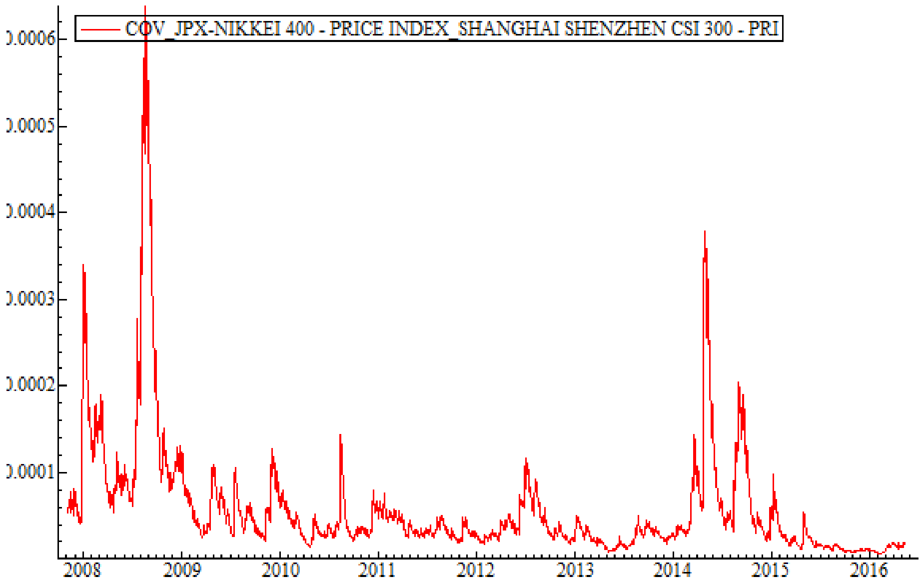
Table 4. Estimates of the multivariate DCC-GARCH (1,1) model, degrees of freedom, log-likelihood

	JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX
alpha *(α)*	0,011949***
t-Statistic	4,849
p-Value	0,0000
beta *(β)*	0,957877***
t-Statistic	105,7
p-Value	0,0000
degrees of freedom (*df*)	6,159799***
t-Statistic	14,45
p-Value	0,0000
log-likelihood	32334,771

Source: Datastream Database

Figure 9 plots the Conditional covariance of JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300. The Conditional covariance is positive and extreme volatile. The diagram states clear that the Conditional covariance presents a downward trend over time. Additionally, significant peaks and troughs are indicated during the under investigation time. Specifically, I see two of the most significant peaks during 2008 and 2014. As far as troughs are concerned, the most significant ones were observed in 2010 and 2013. Despite the fact that there are troughs and peaks during the review period, the values that were observed were not so extreme, thereby leading to the fact that the conditional covariance line is somehow normalized. Another conclusion derived from the plot in Figure 9 is the downward slope of the line, which indicates that the performance of the stock markets under discussion has been somewhat declining over the review period.

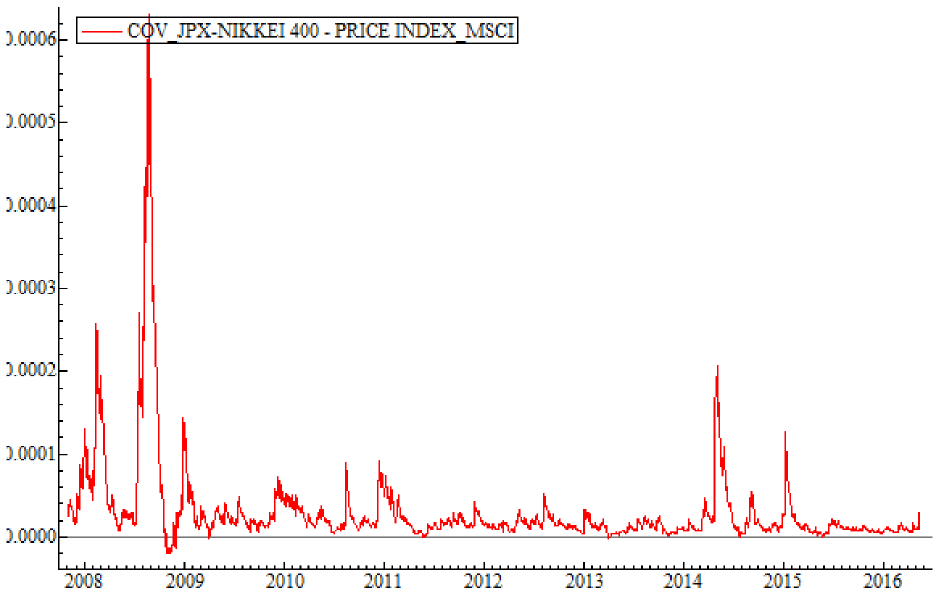
Figure 9. Conditional covariance for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

In Figure 10, the Conditional covariance of JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI are plotted. The Conditional covariance is positive and extreme volatile, except a sub-period in 2008, where the Conditional covariance presents negative values. Moreover, the diagram states that the Conditional covariance presents a downward trend over time. In addition, significant peaks and troughs are overt during the under investigation time. Specifically, I see two of the most significant peaks in 2008. In addition, two of the most significant troughs are observed during 2008 and 2009. Moreover, while there are significant peaks and troughs, in sub-periods, there are not so many extreme values, and a more normalized line of the Conditional covariance is also observed. Furthermore, the general downward trend of the line means possibly the general decrease of the two under investigation markets.

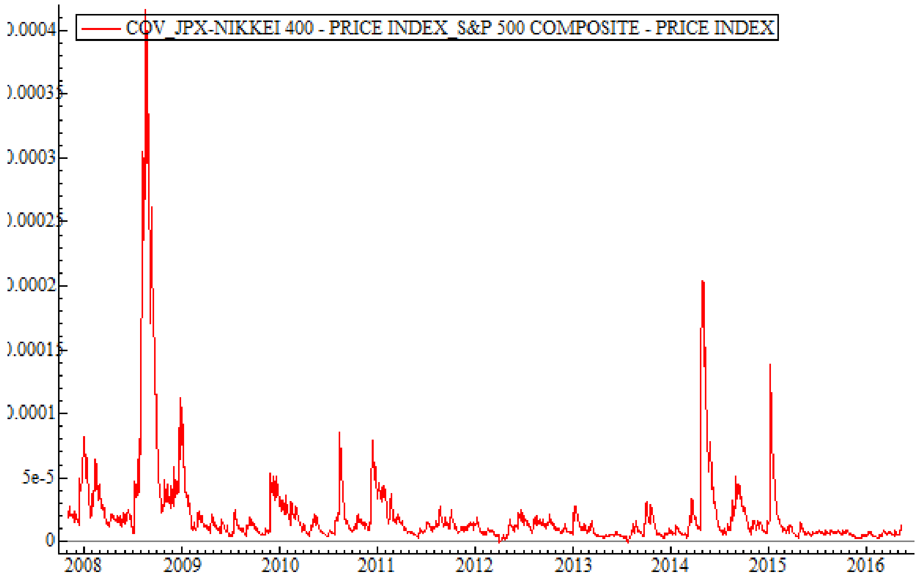
Figure 10. Conditional covariance for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

Figure 11 shows the Conditional covariance of JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX. The Conditional covariance is positive and extreme volatile. Moreover, the diagram states clear that the Conditional covariance presents a downward trend over time. Significant peaks and troughs are observed in the whole period. Specifically, the two of the most significant peaks were in 2008 and 2014. As far as troughs are concerned, 2012 and 2013 were the years with the most significant ones. Despite the abovementioned peaks and troughs, in general there are not so extreme values identified during the review period, thereby constituting the line of the conditional covariance as one that is mostly met in cases of normal distribution. It is also important to comment on the negative slope of the conditional covariance line, which indicates that the stock markets under examination have reported a declining performance over the review period.

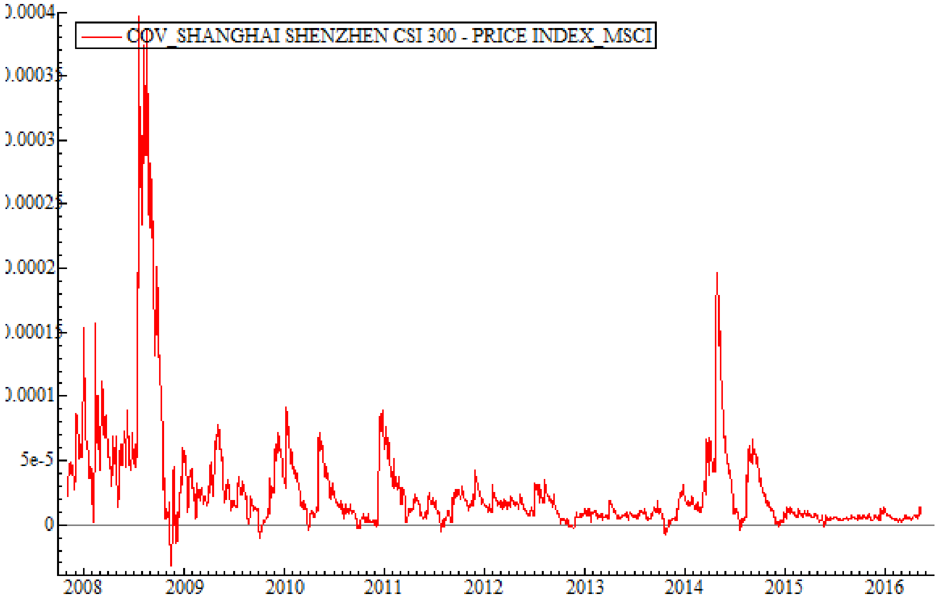
Figure 11. Conditional covariance for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

In Figure 12, the Conditional covariance of SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI is presented. As in the previous case, the conditional covariance with respect to these two markets is again positive and extremely volatile. in contrast, though, there are also time periods within the overall review period where conditional covariance is subject to negative values. As with the two markets previously analyzed, the conditional covariance line of SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI is subject to a progressively negative slop over time, which again indicates that the performance of the markets under discussion has been diminishing over time. The fluctuations in conditional covariance have obviously led to the development of peaks and troughs. The two most significant peaks of the period were identified in 2008 and 2014. Regarding troughs, the most significant ones were identified in 2008, 2009, and 2013. Also, despite peaks and troughs, not significant extremes were identified for the conditional covariance over the whole review period.

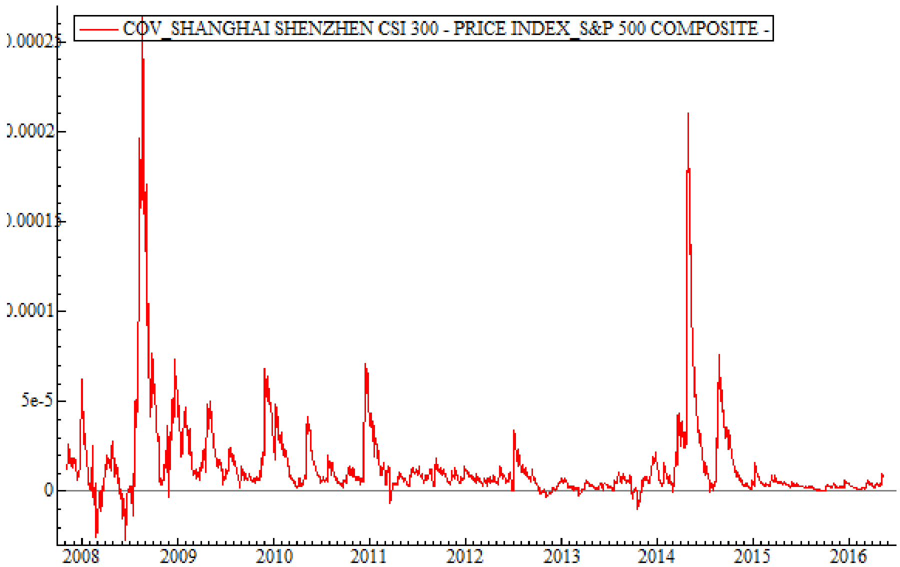
Figure 12. Conditional covariance for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

The results of the analysis were also the same for the conditional covariance SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX. Indeed, as illustrated in Figure 13 that follows, the conditional covariance is subject to positive values and extreme volatilities, again with some negative values over some years, which inevitably create some peaks and troughs. As in the markets previously analyzed, the years 2008 and 2014 were those where the most significant peaks were observed, while the most significant troughs were observed in 2008 and 2013. The slope of the conditional covariance was once again of negative slope, which reflects the diminishing performance of the markets under discussion. Last but not least, no significant extreme values were observed over the review period.

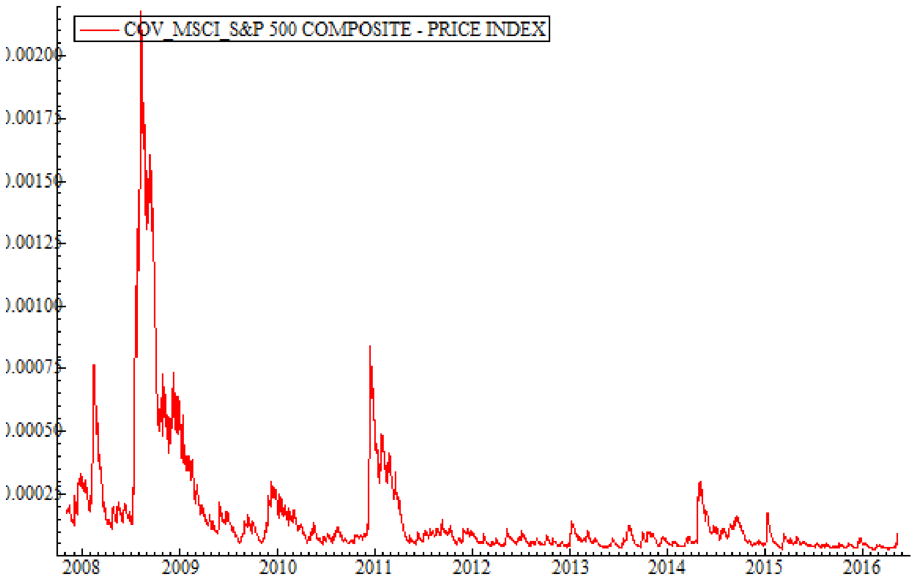
Figure 13. Conditional covariance for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

The conditional covariance analysis for MSCI - S&P 500 COMPOSITE - PRICE INDEX did not significantly differ from those that were held for the other markets. Specifically, as shown in Figure 14, the conditional covariance for these markets is also highly positive, while volatility at high levels was also observed. In this market, conditional covariance also seems to have been declining over time, with significant peaks being observed in 2008 and 2010, while major troughs are evident for 2008 and 2009. Again, no extreme values were observed, while the general conclusion here as well is that there is a declining trend and, thus, performance, for these two markets under research as well.

Figure 14. Conditional covariance for the pairs of markets MSCI - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

4.1.5 Estimates of the Average Correlations for DCC-GARCH (1,1) model

Table 5 presents the results of the average correlations that were calculated for the multivariate GARCH(1,1)-DCC model. Based on the corresponding correlation coefficients, there is a statistically significant correlation between the four stock markets under review in this research study.

Table 5. Estimates for the average correlations of the multivariate DCC-GARCH (1,1) model

	Coefficient	t-Statistic	p-Value
JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300	0,213440***	8,781	0,0000
JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI	0,087924***	3,187	0,0015
JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX	0,106904***	4,050	0,0001

SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI	0,062967**	2,556	0,0107
SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX	0,062890**	2,466	0,0137
MSCI - S&P 500 COMPOSITE - PRICE INDEX	0,633690***	33,55	0,0000

Source: Datastream Database

4.1.6 Diagnostic Tests, Hypothesis Testing and Information Criteria for the bivariate DCC-GARCH (1,1) model

Table 6 presents the results of the estimated hypothesis testing that was held for comparing the four major stock markets under discussion. The results of the analysis indicate that spillovers were identified, thereby rejecting the null hypothesis at the level of statistical significance 1%. Further to the above, the results of the Ljuing-Box test that was held indicated that there was no serial autocorrelation, while the estimated DCC-GARCH (1,1) model was not found to be subject to misspecification errors.

Table 6. Diagnostic tests and information criteria of the multivariate DCC-GARCH (1,1) model

	JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX
x^2 (6)	12355**
p-Value	0,0000
Hosking^2 (50)	743,680
p-Value	0,9154410
Li-McLeod^2 (50)	745,570
p-Value	0,9074972
Akaike	0,009656
Schwarz	0,064856
Shibata	0,009482
Hannan-Quinn	0,029630

Source: Datastream Database

4.1.7 Analysis of Dynamic Conditional Correlation Coefficients

Tables 7 and 8 present the results of the dynamic conditional correlation analyses (DCCs) that were held, as a means of making one more comparison of the four major stock markets under discussion.

Table 7. Descriptive statistics of the DCCs

	CORR_ JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300	CORR_ JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI	CORR_ JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX
Min	0,092482	-0,022821	-0,0074621
Mean	0,22266	0,09462	0,11931
Max	0,37844	0,36978	0,39563
Std.dev.	0,046497	0,049522	0,045654
Skewness	0,19541***	0,98918***	1,4884***
t-Statistic	4,1222	20,867	31,397
p-Value	3,7534e-005	1,0744e-096	2,2136e-216
Excess Kurtosis	0,031163	3,1339***	6,0548***
t-Statistic	0,32882	33,067	63,886
p-Value	0,74229	8,7231e-240	0,0000
Jarque-Bera	17,081**	1526,3**	5058,5**
p-Value	0,00019539	0,0000	0,0000

Source: Datastream Database

Table 8. Descriptive statistics of the DCCs

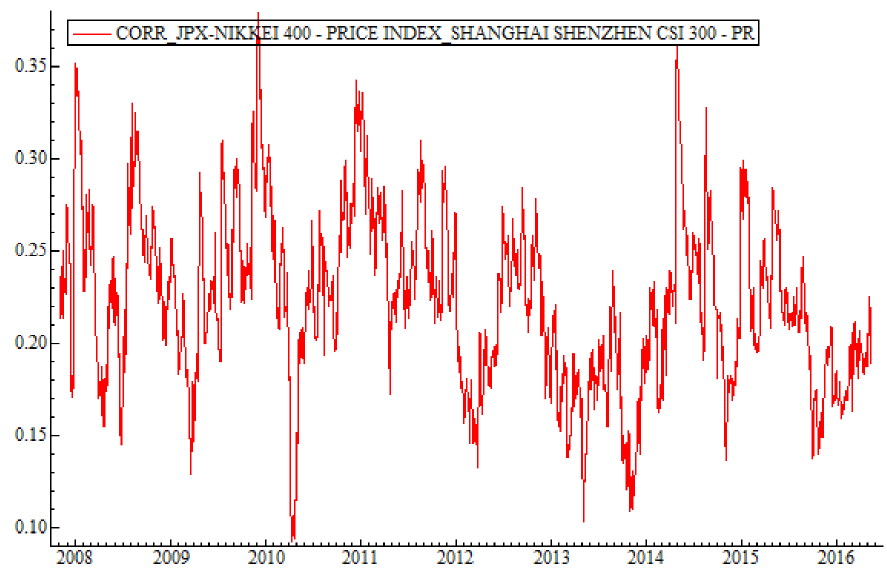
	CORR_ SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI	CORR_ SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX	CORR_ MSCI - S&P 500 COMPOSITE - PRICE INDEX
Min	-0,038194	-0,061119	0,21554
Mean	0,071302	0,071146	0,617
Max	0,23879	0,25688	0,72718
Std.dev.	0,044079	0,043225	0,066793
Skewness	0,62210***	0,28951***	-2.4709***
t-Statistic	13,123	6,1071	52,124
p-Value	2,4249e-039	1,0145e-009	0,0000
Excess Kurtosis	0,61886***	0,89050***	10,062***
t-Statistic	6,5299	9,3961	106,17
p-Value	6,5808e-011	5,6622e-021	0,0000
Jarque-Bera	214,58**	125,38**	13965**
p-Value	2,5322e-047	5,9540e-028	0,0000

Source: Datastream Database

MSCI, CORR_ JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX, CORR_ SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI, CORR_ SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX and CORR_ MSCI - S&P 500 COMPOSITE - PRICE INDEX. I notice the lowest min value (-0,061119) for SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX, whilst the pair of markets MSCI - S&P 500 COMPOSITE - PRICE INDEX present the highest max value (0,72718) and greater mean value (0,617). Additionally, the pair of markets MSCI - S&P 500 COMPOSITE - PRICE INDEX shows the highest std. deviation (0,066793) indicating larger fluctuations for the DCCs. Further to the above, DCCs were not found to be subject to normal distribution, as this was evident through the results of corresponding statistical tests that were held, namely Skewness, Excess Kurtosis and the Jarque-Bera tests.

DCC result for JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI are presented and illustrated in Figure 15. As with other markets, DCC was found to be positive and subject to very high volatility rates, while again a downward trend was identified in the corresponding line, once again revealing that the performance of the two markets has been declining, as years have passed by over the review period. The years 2009 and 2014 were the two years when the highest DCC values were observed. Unlike the other markets under review, the two most major troughs were observed in these markets during the years 2010 and 2013. At the same time, the common findings of not observing extreme values over the whole review period once again prevailed, together with the common finding of observing a declining performance of the two stock markets under review.

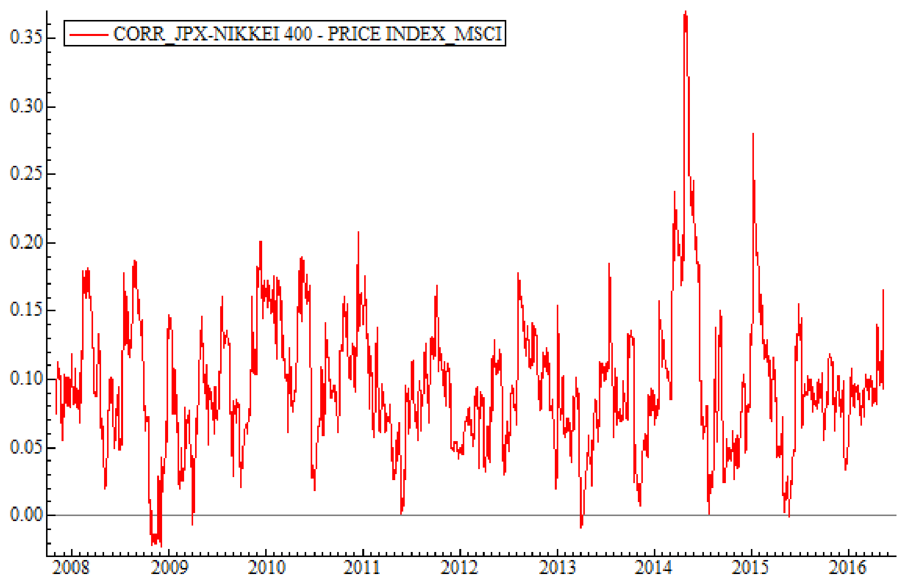
Figure 15. Dynamic conditional correlations for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

DCC for JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI is illustrated in Figure 16, to reach again the same conclusions as other markets, with respect to the positive nature of the correlation, as well as the volatility of the particular markets. In contrast to the previous markets that were reviewed, the slope of the corresponding line here is neither negative, nor positive, obviously reflecting a more stable overall market performance. The above stability has been evident, despite the fact that peaks and troughs were also observed in these markets, with the former mainly being observed in 2014 and the latter in 2008 and 2009.

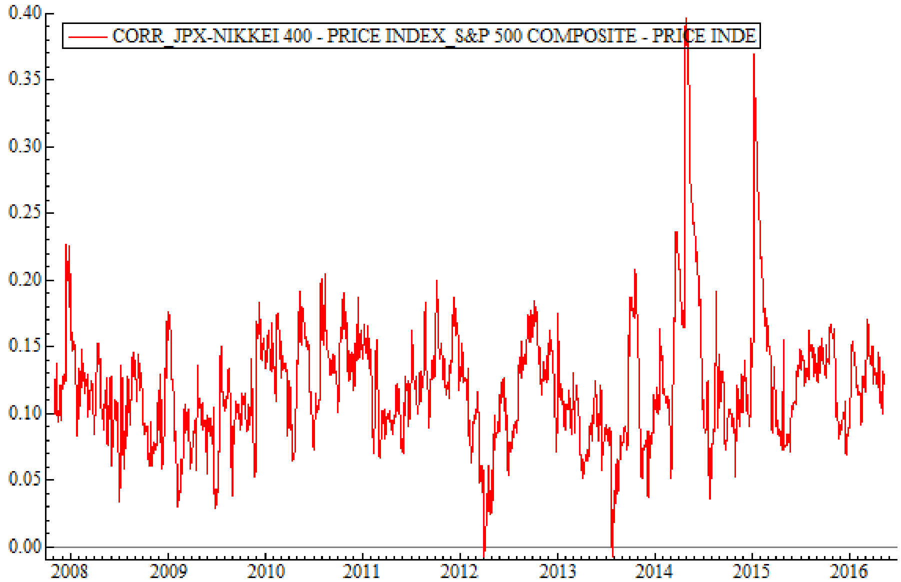
Figure 16. Dynamic conditional correlations for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

DCC for JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX, as illustrated in Figure 17, are of the same nature as in the other markets, with the difference here being that contagion effects are evident throughout all the years under review, except for the years 2012 and 2013. The slope of the corresponding line was again somehow straight, again indicating a more or less stable market performance, with peaks being again identified in 2014 and troughs being identified in 2012 and 2013.

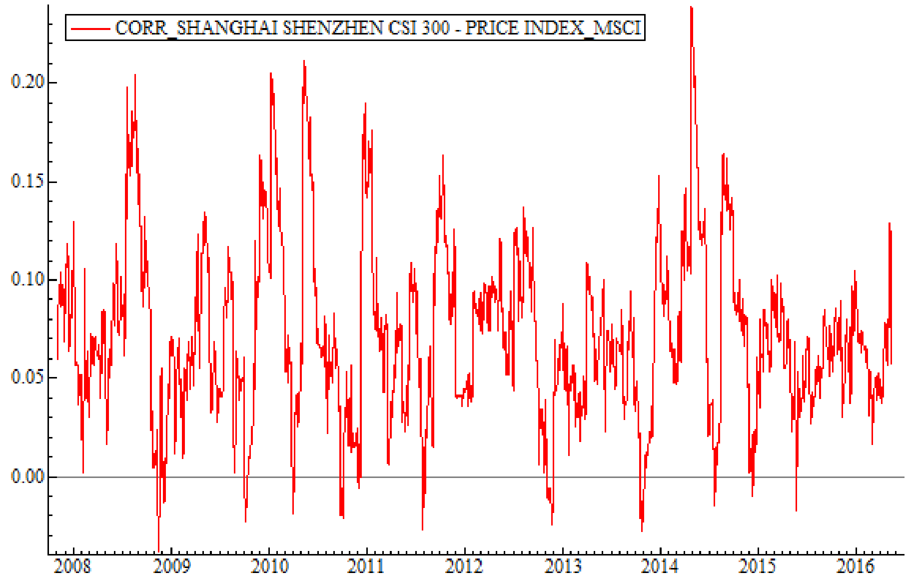
Figure 17. Dynamic conditional correlations for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

DCC for SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI is illustrated in Figure 18. Contagion effects were also identified in these markets, also given the positive correlation and the extreme volatility that characterized all markets under discussion over the review period. Again, the years 2010 and 2014 were those when peaks were mostly observed, whereas in 2008 and 2009 the lowest DCC values were observed. In the same context as before, the corresponding line was neither downward, nor upward-sloping, which indicates a more or less stable market performance over the review period.

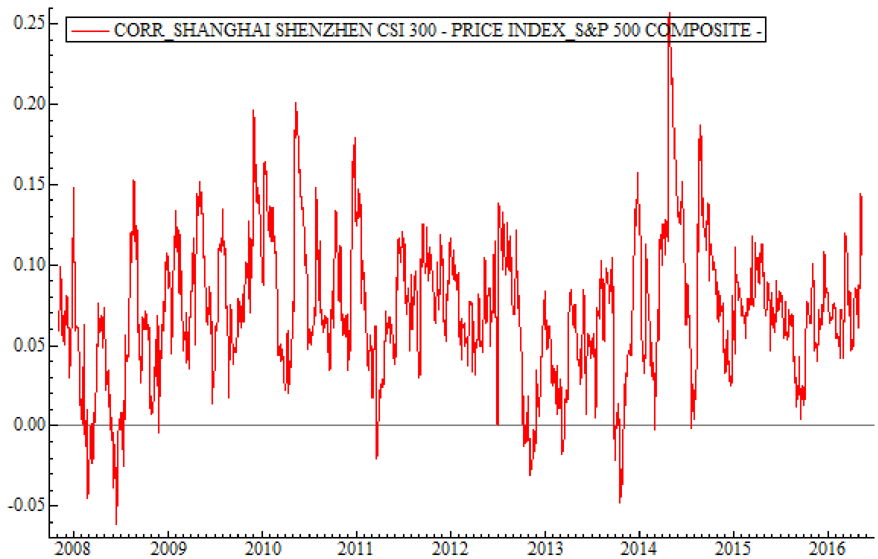
Figure 18. Dynamic conditional correlations for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

The DCC for SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX, as illustrated in Figure 19, indicated once again a positive correlation accompanied by extreme volatility, but with the presence of contagion effects. as well. These effects were identified throughout the whole review period, apart from the years 2009, 2012 and 2013. In these three years, DCC was found to be negative. Again, the most major peaks were observed in 2010 and 2014, whereas the year 2008 was the one when the most negative DCC value was observed.

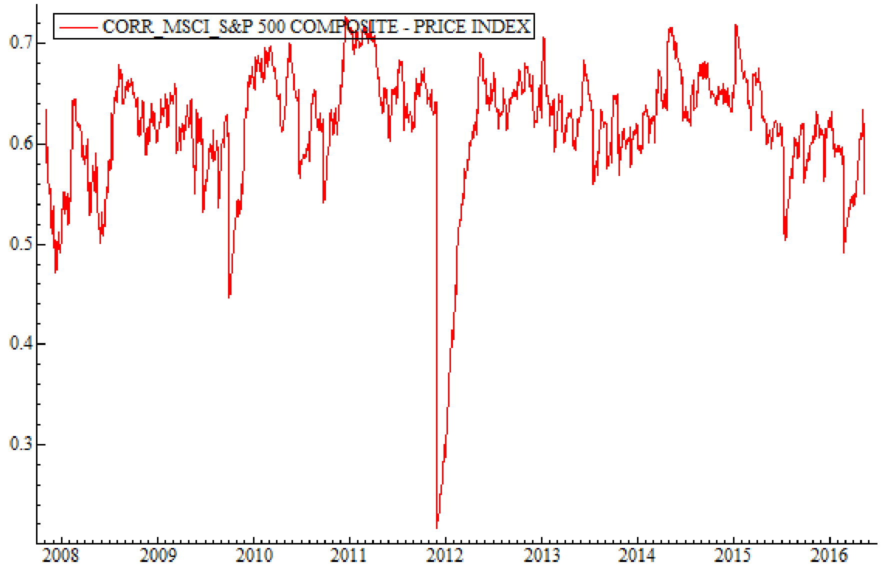
Figure 19. Dynamic conditional correlations for the pairs of SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

Last but not least, Figure 20 illustrates the findings of DCC that was held for the specific case MSCI - S&P 500 COMPOSITE - PRICE INDEX. Based on the corresponding figure, DCC was also found to be positive, the markets also being subject to great volatility, while contagion effects were also evident. As in the previous cases, the trend line for these markets did not have either a negative or positive slope. This time, the peak of the market was found to be in 2014, while in 2011 the lowest values were identified.

Figure 20. Dynamic conditional correlations for the pairs of markets MSCI - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GARCH (1,1) model



Source: Datastream Database

4.2 DCC-GJR GARCH MODEL

In this section, the outcomes of the univariate GJR model analysis are presented and analyzed. In the sub-sections that follow, the results of the various statistical tests that were held respectively are analyzed respectively, namely the results of the normality test, the diagnostic tests and information criteria, the bivariate DCC- GJR model, degrees of freedom and log-likelihood, the average correlations for the univariate DCC-CJR model, as well as the diagnostic tests, hypothesis testing and information criteria of the fourvariate DCC- GJR model. Also, DCCs for the four markets under research are presented and analyzed.

4.2.1 Estimates of the univariate GJR model

Table 9 states the estimated values for mean equation and univariate GJR model regarding for the following markets: JPX-NIKKEI 400 - PRICE INDEX, SHANGHAI SHENZHEN CSI 300 - PRICE INDEX, MSCI and S&P 500 COMPOSITE - PRICE INDEX. The mean equation shows significant μ value for all the under investigation markets. Additionally, variance equation demonstrates significant ω value. Additionally, ARCH (a) and GARCH (b) terms are significant.

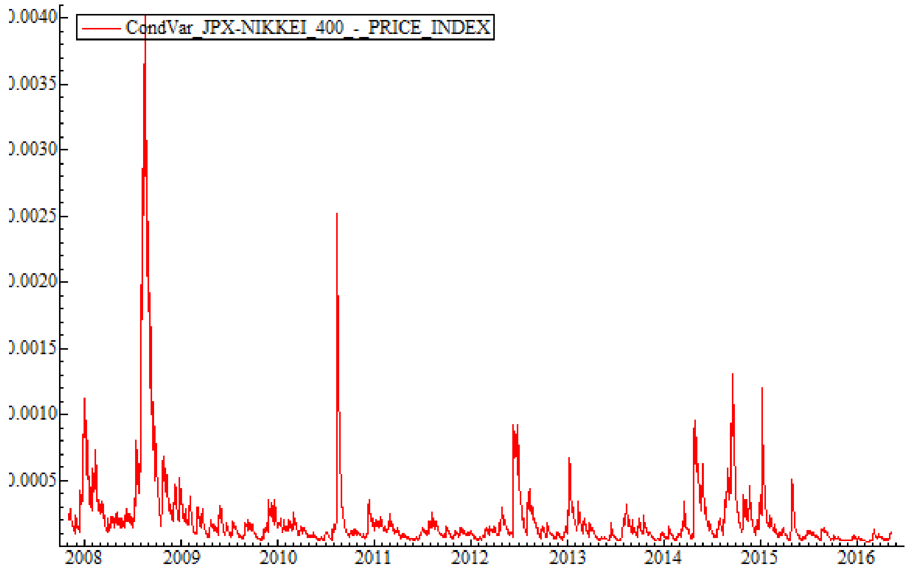
Table 9. Estimates of univariate GJR model

	JPX-NIKKEI 400 - PRICE INDEX	**SHANGHAI SHENZHEN CSI 300 - PRICE INDEX**	**MSCI**	**S&P 500 COMPOSITE - PRICE INDEX**
constant *(μ)*	0,000243*	0,000356*	0,000961***	0,000284*
t-Statistic	1,171	1,537	3,172	1,966
p-Value	0,2417	0,1244	0,0015	0,0494
constant (ω)	0,050851***	0,004955*	0,238496*	0,020582***
t-Statistic	3,519	1,436	1,402	4,955
p-Value	0,0004	0,1511	0,1610	0,0000
ARCH *(Alpha1)*	0,026794*	0,049712***	0,130666*	-0,017071*
t-Statistic	1,349	4,727	1,720	-1,450
p-Value	0,1775	0,0000	0,0855	0,1472
GARCH *(Beta1)*	0,870793***	0,948649***	0,790801***	0,890030***
t-Statistic	47,62	92,32	11,03	55,60
p-Value	0,0000	0,0000	0,0000	0,0000
GJR *(Gamma1)*	0,144459***	0,002949	0,112301*	0,211504***
t-Statistic	3,364	0,2258	1,852	6,632
p-Value	0,0008	0,8214	0,0642	0,0000

Source: Datastream Database

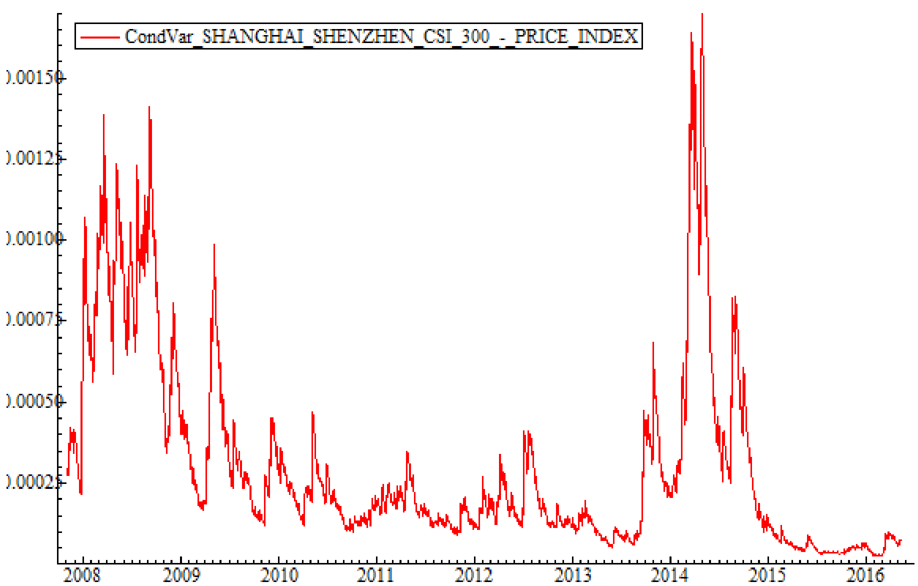
Figures 21 to 24 depict the calculated conditional variances.

Figure 21. Conditional variances for the JPX-NIKKEI 400 - PRICE INDEX of the univariate GJR model



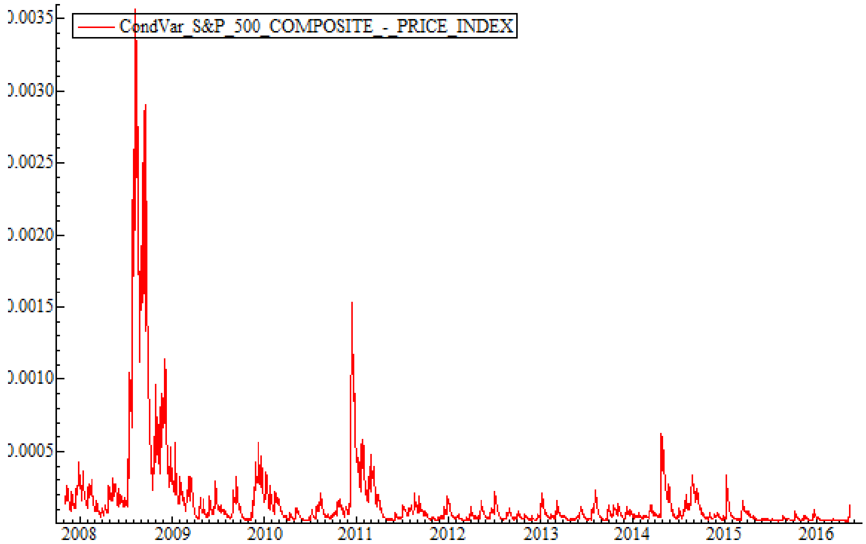
Source: Datastream Database

Figure 22. Conditional variance for the SHANGHAI SHENZHEN CSI 300 - PRICE INDEX of the univariate GJR model



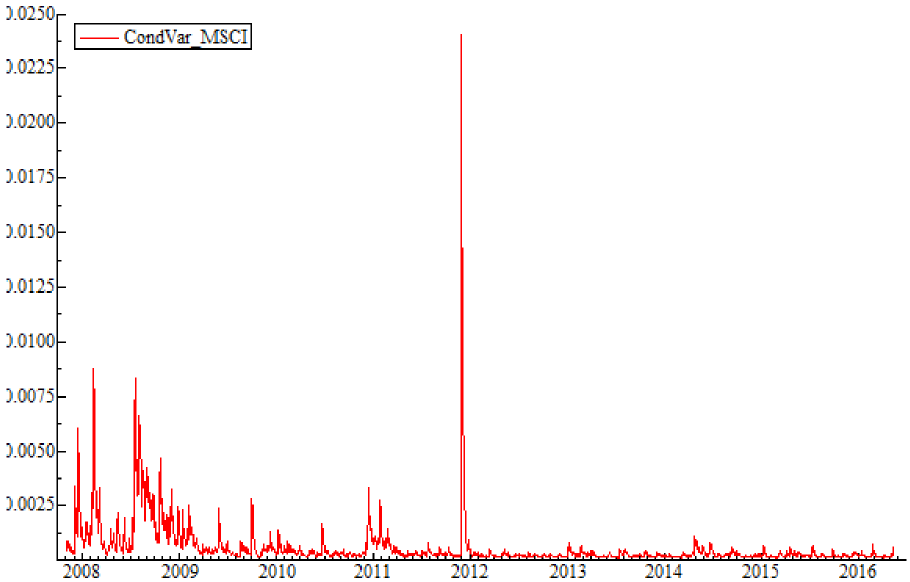
Source: Datastream Database

Figure 23. Conditional variance for the S&P 500 COMPOSITE - PRICE INDEX of the univariate GJR model



Source: Datastream Database

Figure 24. Conditional variance for the MSCI of the univariate GJR model



Source: Datastream Database

4.2.2 Normality Test of univariate GJR model

In Table 10, the normality test results are observed for the univariate GJR model for the markets JPX-NIKKEI 400 - PRICE INDEX, SHANGHAI SHENZHEN CSI 300 - PRICE INDEX, MSCI and S&P 500 COMPOSITE - PRICE INDEX. Empirical results show a non-normal distribution for the three markets based on the statistically highly significant skewness, Excess Kurtosis, and the Jarque-Bera test statistics.

Table 10. Normality Test of univariate GJR model

	JPX-NIKKEI 400 - PRICE INDEX	SHANGHAI SHENZHEN CSI 300 - PRICE INDEX	MSCI	S&P 500 COMPOSITE - PRICE INDEX
Skewness	-0,43845***	-0,29060***	-4,3802***	0,22280***
t-Statistic	9,2490	6,1303	92,401	4,6999
p-Value	0,0000	0,0000	0,0000	0,0000
Excess Kurtosis	2,5846***	2,0425***	110,45***	9,3695***
t-Statistic	27,271	21,552	1165,4	98,862
p-Value	0,0000	0,0000	0,0000	0,0000
Jarque-Bera	827,79**	501,14**	1.3641e+006**	9777,4**
p-Value	0,0000	0,0000	0,0000	0,0000

Source: Datastream Database

4.2.3 Diagnostic Tests and Information Criteria of univariate GJR model

Table 11 demonstrates the diagnostic tests of the univariate GJR model for JPX-NIKKEI 400 - PRICE INDEX, SHANGHAI SHENZHEN CSI 300 - PRICE INDEX, MSCI and S&P 500 COMPOSITE - PRICE INDEX. Results show absence of serial autocorrelation.

Table 11. Diagnostic tests of the univariate GJR model

	JPX-NIKKEI 400 - PRICE INDEX	SHANGHAI SHENZHEN CSI 300 - PRICE INDEX	MSCI	S&P 500 COMPOSITE - PRICE INDEX
Box/Pierce^2 (50)	54,4457	48,5704	37,3331	0,990964
p-Value	0,3091396	0,5308681	0,9073594	0,9959483

Source: Datastream Database

4.2.4 Estimates of the bivariate DCC-GJR model, degrees of freedom, log-likelihood

Table 12 presents the calculated fourvariate DCC model for JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX. DCC model results present statistically significant α and β, showing major ARCH and GARCH effects for JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX, suggesting that the markets are integrated. Moreover, the calculated degrees of freedom (v) and the log-likelihood are analyzed.

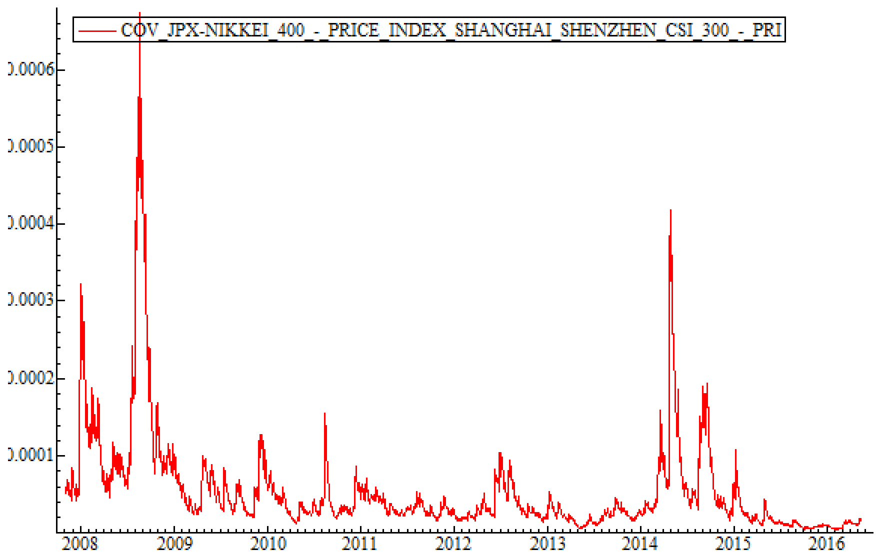
Table 12. Estimates of the multivariate DCC-GJR model, degrees of freedom, log-likelihood

	JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX
alpha *(α)*	0,010950***
t-Statistic	4,541
p-Value	0,0000
beta *(β)*	0,963518***
t-Statistic	111,8
p-Value	0,0000
degrees of freedom *(df)*	6,481474***
t-Statistic	17,47
p-Value	0,0000
log-likelihood	32327,730

Source: Datastream Database

Figure 25 presents the Conditional covariance of JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300. The Conditional covariance is positive and extreme volatile. Moreover, it is clear from the diagram that the Conditional covariance presents a downward trend over time. Furthermore, significant peaks and troughs are noticed during the under investigation time. The two of the most significant peaks were during 2008 and 2014. In addition, two of the most significant troughs were during 2010 and 2013. While major peaks and troughs are overt, in sub-periods not so many extreme values are observed while a more normalized line of the Conditional covariance is observed. The general downward trend of the line means possibly the general decrease of the two under investigation markets.

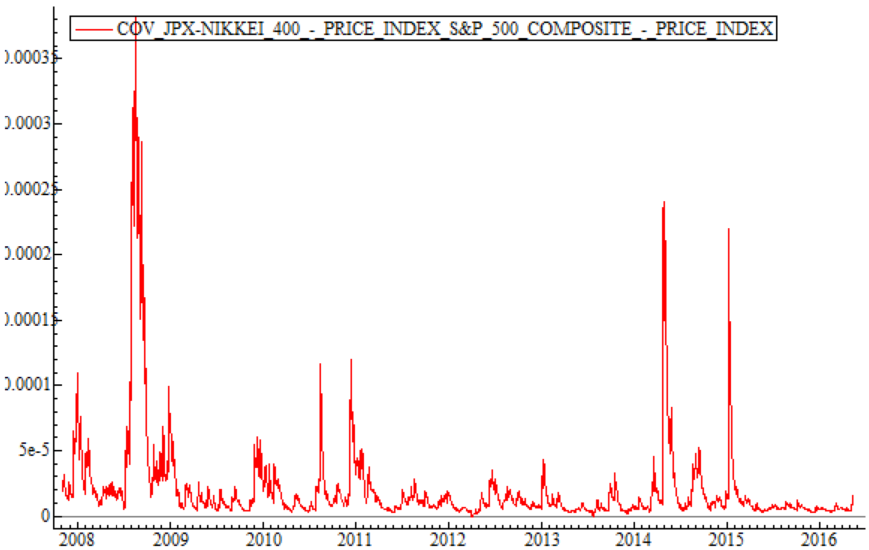
Figure 25. Conditional covariance for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 of the multivariate DCC-GJR model



Source: Datastream Database

Figure 26 presents the Conditional covariance of JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX. The Conditional covariance is positive and extreme volatile. Additionally, it is clear from the diagram that the Conditional covariance presents a downward trend over time. Significant peaks and troughs are observed during the under investigation time. Two of the most major peaks are observed in 2008 and 2014 and two of the most major troughs were during 2009 and 2013. Furthermore, although there are significant peaks and troughs, in sub-periods there are not so many extreme values, and a more normalized line of the Conditional covariance is observed. Additionally, the general downward trend of the line means possibly the general decrease of the two under investigation markets.

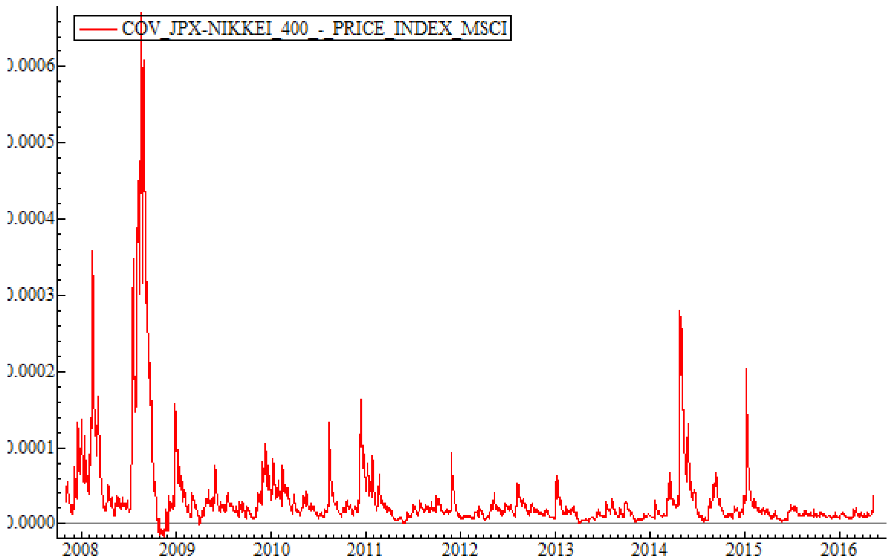
Figure 26. Conditional covariance for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GJR model



Source: Datastream Database

Figure 27 plots the Conditional covariance of JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI. It is observed that the Conditional covariance is positive and extreme volatile, except a sub-period in 2008, where the Conditional covariance has negative values. Additionally, it is clear from the diagram that the Conditional covariance presents a downward trend over time. Significant peaks and troughs during are seen to be in the whole period. Two of the most significant peaks are noticed in 2008, while two of the most significant troughs are observed during 2008 and 2013. Moreover, while there are significant peaks and troughs, in sub-periods There are not so many extreme values, and a more normalized line of the Conditional covariance is observed. In addition, the general downward trend of the line means possibly the general decrease of the two under investigation markets.

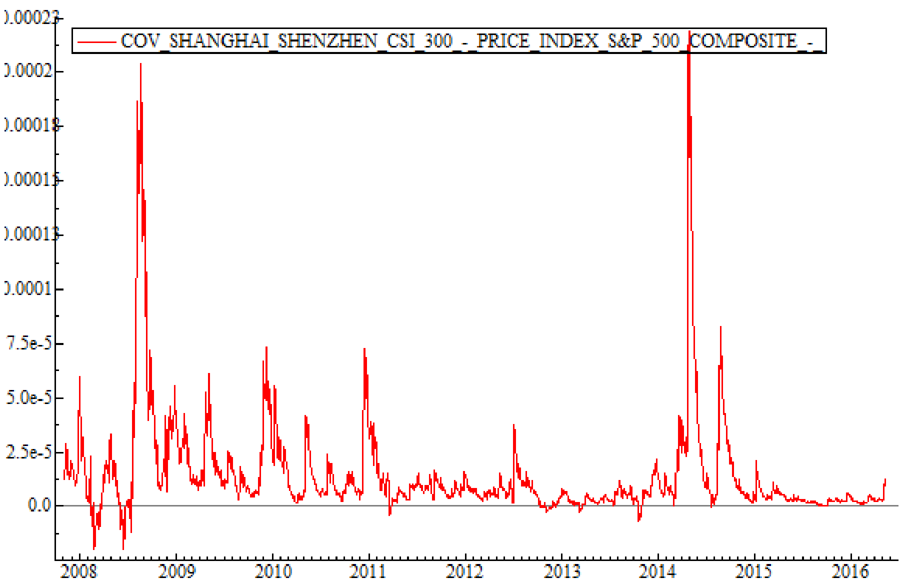
Figure 27. Conditional covariance for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI of the multivariate DCC-GJR model



Source: Datastream Database

Figure 28 shows the Conditional covariance of SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX. It is observed that the Conditional covariance is positive and extreme volatile, except sub-periods in 2008, 2011 and 2013, where the Conditional covariance presents negative values. It becomes clearly evident from the diagram that the trend line for the conditional covariance has a downward slope, with peaks being identified in the years 2008 and 2014 and historic lows in 2008. Extreme values were again not identified over the review period, leading to a more normal distribution, as far as the conditional covariance is concerned. Furthermore, the general downward trend of the line means possibly the general decrease of the two under investigation markets.

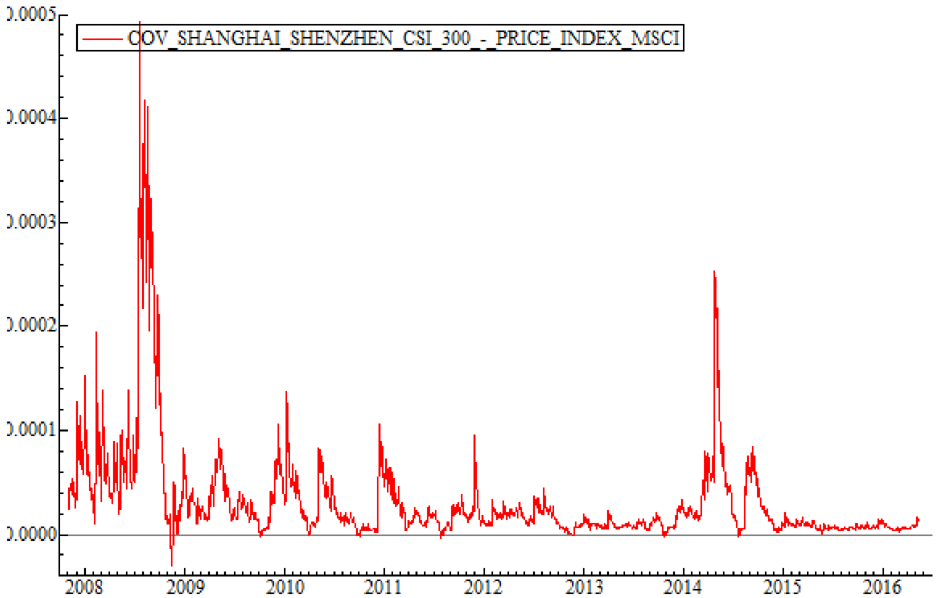
Figure 28. Conditional covariance for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GJR model



Source: Datastream Database

In Figure 29, I notice the Conditional covariance of SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI. The Conditional covariance is positive and extreme volatile, except sub-periods during 2008, where the Conditional covariance has negative values. Also, the Conditional covariance presents a downward trend over time. Significant peaks and troughs are seen to be during the whole period. also, two of the most significant peaks are in 2008 and 2014, while two of the most significant troughs are during 2008 and 2011. In addition, while there are significant peaks and troughs, in sub-periods there are not so many extreme values and I observe a more normalized line of the Conditional covariance. The general downward trend of the line means possibly the general decrease of the two under investigation markets.

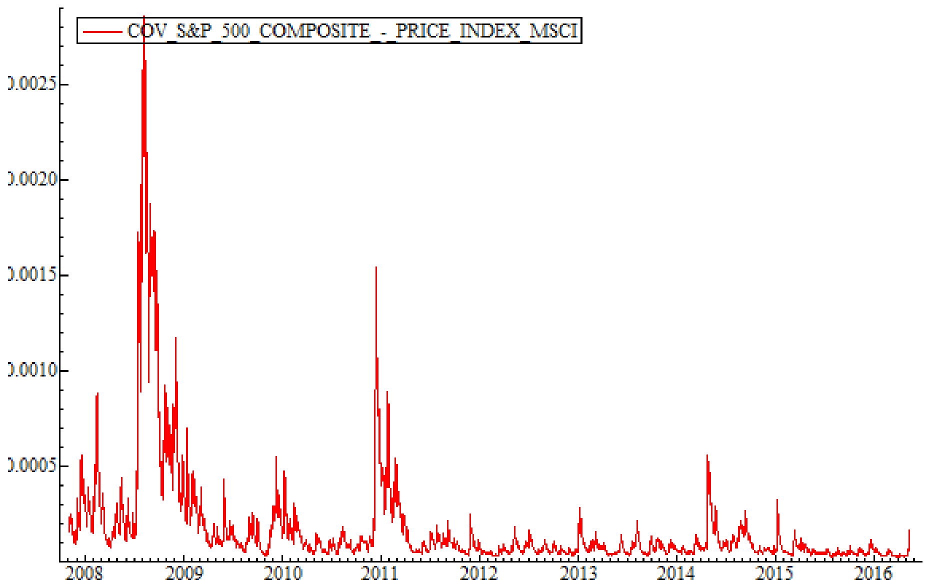
Figure 29. Conditional covariance for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI of the multivariate DCC-GJR model



Source: Datastream Database

In Figure 30, I see the Conditional covariance of MSCI - S&P 500 COMPOSITE - PRICE INDEX. It is observed that the Conditional covariance is positive and extreme volatile. Additionally, it is clear from the diagram that the Conditional covariance presents a downward trend over time. Significant peaks and troughs are observed during the whole period, two of the most significant peaks are in 2008 and 2010, whilst two of the most significant troughs during 2009 and 2010. Moreover, although there are significant peaks and troughs, in sub-periods there are not so many extreme values, and a more normalized line of the Conditional covariance is observed. Also, the general downward trend of the line means possibly the general decrease of the two under investigation markets.

Figure 30. Conditional covariance for the pairs of markets MSCI - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GJR model



Source: Datastream Database

4.2.5 Estimates of the Average Correlations for DCC-GJR model

Table 13 provides a detailed summary of the tests that were held for average correlations of the fourvariate GJR-DCC model. Based on the outcomes of these tests, all average correlations were statistically significant for all four markets the model comprised of.

Table 13. Estimates for the average correlations of the multivariate DCC-GJR model

	Coefficient	t-Statistic	p-Value
JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300	0,205561***	8,649	0,0000
JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI	0,094946***	3,260	0,0011
JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX	0,107798***	4,184	0,0000
SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI	0,068754***	2,616	0,0089
SHANGHAI SHENZHEN CSI 300 -	0,066728***	2,631	0,0086

PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX			
MSCI - S&P 500 COMPOSITE - PRICE INDEX	0,652858***	36,29	0,0000

Source: Datastream Database

4.2.6 Diagnostic Tests, Hypothesis Testing and Information Criteria if the bivariate DCC-GJR model

Table 14 provides a summary of the results of the statistical tests that were held, in order to calculate the estimated hypothesis and information criteria for all four indexes under research. The results of the statistical tests indicated that spillover effects were identified, thereby rejecting the null hypothesis at the level of significance 1%. As in the previous same tests that were held, no serial autocorrelation was identified.

Table 14. Diagnostic tests and information criteria of the multivariate DCC-GJR model

	JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI - S&P 500 COMPOSITE - PRICE INDEX
x^2 **(8)**	12404**
p-Value	0,0000
Hosking^2 (50)	759,772
p-Value	0,8304311
Li-McLeod^2 (50)	761,551
p-Value	0,8185566
Akaike	-24,221020
Schwarz	-24,156988
Shibata	-24,221253
Hannan-Quinn	-24,197850

Source: Datastream Database

4.2.7 Analysis of Dynamic Conditional Correlation Coefficients

Tables 15 and 16 present the descriptive statistics of the dynamic conditional correlations (DCCs) for all combinations of the four indexes of the research sample. As shown in the corresponding tables, the lowest min value was found for SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX, while the greatest max value was found for MSCI - S&P 500 COMPOSITE - PRICE INDEX along with the highest mean value and the highest standard deviation.

Table 15. Descriptive statistics of the DCCs

	CORR_ JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300	**CORR_ JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI**	**CORR_ JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX**
Min	0,092019	-0,019648	-0,005679
Mean	0,21657	0,097902	0,11917
Max	0,36214	0,29473	0,36872
Std.dev.	0,04319	0,043757	0,043933
Skewness	0,057061*	0,53060***	1,1246***
t-Statistic	1,2037	11,193	23,724
p-Value	0,22871	0,0000	0,0000
Excess Kurtosis	-0,27148**	1,1743***	3,9995***
t-Statistic	2,8645	12,391	42,201
p-Value	0,0041761	0,0000	0,0000
Jarque-Bera	9,6375**	278,39**	2339,8**
p-Value	0,0080768	0,0000	0,0000

Source: Datastream Database

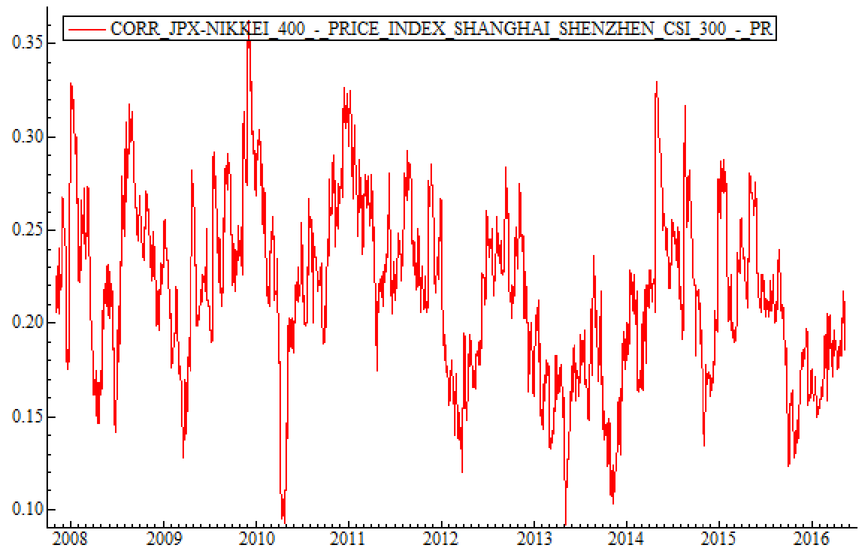
Table 16. Descriptive statistics of the DCCs

	CORR_ SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI	CORR_ SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX	CORR_ MSCI - S&P 500 COMPOSITE - PRICE INDEX
Min	-0,031562	-0,056447	0,2533
Mean	0,075147	0,073417	0,62751
Max	0,19988	0,21823	0,73628
Std.dev.	0,038684	0,041851	0,060993
Skewness	0,45000***	0,039670	-2,5297***
t-Statistic	9,4928	0,83685	53,364
p-Value	0,0000	0,40268	0,0000
Excess Kurtosis	0,21219**	0,36808***	10,350***
t-Statistic	2,2389	3,8838	109,20
p-Value	0,025160	0,0000	0,0000
Jarque-Bera	95,016**	15,755**	14747**
p-Value	0,0000	0,0000	0,0000

Source: Datastream Database

Figure 31 depicts the dynamic conditional correlation of JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300. It is noticed that the dynamic conditional correlation is positive and extreme volatile, implying contagion effects. Moreover, it is noticed that the dynamic conditional correlation presents a downward trend over time. Also, significant peaks and troughs are seen to be during the under investigation time. Two major peaks are observed during 2009 and 2014 and two major troughs during 2010 and 2013.

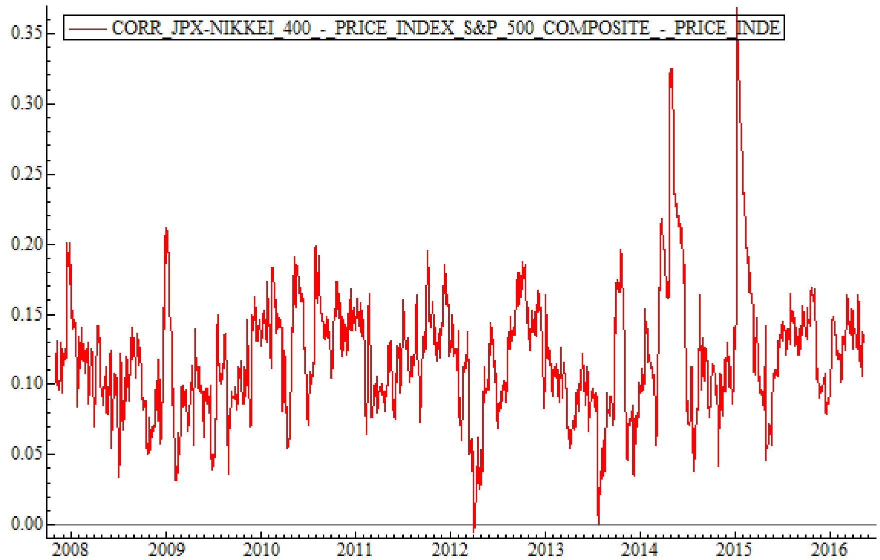
Figure 31. Dynamic conditional correlations for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - SHANGHAI SHENZHEN CSI 300 of the multivariate DCC-GJR model



Source: Datastream Database

Figure 32 shows the dynamic conditional correlation of JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX. It is noticed that the dynamic conditional correlation is positive and extreme volatile, implying contagion effects except sub-periods in 2012 and 2013, where the dynamic conditional correlation presents some negative prices. Moreover, neither a downward nor an upward trend is observed over time of the dynamic conditional correlation. Significant peaks and troughs are observed during the whole period. Two of the most significant peaks are seen to be in 2014, while two of the most significant troughs are observed during 2012 and 2013.

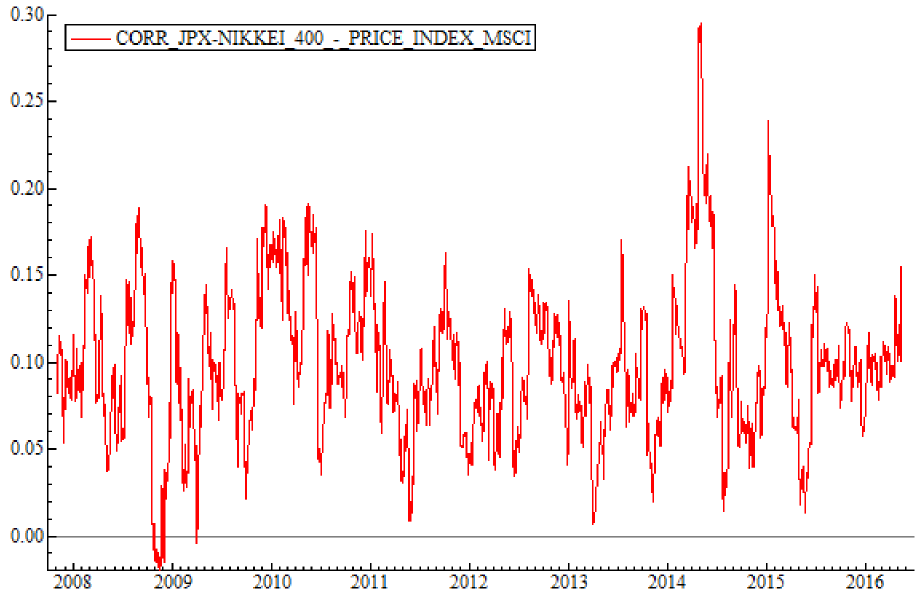
Figure 32. Dynamic conditional correlations for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GJR model



Source: Datastream Database

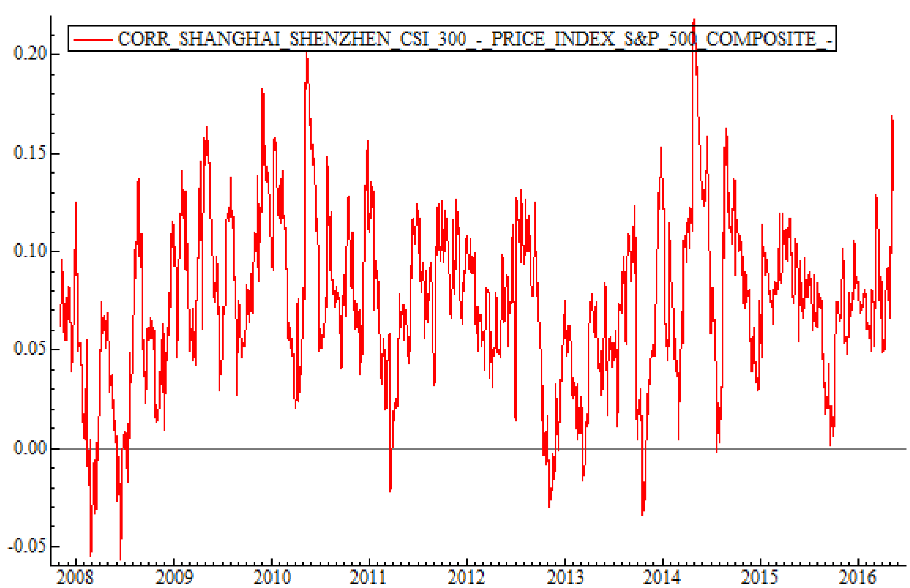
Figure 33 presents an illustration of the DCC for JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI. With the only exception being the year 2008, contagion effects were observed in a review period characterized by positive correlation and extreme volatility. A more or less steady slope in the corresponding trend line is identified, which shows peak values in 2014 and 2015, as well as bottom values in 2008 and 2009. Figure 34 presents the respective results for the indexes SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX, which have been identical with the results presented for the indexes JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI. The only difference lies is that peaks were identified in 2010 and 2014, whereas the most major trough was found to exist in the year 2008.

Figure 33. Dynamic conditional correlations for the pairs of markets JPX-NIKKEI 400 - PRICE INDEX - PRICE INDEX – MSCI of the multivariate DCC-GJR model



Source: Datastream Database

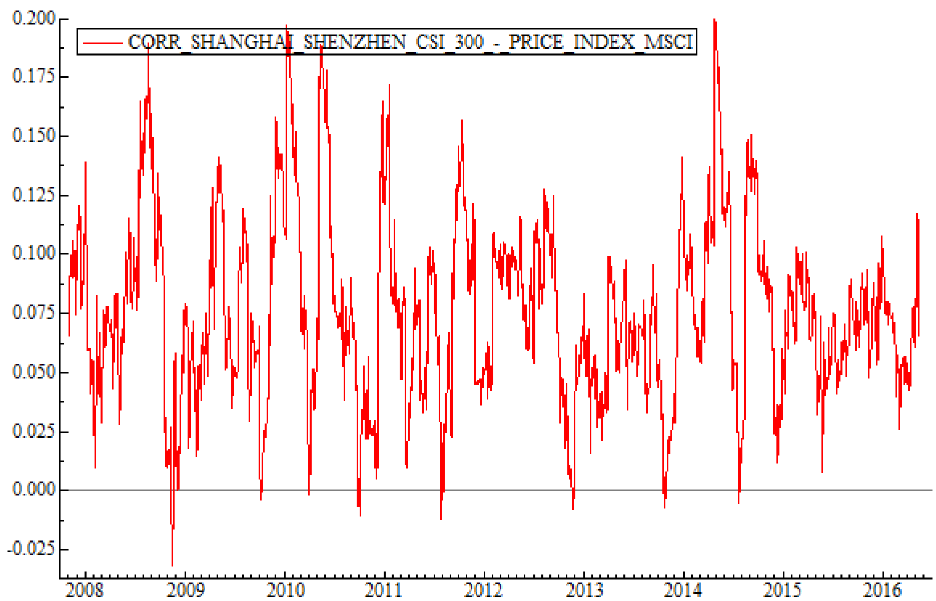
Figure 34. Dynamic conditional correlations for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GJR model



Source: Datastream Database

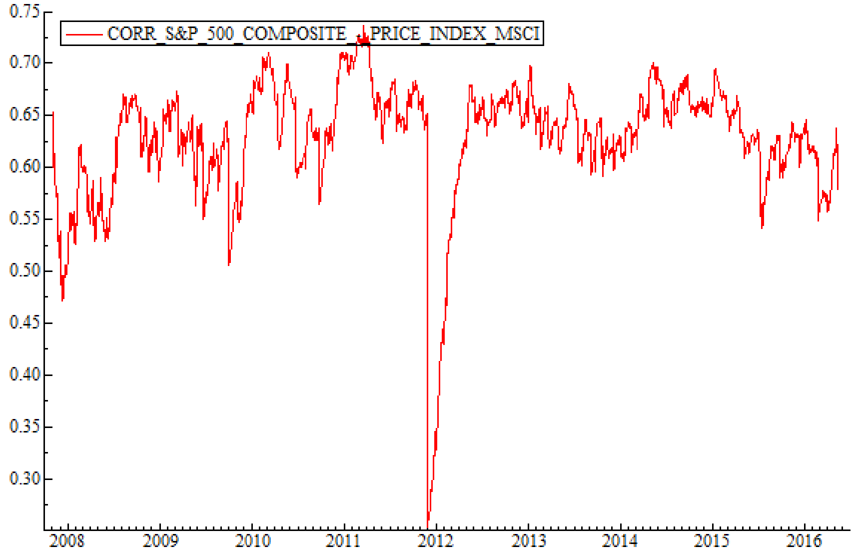
Figure 35 illustrates the outcomes of the DCC tests that were held for the indexes SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI. Once again, the same results were observed. In specific, DCC was found to be positive at subject to high levels of volatility, with contagion effects being present. As shown in the Figure during 2008 and 2009 DCC was found to be at its lowest levels, while in 2010 and 2014 the peaks of the review period were identified. The trend line of the evaluated relationship was neither positive, nor negative, providing once again an indication of a more or less stable performance and relationship between the two stock markets under discussion. Finally, exactly the same are the results for MSCI - S&P 500 COMPOSITE - PRICE INDEX, as illustrated in Figure 36, with the only exceptions being that this time the peaks of the period were found in 2010 and 2011, with the last months of the latter being the period whereby the bottom DCC values over the review period were observed.

Figure 35. Dynamic conditional correlations for the pairs of markets SHANGHAI SHENZHEN CSI 300 - PRICE INDEX – MSCI of the multivariate DCC-GJR model



Source: Datastream Database

Figure 36. Dynamic conditional correlations for the pairs of markets MSCI - S&P 500 COMPOSITE - PRICE INDEX of the multivariate DCC-GJR model



Source: Datastream Database

5. CONCLUSIONS

The aim of this thesis was to investigate whether volatility spillover effects of MSCI on the NIKKEI 400, S&P 500 and CSI 300 exist, using the DCC-GARCH model and the respective dynamic conditional correlations. For the purposes of the study, day-to-day data was collected for a period that encompassed growth, crisis decline and re-growth, i.e. the period between 25th November 2007 and 12th May 2016. Based on the empirical findings of the research, MSCI has a statistically significant positive effect on the investment returns enjoyed in the equity markets that were examined at a level of significance $\alpha=0.05$, with conditional covariance between MSCI and equity markets being positive and extremely volatile. Further, the results of the empirical analysis that was held with the trivariate DCC-GARCH model indicated that spillover effects are indeed evident between the three major stock markets that were reviewed and compared ($p<0.05$). As far as the analysis of DCCs is concerned, research findings revealed that major contagion effects exist among the markets across the years of the review period, with the corresponding trend lines being more or less straight over the period, indicating a more or less stable equity markets' performance over the review period.

As analyzed before, such research findings are very important for investors. Through analyzing the results of the statistical analyses that were held, investors shall have the ability to measure the risk they are involved in the three stock markets under review with quantifiable terms, while also gaining the necessary flexibility to monitor progress in the stock markets of their interest and explore the potential to maximize the profits of their investments at any time. The most important conclusion for them that is derived from research findings is that they have to be very careful with making simultaneous investments in stock markets that are subject to contagion effects. Last but not least, research findings are also important for policy makers, with their emphasis being placed on the spillover effects that shall emerge during crises that may take place in the future.

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