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The dynamic evolution of stock market integration between China, Japan and South Korea. What are the key determinants of regional stock market integration between these countries?

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Abstract

This paper investigates the dynamic evolution of the conditional correlation between the stock markets of China, Japan and South Korea by using the DCC-MGARCH model and investigates the key determinants of regional stock market integration by using a linear equation framework. The sample period is from January 1995 until December 2012. We first derive the dynamic conditional correlation between the pairwise countries' stock markets and then DCC is regressed on bilateral trade intensity, bilateral FDI intensity and the absolute difference of rate of inflation and short-term interest rate. We find that there is weak stock market integration between the three countries and that Chinese stock markets are very attractive markets to invest in for investors in order to benefit from the diversification effect according to asset allocation theory. The key determinant of stock market integrations for Japan-South Korea is interest rate; for China-Japan are interest rate and bilateral FDI intensity and for China-South Korea are bilateral FDI intensity and bilateral trade intensity.

Key Words: China, Japan, South Korea, stock market integration, DCC- MGARCH model, bilateral FDI intensity, bilateral trade intensity, interest rate, inflation.

Content

1. Introduction

The economic development of emerging countries in East Asia, e.g. China, with its high growth rates has been unprecedented in world history. The rise of the emerging countries in East Asia also stimulates the development of the economies in the developed industrial countries Japan and South Korea. The Asian crisis in 1997 caused an abrupt end to the booming economic development in East Asia but rapidly returned to the growth path of the past in the first decade of the 21st century. Only in 2001 and 2008 there have been major financial shocks, starting in the United States with the bursting of the dot-com bubble and the triggering of the subprime crisis, which spread out worldwide. Especially the 2008 financial crisis had a very negative impact on the economies in East Asia since it caused a sharp rise in unemployment rates. The Chinese, Japanese and South Korean governments decided to implement economic stimulus programs in order to cushion the negative effects spilling over from USA and Europe. One of the driving forces behind the high growth rates in these three countries has been their exports to USA and Europe. As a negative byproduct of the 2008 financial crisis the exports of goods from East Asia to USA and Europe plummeted, resulting in a decline of world trade activity. Therefore as a reaction to the most recent economic recession which has been the most severe since the Great Depression in the 1930s, the governments of China, Japan and South Korea decided to hold annual China–Japan–South Korea trilateral summits, the first one held in December 2008. This Political cooperation is likely to strengthen the economic cooperation between the three countries. The question arises if it had a positive impact on stock market integration between the three countries. According to Chiang et al. (2007) and Wang et al. (2009) findings it is the impact of financial crises that cause stock market correlations to increase substantially after they broke out. Besides the increased cooperation as a result of the China-Japan-South Korea trilateral summits is expected to lead to a convergence in economic and financial policies between the three countries, which should accelerate stock market integration. With the enhancing stock markets integration, information in one country tends to be transmitted to other countries more easily, therefore, it is expected that there are stronger spillover effects between financial markets, mainly in stock returns and volatilities. However when looking at the current different economic situations for example in China and Japan it is questionable if the stock markets in East Asia have become more integrated over time. Japan is still fighting against deflation and by following an expansionist monetary policy. On the other side China in the last couple of years until beginning of 2013 was following a restrictive monetary policy with high interest rates in order to fight against inflation and to cushion the speculation in the real estate market. In this case, the differences of two countries economic states will prevent economic or financial integration and in the end will result in stock market divergence, rather than convergence. The investing environment, trade activity and the adjustment of macroeconomic policies etc. are potential factors influencing the co-movement between different stock markets. In this empirical study we therefore want to investigate the regional stock market integration between China, Japan and South Korea and its determinants.

We decided to choose these three East Asian countries because they are the most important and dominant countries in economic terms in Asia and because previous studies about these three countries have neglected to focus on determinants of regional stock market integration since they only investigate the stock market correlation between Asian countries with developed countries like the USA or Europe, e.g. Chueng, Fung and Tam (2008). On the other hand previous studies about regional stock market integration in East Asia focused on only analyzing the evolution of stock market correlation, e.g. Chiang et al. (2007), whereas we want to do both: The research objective of this paper is, first, to explain the stock market integration in China, Japan, and South Korea by analyzing the pairwise dynamic conditional correlation between the three countries. By using dummy variables we take into account the impact of global shocks for example financial crises and also the impact of political events on the stock market integration in East Asia. Second, we compare the results and analyze the driving forces behind stock market integration between Japan, China and South Korea. We think that our research topic is interesting with respect to asset pricing/allocation, portfolio diversification and risk management for researches, investors, international companies and policy makers.

We are going to use the dynamic conditional correlation (DCC) from the multivariate GARCH model introduced by Engle (2002) in order to examine the extent to which the stock markets in China, Japan and South Korea have become integrated with each other over time, during the sample period from January 1995 until December 2012 using monthly data. The main advantage of the DCC-model compared to other similar models is that it allows presenting a more direct indication on the evolution of the financial market co-movement since it permits the dynamics of correlation, which is time dependent, to be modeled together with those of the volatility of the returns. Most importantly the DCC model is able to detect possible changes in conditional correlations over time by accounting for the time-varying behavior of time series data. And even more importantly, we use the estimated conditional correlation by DCC model as dependent variable to examine the determinants of stock market integration.

The outline of the thesis is as following: In the second chapter we summarize previous literatures. In the third part we illustrate possible explanatory variables of stock market integration which we are going to use in our regressions. The forth part presents the methodology of the DCC-MGARCH model, which we use to investigate the stock market integration, and also presents the linear equation framework, which we use to model the determinants of time-varying conditional correlation. The fifth part provides the data description. In the sixth part we present our empirical results, which we are going to analyze and interpret. In the conclusion we will summarize our main findings.

2. Literature review

2.1 Increased empirical research on regional and global stock market integration

In recent years, stock market integration has become a hot topic with a large number of researchers, investors and policy makers paying attention to it. There are many literatures concerning to stock market integration and spillover effects in global and regional scopes over the latest two decades. In summary, we notice that researchers mainly studied the spillover effects among the most developed economics: the U.S., Japan and the U.K, pioneered by Hamao et al. (1990). With the formation of the World Trade Organization (WTO), Association of Southeast Asian Nations (ASEAN), the Asia-Pacific Economic Cooperation (APEC) and European Union (EU) etc, researchers began to investigate the spillover effects and market integration in these regions. For instance, Asian countries (Sang (2009), Chan and Mohd (2010)), South African countries (Mumba (2011)), Latin America countries (Yiu et al. (2010)), and European countries (Baele (2005), Kanas (1998), Savva et al. (2005)). At the same time the return and volatility spillover from the U.S. and Japan have been studied by Bekaert, Harvey and Ng (2005), Fujii, Cheung and Chinn (2003), Fujiwara and Takahashi (2012). Moreover, it is also possible for researchers to analyze the market integration and spillover effects in both the mature countries and emerging countries, e.g. John et al. (2009) and Worthington and Higgs (2004).

2.2 Methodologies used in empirical research

When it comes to the models used to investigate stock market integration the range of models used goes from relative simple methods like exponential smoothing or rolling historical correlations (for example used by King and Wadhwani in 1990, Lee and Kim in 1993 and Forbes and Rigobon in 2002) to more sophisticated models like multivariate cointegration techniques in combination with the allied concept of error correction models, impulse response functions and Granger causality, which have been used by Richard (1995), Voronkova (2004) , Kasa (1992), Wang and Lee (2009). Furthermore the GARCH model (Bakaert and Harvey (1997)) is still most popular model for investigation stock market correlation. There are a variety of GARCH models, which are widely used: exponential-EGARCH (Kanas (1998), Chan and Mohd (2010), Savva et al. (2005)), asymmetric power- APARCH (Giorgio, Sunil and Stephen (2007)), BEKK-GARCH (Worthington and Higgs (2004)), the DCC-GARCH model (Yiu et al. (2010), Savva et al. (2005), Lean and Teng (2013)) has also been applied. In addition, to examine the short-term and long-term interdependences in international financial markets, vector autoregressive (VAR) model (Chelley-Steeley (2005), Grobys (2010)), vector error correction (VEC) model and Johansson cointegration test (Johansson and Ljungwall, (2009), Sakthivel, Bodkhe and Kamaiah (2012)) are employed.

2.3 Literature before 2002

The old literature before 2002 when Engle developed the DCC multivariate GARCH model faced the limitation that they were not able to show the evolution of cross-market co-movement or linkages by using the methodologies mentioned above in order to capture stock market integration. This is because the integration of stock markets is influenced largely by market forces. However market forces are subject to regulation and structural changes in the economy. Therefore the level of integration is not constant over time because of economic developments and regulatory changes. In previous studies researchers divided the sample period into different phases according to regime change in order to assess the varying degrees of integration. Because of cut-off dates, which are designed subjectively, the old studies about stock market integration cannot effectively describe the evolution of the changes on financial market co-movement over time. Multivariate GARCH models of course can estimate the variance-covariance transmission mechanism of market volatility; however it lacks the ability of identifying the significant changes of this transmission.

2.4 Literature after 2002

The new literature since 2002 provides new insights in the integration of stock markets by using more sophisticated research models. For example Kim (2005) uses the exponential GARCH (EGARCH) model to derive the time variations in conditional correlations for his study on the developed European Union (EU) stock market. The bivariate EGARCH model with DCC specification was used by Wang et al. (2008) in their study about stock market integration between emerging Central Eastern European stock markets and the aggregate Eurozone market. For the period of the financial crisis from 1997 until 1998 the authors find significant dynamic correlations for the emerging markets with the Eurozone market and for the aftermath of the crisis they document a higher level of correlation. When the emerging countries in the sample joined the EU this also has strengthened the correlation.

Over the last two decades, it has been found that it is likely that the higher the international financial integration, the stronger spillover effects from developed stock markets to developing or emerging markets. Bekaert, Harvey and Ng (2005), as the main representatives found that there is an increase in correlation and spillover effects especially during financial crisis and there exists increased spillover effect. Many empirical papers find that the European stock markets correlations have increased over time (Grobys (2010), Savva et al. (2005)), but there is weak integration of Asian stock markets (Joshi (2011)), and the markets become more interdependent after crisis. Besides, it is common to conclude that the U.S.A and Japan are the dominant forces of fluctuations on other stock markets, and that in recent years China has acquired a dominant role in Asia. (Fujiwara and Takahashi (2012)).

2.5 Literature on Asian stock market integration

There are also several studies about stock market integration between Asian stock markets in particular with respect to U.S stock markets. Chiang et al. (2007) who examined the integration of nine Asian stock markets using the DCC model over the period from 1990 to 2003. For the period of the financial crisis in 1998 they found an increase in correlation, which they termed as contagion effect. Furthermore the correlation was continuing at a very high level in the aftermath of the crisis because of herding effects. Therefore he comes to the same conclusion as Wang et al. (2008) however for a different region. Cheung (2007) studied the linkage between four Asian emerging markets (Hong Kong, Taiwan, South Korea and Singapore) and the change in the information structure triggered by the Asian crisis in 1997. They conclude that the U.S market leads the four Asian emerging markets before, during and after the Asian crisis in 1997-98 while the U.S market is Granger-caused by these four markets during the crisis period. The interdependence between equity markets in the Executives' meeting of East Asian Pacific Central Banks (EMEAP) region and the U.S as well as across the EMEAP markets was assessed by Chueng, Fung and Tam (2008) by using a DCC model. For the most recent financial crisis in 2008 the authors find that the average correlation of EMEAP economies with respect to other equity markets in the region increases to a large extent in the late 2008. Interestingly they do not find direct evidence for a contagion effect of shocks from U.S equity markets to Asian equity markets to the full extent. In a working paper Yiu et al. (2010) investigate financial spillover to Asian and Latin American markets however compared to Chueng, Fung and Tam (2008) they use a different approach by examining the dynamic conditional correlation between the U.S equity market and Asian equity markets directly with the DCC framework. In order to extract the major force behind the Asian equity markets in their sample the authors use a principal component analysis and then estimate the dynamic conditional correlation between this driving force and the U.S equity market. This approach is different to the one by Chueng, Fung and Tam (2008) since they estimated the DCC of the eleven Asian economies compared to the U.S equity market at the same time and then looking at the pair-wise dynamic conditional correlations between these economies and the U.S. The approach adopted by Yiu et al. (2010) has the benefit of eliminating the market specific component which exists in each individual market within the region and enables them to focus only on the interplay between the regional equity market as a whole and the U.S equity market. Jeong (2012) implemented VAR model, risk decomposition model, cointegration and DCC model to examine the short-run and long-run relationships among three Asian stock markets from January 2000 to September 2010. The author found that China is more influenced by regional markets than global markets, compared to Korea and Japan. Except for this Jeong finds an increase in stock market integration especially after the financial crisis and the degree of integration changes over time. It is worth to mention that Kim and Kim (2011) proposed a DCCX-MGARCH model not only to investigate the spillover effects of 2008 U.S. financial crisis on five Asian financial markets but also to examine how exogenous variables (element X) affect the correlations of cross-countries, so as to identify the channels of contagion. They confirmed the existence of contagion and found that foreign investment is the key factor influencing the conditional correlations in international equity markets. It is innovative to involve the effects of explanatory variables on dynamic conditional correlation in one system.

2.6 Literature on stock market integration on rest of the world

Wang and Moore (2008), Syllignakis and Kouretas (2011) applied the DCC model on emerging Central Eastern European (CEE) stock markets. Both of them included seasonally adjusted data for industrial production, three-month interbank rate, exchange rate volatility in their regressions in order to explore the factors driving the stock markets correlations. However there are differences with respect to the dependent variables and the objectives their papers focused on[1]. The former article investigates the integration of emerging CEE stock markets with the Eurozone market from 1994 to 2006, and found higher stock market linkages after the Asian and Russian crises and the post-entry period to the European Union (EU). They also concluded that the development of the financial sector determines the financial market integration. Whereas the latter article captures the potential contagion effects among the U.S., German, Russian and the CEE stock markets from 1997 to 2009. They found increased conditional correlations, particularly during the 2007–2009 financial crises, implying that these emerging markets are exposed to external shocks. Besides, they demonstrated that macroeconomic variables, such as the domestic and foreign monetary indices have substantial explanatory power on the stock market correlations.

3. Determinants of stock market integration

3.1 Determinants of stock market integration in previous research

In terms of the determinants of stock market integration, there are various factors, such as economic and financial, which have an effect on the integration of stock markets between different countries. In line with the viewpoint of Bekaert and Harvey (1997, 2000), many other researchers argue that the fundamental driving forces of market integration can be divided into three categories, which are global, regional and

[1] See Wang and Moore (2008), Syllignakis and Kouretas (2011)

local factors. Guesmi (2011) showed that regional trade openness and market development explain the time-varying degree of integration of Latin American, South Eastern Asian, and South Eastern European stock markets, whereas local factors such as market volatility and inflation play a significant role in the stock market integration of countries in the Middle East. Wang and Moore (2013) found that trade balance is a main determinant for explaining the dynamic correlation in Asian stock markets, that interest rate differential is the driving force for explaining stock market integration in the developed markets and that there is little effect of financial development on the correlation. In general there are several variables which are common to be included in regressions for stock market integration: the values of total trade (export and import), industrial production (often used as a proxy for business cycles), inflation rate (Consumer Price Index), short-term interest rate (three-month interest rate/interbank rate) and the exchange rate volatility. For example Buettner and Hayo (2009), Mukherjee and Moshra (2006), Pretorius (2002), Wang and Moore (2008), Syllignakis and Kouretas (2011) have used these variables in order to explain stock market integration. Sometimes, when the explanatory factors are considered not to be well-represented by specific measurements, authors tend to introduce dummy variables for capturing the impact of major events such as financial liberalization, trade liberalization and change in exchange rate regime on the dynamic correlation. For example Beine and Candelon (2006) in their paper investigate the impact of trade and financial liberalization on the degree of stock market co-movement among emerging economies by using dummy variables, while Pretorius (2002) uses regional dummy variables in order to test the impact of regional factors on the dynamic correlation.

However, in order to analyze the determinants of stock market integration, we should keep in mind that the stock markets interdependency is influenced by the degree of co-movement between two countries' economic, financial and trade connections. That is to say, the correlation of these variables affect the stock markets integration, the stronger theses variables i.e., industrial production, inflation and interest rate ties between two countries, the higher the correlation of the stock markets, similarly, if these economic factors which influence the stock markets in two countries are convergent (divergent), we should expect convergence (divergence) in stock market movements. On the scope of market overall conditions, e.g. banking sector development, market development, market capitalization and market liquidity, the less variation there is between the stock markets, the higher the level of stock market integration.

To examine the effects of industrial production, inflation and exchange rate on the conditional correlations between two countries, some papers employ the industrial production growth differential and inflation differentials, for instance Buettner, D. and Hayo, B. (2009), Mukherjee and Mishra (2006), Pretorius, E.(2002). In terms of the exchange rate factor, to our knowledge, Wang and Moore (2008) and Syllignakis and Kouretas (2011) used the exchange rate volatility to capture the currency risk premium. As far as we consider the change of exports and imports of a country, or the change of trade value it is a reflection of the appreciation and depreciation of a country's currency. In other words, the exchange rate fluctuations lead to changes in trade values, such that the exchange rate illustrates the international trade activities and openness. Therefore, we resort to analyze the indicator of trade openness or trade intensity instead of exchange rate differentials between two countries.

As Shi et al. (2010) and Kim and Kim (2011) point out that foreign direct investment (FDI) can explain the stock market integration. Shi et al. (2010) demonstrate that the higher the bilateral FDI levels and flows, the higher the Australia's stock market integration with its major trade partners. As far as we consider with the increased cooperation between different countries, the trade and investment activities are more frequent than before. Therefore it is interesting to see the effects of FDI and trade factors on the stock market integration.

3.2 Determinants of stock market integration for China, Japan and South Korea

In our research about the stock market integration between China, Japan and South Korea we use the absolute differential value of inflation and short-term interest rate, as well as the bilateral trade intensity and bilateral FDI intensity as explanatory variables to investigate the determinants of stock markets integration in our linear equation framework, described in section 4.2.

3.2.1 Bilateral FDI Intensity

According to Shi et al. (2010: 268-269) FDI defines a long-term investment in which an investor obtains a lasting interest in a foreign economy. FDI involves an initial transaction and also any subsequent capital transactions between two entities and therefore establishes a long-term relationship between them. This variable makes economies to become more integrated by linking them to each other and this leads to higher stock market integration. There are two FDI statistics recorded, one is the Inward FDI (FDI in the reporting economy), the other is Outward FDI (or FDI abroad). A commonly used measure for bilateral FDI intensity is to take the average of inward and outward FDI flows divided by GDP, which is named as FDI intensity as % of GDP. *A higher index indicates higher new FDI during the period in relation to the size of the economy as measured by GDP. If this index increases over time, then we can say that the country/zone is becoming more integrated within the international economy.*[2] We use this measurement for bilateral FDI intensity as one of the determinants of stock market integration. The calculation is expressed as:

$$\frac{\frac{\text{Inward FDI}_{ij}+\text{Outward FDI}_{ij}}{\text{GDP}_i}+\frac{\text{Inward FDI}_{ji}+\text{Outward FDI}_{ji}}{\text{GDP}_j}}{2} \quad (1)$$

where Inward FDI_{ij} and Outward FDI_{ij} are the values of the inward and outward FDI flows from country i to country j. GDP_i is the GDP in country i, GDP_j is the GDP in country j.

From the formula, we can see the strength of the bilateral FDI relationship between country i and j. The higher the bilateral FDI intensity the higher the stock market integrations between two countries. According to theory it is expected that $\text{Inward FDI}_{ij}=\text{Outward FDI}_{ji}$, which means that the inward FDI flows from country i

[2] http://europa.eu/estatref/info/sdds/en/bop/bop_fdi_sm.htm

to country j equal the outward FDI flows from country j to country i. We use this assumption for China inward and outward FDI flows to Japan and South Korea since we were not able to collect the specific inward and outward FDI flows for China with their partner countries Japan and South Korea. The bilateral inward and outward FDI data for Japan and South Korea are not the same values since we managed to get the specific dataset from OECD. Graphs 1 to 3 plot the evolution of the bilateral FDI intensity for the three pairs. We can see that the bilateral FDI intensity between China and Japan decreases modestly from 2.4% to slightly above 0.8%, whereas the bilateral FDI intensity between China-South Korea and Japan-South Korea increased slightly over time.

3.2.2 Inflation and Interest rate

Pretorius (2002: 91-92) states that several local macroeconomic variables are influencing the stock market performance according to the cash flow model:

$$P = \frac{(1+g)*D_0}{k-g} \quad (2)$$

where g is the constant growth rate, D_0 is the last dividend paid and k is the discount rate. Chen et al. (1986: 383) documented that macroeconomic variables such as interest rate, inflation and industrial production have an influence on the expected cash flows and therefore also on the stock prices since any factor that influences the stream of cash flows or the discount rate in the cash flow model will systematically influence the stock prices. Since the macroeconomic variables influence the stock market performance of a country the inference is that if the macroeconomic variables in two countries are similar than the stock market performance will also be similar. For example if the Central Banks of two countries follow the same monetary policy then the interest rate of the two countries will move in the same direction over time. For each pair we calculated the absolute inflation differential value by the following formula:

$$\pi_{ij} = |\pi_i - \pi_j| \quad (3)$$

where π_i denotes the inflation rate in country i and π_j the inflation rate in country j. The absolute short-term interest rate differential value was calculated by:

$$r_{ij} = |r_i - r_j| \quad (4)$$

where r_i denotes the short-term interest rate in country i and r_j the short-term interest rate in country j. The larger the absolute difference values of inflation and interest rate between two countries, the larger the stock market divergence, which means that the two macroeconomic variables have a negative impact on the stock market integration between two countries. We decided to follow Pretorius (2002: 95) who used absolute difference values for inflation and interest rates since it does not matter which county's interest rate or rate of inflation is higher, however what matters is how large the difference is. This is because stock market correlation does not involve a direction of causality. Graphs 4 to 6 plot the absolute difference in the rate of inflation between China-Japan, China-South Korea and Japan-South Korea. We can see that over time the absolute difference is significantly decreasing between China and Japan, as well as between China and South Korea. Only for the pair Japan-South Korea the decrease in the absolute difference has been modest but this is due to the fact that the difference has never been as high as between the other two pairs. Graphs 7 to 9 all exhibit a similar pattern that the absolute difference in the rate of interest between the three countries decreases over time.

3.2.3 Bilateral Trade Intensity

The last variable we use as a determinant for stock market integration is bilateral trade intensity. According to the theory of stock market integration bilateral trade intensity has a positive impact on stock market integration, e.g. Pretorius (2002). This is because the tighter the trade ties between two countries the higher the stock market integration. Bekaert and Harvey (1997: 38) argue that high trade intensity between two countries induces correlation between business cycles and consumption, and also results in asset pricing that reflects higher risk. This statement by Bakaert and Harvey (1997) is intuitive because if two countries are depending on each other because of tight trade linkages then an external shock, e.g. a recession in country j, which leads to a sharp decrease in imports of country j from country i will cause a drop in exports of country i to country j and in this way the external shock will spillover from country j to country i. As a result the business cycles of the two countries will converge. Therefore trade intensity has a positive effect on stock market integration between two countries but investors face higher risks since the performance of the stock index in country i is also depending on the state of the economy of the country j, which is a negative byproduct of increased trade intensity.

Trade intensity can be measured by several formulas. We use two formulas in order to get a robust result for our regressions. Firstly we examine the impact of bilateral trade intensity on the stock market correlation between China, Japan and South Korea by using the following formula:

$$\frac{x_{ij}+z_{ij}}{X_i+Z_i} + \frac{x_{ji}+z_{ji}}{X_j+Z_j} \quad (5)$$

where x_{ij} and z_{ij} are the value of bilateral exports and imports from country i to country j while X_i and Z_i are the value of total exports and imports of country i. By using this formula we can measure how important country j is to country i as trading partner and export market for country i's products and vice versa. A high number of the sum of the two parts indicates a strong bilateral trade relationship between country i and country j, which should result in convergence between the stock markets of the two countries. According to theory it is expected that $x_{ij}=z_{ji}$, which means that the exports of country i to country j equal the imports of country j from country i. However for our data this equation does not hold since we have $x_{ij}\neq z_{ji}$. There are several reasons for this discrepancy to occur, e.g. there is a time lag between the recordings of exports by the exporting country. The second formula for trade intensity is:

$$\frac{x_{ij}+z_{ij}}{GDP_i} + \frac{x_{ji}+z_{ji}}{GDP_j} \quad (6)$$

In this formula we use the GDP of country i and country j as denominator in order to normalize the bilateral exports and imports. The higher the sum of the two parts the higher the bilateral trade intensity and the higher the stock market integration. Graphs 10 to 12 plot the evolution of bilateral trade intensity between China-Japan, China-South Korea and Japan-South Korea calculated by using bilateral trade intensity formula 1 and 2. For the bilateral trade intensity between China and Japan calculated the formula 1 the bandwidth ranges from 25% to 32% over time, for the second formula the bandwidth only ranges from 1.6% and 4.8%. There is a negative trend in the bilateral trade intensity between Japan and South Korea calculated by the first formula as the evolution of the line indicates. Over time the bilateral trade intensity between the two countries decreases from slightly above 26% to 16%. The line for the bilateral trade intensity calculated by the second formula evolves in a very narrow bandwidth between 2% and 4%. In graph 12 we can see a positive trend in the evolution of bilateral trade intensity between China and South Korea for both formulas. The line standing for the calculation with the first formula shows a sharp increase in bilateral trade intensity from 11% to 27.5% over time. For the second formula this increase in bilateral trade intensity is smaller from 1% to 7% over time. Table 1 summarizes the determinants of stock market integration used in the linear regressions.

Table 1: Determinates for stock market integration between China, Japan and South Korea

<table>
<tr><td>Determinant</td><td colspan="4">Bilateral FDI Intensity</td></tr>
<tr><td>Expected sign</td><td colspan="4">positive</td></tr>
<tr><td>Calculation</td><td colspan="4">$\frac{\frac{\text{Inward FDI}_{ij} + \text{Outward FDI}_{ij}}{GDP_i} + \frac{\text{Inward FDI}_{ji} + \text{Outward FDI}_{ji}}{GDP_j}}{2}$</td></tr>
<tr><td>Determinant</td><td>Inflation</td><td>Interest Rate</td><td>Bilateral Trade Intensity 1</td><td>Bilateral Trade Intensity 2</td></tr>
<tr><td>Expected sign</td><td>negative</td><td>negative</td><td>positive</td><td>positive</td></tr>
<tr><td>Calculation</td><td>$\pi_{ij} = |\pi_i - \pi_j|$</td><td>$r_{ij} = |r_i - r_j|$</td><td>$\frac{x_{ij}+z_{ij}}{X_i+Z_i} + \frac{x_{ji}+z_{ji}}{X_j+Z_j}$</td><td>$\frac{x_{ij}+z_{ij}}{GDP_i} + \frac{x_{ji}+z_{ji}}{GDP_j}$</td></tr>
<tr><td colspan="5">where x_{ij} and z_{ij} are the value of exports and imports from country i to country j while X_i and Z_i are the value of total exports and imports of country i.</td></tr>
</table>

4. Methodology

The method we apply in our empirical study is Engle's (2002) dynamic conditional correlation (DCC) model from the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model. This model is suitable for financial time series to capture the volatility spillover effects and to estimate time-varying conditional correlations. It is not linear and can be estimated by the likelihood function using univariate GARCH or two-step methods.

Other MGARCH models, such as VEC, BEKK, Cholesky factor GARCH, Constant Conditional Correlation (CCC) can also take this responsibility, however these models require the imposition of restrictions in order to satisfy the positive definiteness in terms of reparameterization of the variance covariance matrix. Therefore the DCC model is superior to the other MGARCH models. Moreover, DCC model overcomes the disadvantages that there are a large number of parameters to estimate and the parameters are hard to be interpreted in other MGARCH models. Furthermore the assumption in the CCC model that the correlations are constant is unrealistic. In addition, because the DCC-MGARCH model has the flexibility of the univariate GARCH model with parsimonious parameters for the correlations and covariance matrices, it seems to be the appropriate model and it is more robust for investigating the time-varying conditional covariances and correlations among these stock markets. Furthermore, thanks to this advantage, the timing of crisis periods are shown by analyzing DCC model, the exact dates of the beginning and ending of integration or contagion are acknowledged by this method, so that we do not take account of sub-sample analyses. In addition, as the parameters are easily to be explained, it is accessible for proposing suggestions for different parties. The main finding of Engle (2002) illustrates that compared with other MGARCH models, the DCC - bivariate version is the most appropriate one to use and often the most accurate one to a variety of dynamics correlation processes. Moreover, the feature of the DCC model that multivariate and univariate volatility forecasts and correlations of n variables are consistent with each other, i.e., the original volatility forecasts will be and correlations may remain unchanged when introducing new variables to the system.[3] The DCC model presented below is for a bivariate case.

4.1 DCC model

According to Lu (2013) the DCC model assumes that the correlations between assets are time-varying.

$$\mathbf{y}_{\boldsymbol{t}} = \boldsymbol{\mu} + \boldsymbol{u}_{\boldsymbol{t}} \quad (7)$$

$$\boldsymbol{u}_{\boldsymbol{t}} = \boldsymbol{H}_{\boldsymbol{t}}^{\mathbf{1/2}}\varepsilon_t,\ \varepsilon_t|\varphi_{t-1} \sim \mathrm{N}(0,\ \boldsymbol{H}_t) \quad (8)$$

where $\mathbf{y}_{\boldsymbol{t}}$ is the asset returns/countries. $\boldsymbol{u}_{\boldsymbol{t}}$ is the random variables, φ_{t-1} is the set of information at time t-1.

$$\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t \qquad (9)$$

$$\boldsymbol{\epsilon}_{\mathbf{t}} = \boldsymbol{D}_{\mathrm{t}}^{-1}\boldsymbol{u}_{\mathrm{t}} \qquad (10)$$

where $\boldsymbol{H}_{\boldsymbol{t}}$ is positive conditional variance matrix of returns**.** $\boldsymbol{D}_t$ is the conditional standard deviations, and $\boldsymbol{R}_t$ is the conditional correlation of $\boldsymbol{y}_t$. $\boldsymbol{D}_t$, $\boldsymbol{H}_{\boldsymbol{t}}$ and $\boldsymbol{R}_t$ are respectively:

$$\boldsymbol{D}_t = \mathrm{diag}(\sigma_{i,t}) \quad (11)$$

$$\boldsymbol{H}_{\boldsymbol{t}} = \mathrm{E}_{t-1}(\boldsymbol{u}_{t-1}\boldsymbol{u}_{t-1}^{'}) \quad (12)$$

$$\boldsymbol{R}_t = \begin{pmatrix} 1 & \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \\ \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} & 1 \end{pmatrix} = \begin{pmatrix} 1 & \rho_{12,t} \\ \rho_{12,t} & 1 \end{pmatrix} \quad (13)$$

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[3] See Engle (2002)

where the conditional correlation between two random variables u_1 and u_2 that have mean zero is defined as:

$$\rho_{12,t}= \frac{E_{t-1}(u_{1,t}u_{2,t})}{\sqrt{E_{t-1}(u_{1,t}^2)E_{t-1}(u_{1,t}^2)}} = \frac{E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t})}{\sqrt{E_{t-1}(\varepsilon_{1,t}^2)E_{t-1}(\varepsilon_{1,t}^2)}} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t}) \quad (14)$$

To estimate DCC model, we construct an univariate GARCH(1,1) model to compute the diagonal elements in $\boldsymbol{D}_t^2$:

$$\boldsymbol{D}_t^2 = \mathrm{diag}(\sigma_{i,t}) = \mathrm{diag}(\boldsymbol{\omega}_i) + \mathrm{diag}(\alpha_i)\boldsymbol{u}_{t-1}\boldsymbol{u}_{t-1}' + \mathrm{diag}(\beta_i)\boldsymbol{D}_{t-1}^2 \quad (15)$$

$$or \quad D_t^2 = \omega_i + \alpha_i u_{t-1}^2 + \beta_i D_{t-1}^2 \quad (16)$$

where "ω_i *is a constant mean,* α_i *is the ARCH effect,* β_i *is the GARCH effect. A positive coefficient of* β_i *implies volatility clustering and persistency in the positive changes of a stock index.* $\alpha_i + \beta_i$ *indicates the persistency of the volatility shock*"[4] and $\alpha_i + \beta_i < 1$.

And since the $\boldsymbol{R}_t$ can be estimated with the covariance matrix of the standardized residual $\boldsymbol{\epsilon}_t$:

$$\boldsymbol{R}_t = \boldsymbol{D}_t^{-1}\boldsymbol{H}_t\boldsymbol{D}_t^{-1} = E_{t-1}(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') \quad (17)$$

The dynamic correlation structure is expressed as:

$$\boldsymbol{R}_t = \mathrm{diag}\{\boldsymbol{Q}_t\}^{-1/2}\boldsymbol{Q}_t\mathrm{diag}\{\boldsymbol{Q}_t\}^{-1/2} \quad (18)$$

and we have the GARCH-like equation for $\boldsymbol{Q}_t$ that:

$$\boldsymbol{Q}_t = (1-\kappa-\gamma)\overline{\boldsymbol{Q}} + \kappa\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t' + \gamma\boldsymbol{Q}_{t-1}$$

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[4] See Lean and Teng (2013): p335-336

$$=(1-\kappa-\gamma)\begin{pmatrix}\bar{q}_{11,t} & \bar{q}_{12,t}\\ \bar{q}_{12,t} & \bar{q}_{22,t}\end{pmatrix} + \kappa\begin{pmatrix}\epsilon_{1,t-1}\epsilon_{1,t-1} & \epsilon_{1,t-1}\epsilon_{2,t-1}\\ \epsilon_{1,t-1}\epsilon_{2,t-1} & \epsilon_{2,t-1}\epsilon_{2,t-1}\end{pmatrix} +$$

$$\gamma\begin{pmatrix}q_{11,t-1} & q_{12,t-1}\\ q_{12,t-1} & q_{22,t-1}\end{pmatrix} = \begin{pmatrix}q_{11,t} & q_{12,t}\\ q_{12,t} & q_{22,t}\end{pmatrix} \quad (19)$$

where $\boldsymbol{\bar{Q}}$ is the unconditional correlation/variance matrix of the standardized residual $\boldsymbol{\epsilon_t}$ and κ and γ are scalar parameters which is non-negative and satisfying $\kappa+\gamma<1$ in order to ensure the conditional correlation between -1 and +1, and that the model is mean-reverting. *"The significant of κ and γ implied that the estimators obtained from DCC-MGARCH were dynamic and time-varying. κ indicates short-run volatility impact, implying the persistency of the standardized residuals from the previous period, γ measures the lingering effect of shock impact on conditional correlation, which indicates the persistency of the conditional correlation process. $\rho_{ij,t}$ illustrates the direction and strength of the correlation. If the estimated $\rho_{ij,t}$ is positive, the correlation between returns series is rising and moving in the same direction or vice versa."*[5]

In this way the coefficients of conditional variances and correlations can be obtained. Then we calculate the log likelihood and maximize with respect to the restrictions: $\alpha_i+\beta_i<1$, and $0<\kappa+\gamma<1$. The log likelihood is the sum of log-density.

Log-density function (in bivariate case):

$$\ln f(\boldsymbol{y_t}|\theta) = -\ln(2\pi) - \ln\left(\sqrt{\sigma_{1,t}}\right) - \ln\left(\sqrt{\sigma_{2,t}}\right) - \frac{1}{2}ln(1-\rho_t^2) - \frac{1}{2(1-\rho_t^2)}\left(\frac{u_{1,t}^2}{\sigma_{1,t}} + \frac{u_{2,t}^2}{\sigma_{2,t}} - 2\rho_t\frac{u_{1,t}u_{2,t}}{\sqrt{\sigma_{1,t}}\sqrt{\sigma_{2,t}}}\right) \quad (20)$$

Log likelihood function:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|\boldsymbol{H_t}| + r_t' \boldsymbol{H_t^{-1}} r_t) \quad (21)$$

[5] See Lean and Teng (2013): p335-336

$$= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi)+\log|\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t|+ r_t' \boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1} r_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi)+2\log|\boldsymbol{D}_t|+\log|\boldsymbol{R}_t|+ \varepsilon_t' \boldsymbol{R}_t^{-1} \varepsilon_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi)+2\log|\boldsymbol{D}_t|+ r_t' \boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1} r_t - \varepsilon_t' \varepsilon_t+\log|\boldsymbol{R}_t|+ \varepsilon_t' \boldsymbol{R}_t^{-1} \varepsilon_t)$$

where n is the number of variables, which can be assets returns or countries.

The last equation of the log likelihood function can be rewritten as the sum of a volatility part and a correlation part:

$$L(\theta, \Phi) = L_V(\theta) + L_C(\theta, \Phi) \quad (22)$$

where θ represents the parameters in **D,** Φ denoted as the additional parameters in **R.**

The volatility term is:

$$L_V(\theta) = -\frac{1}{2}\sum_t(n\log(2\pi)+\log|\boldsymbol{D}_t|^2+ r_t' \boldsymbol{D}_t^{-2} r_t) \quad (23)$$

and the correlation component is

$$L_C(\theta, \Phi) = -\frac{1}{2}\sum_t(\log|\boldsymbol{R}_t| + \varepsilon_t' \boldsymbol{R}_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t) \quad (24)$$

Finally we compute the DCC estimation for the parameters μ_i ω_i, α_i, β_i, κ and γ.

4.2 Linear equation framework

In order to investigate the impact of crisis events (external shocks) on the dynamic conditional correlations, we introduce dummy variables for three different crisis periods and for the trilateral summits. In this paper, $DM_{1,t}$ is the dummy variable for the 1997-1998 Asian financial crisis, which began in July 1997 and ended after June 1999; $DM_{2,t}$ is the dummy variable for the 2000-2001 dot-com financial crisis from

March 2000 until November 2001. $DM_{3,t}$ is the dummy variable for the 2008 financial crisis starting in August 2007 and ending in March 2010. $DM_{4,t}$ is the dummy variable for the trilateral summits held between China, Japan and South Korea. The dummy variable starts with the first summit held in December 2008 and ends with the most recent summit held in May 2012.[6] The value of the dummy variables is set equal to one for the crisis events and zero otherwise.

Table 2: The period of dummy variables

Dummy variables	Beginning	Ending
$DM_{1,t}$ for 1997-1998 Asian financial crisis	July 1997	June 1999
$DM_{2,t}$ for 2000-2001 dot.com financial crisis	March 2000	November 2001
$DM_{3,t}$ for 2008 financial crisis	August 2007	March 2010
$DM_{4,t}$ for trilateral summits	December 2008	May 2012

Since we decided to use bilateral FDI intensity, inflation rate, short-term interest rate and bilateral trade intensity as explanatory variables in order to analyze stock market integration between the stock markets of China, Japan and South Korea, we estimate the following linear equation:

$$\rho_{ij,t} = \omega + \alpha_1 DM_{1,t} + \alpha_2 DM_{2,t} + \alpha_3 DM_{3,t} + \alpha_4 DM_{4,t} + \sum_{k=1}^{4} \beta_{1t} X_{k,t} + \eta_{ij,t} \quad (25)$$

where $\rho_{ij,t}$ is the conditional correlation of stock market returns between country i and country j , $\rho_{ij,t}$ are estimated by DCC model, $DM_{k,t}$ are the four dummy variables. $X_{k,t}$ represents the four explanatory variables as determinants of stock market integration. It is noted that the parameters $\omega, \alpha_k, \beta_{kt}$ are different from the one's of the DCC model.

[6] Dates specified like previous researches

Followed by Otto et al. (2001), since the dependent variable $\rho_{ij,t}$, the conditional correlation of stock market returns, must lie between –1 and 1, it cannot be normally distributed, the transformation of the dependent variable is needed and calculated as[7]:

$$w_{ij,t} = \ln\frac{1+\rho_{ij,t}}{1-\rho_{ij,t}} \quad (26)$$

We use the transformed $w_{ij,t}$ values as dependent variable in the following five linear regressions:

$$w_{ij,t} = \omega + \beta_1 X_{\text{Bilateral FDI Intensity},t} + \beta_2 X_{\text{inflation},t} + \beta_3 X_{\text{Interest Rate}} + \beta_4 X_{\text{Bilateral Trade Intensity1},t} + \eta_{ij,t} \quad (27)$$

$$w_{ij,t} = \omega + \beta_1 X_{\text{Bilateral FDI Intensity},t} + \beta_2 X_{\text{inflation},t} + \beta_3 X_{\text{Interest Rate}} + \beta_4 X_{\text{Bilateral Trade Intensity2},t} + \eta_{ij,t} \quad (28)$$

$$w_{ij,t} = \omega + \alpha_1 DM_{1,t} + \alpha_2 DM_{2,t} + \alpha_3 DM_{3,t} + \alpha_4 DM_{4,t} + \beta_1 X_{X_{\text{Bilateral FDI Intensity},t}} + \beta_2 X_{\text{inflation},t} + \beta_3 X_{\text{Interest Rate}} + \beta_4 X_{\text{Bilatetral Trade Intensity1},t} + \eta_{ij,t} \quad (29)$$

$$w_{ij,t} = \omega + \alpha_1 DM_{1,t} + \alpha_2 DM_{2,t} + \alpha_3 DM_{3,t} + \alpha_4 DM_{4,t} + \beta_1 X_{X_{\text{Bilateral FDI Intensity},t}} + \beta_2 X_{\text{inflation},t} + \beta_3 X_{\text{Interest Rate}} + \beta_4 X_{\text{Bilatetral Trade Intensity2},t} + \eta_{ij,t} \quad (30)$$

Where $X_{\text{Bilateral Trade Intensity1},t}$ and $X_{\text{Bilateral Trade Intensity2},t}$ define the two different formulas for calculating bilateral trade intensity, while all the other variables stay the same so that we can get a robust result for this determinant.

$$w_{ij,t} = \omega + \alpha_1 DM_{1,t} + \alpha_2 DM_{2,t} + \alpha_3 DM_{3,t} + \alpha_4 DM_{4,t} + \beta_{1t} X_{k,t} + \eta_{ij,t} \quad (31)$$

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[7] See Appendix A of Otto, G., Voss, G., Willard, L.(2001). Understanding OECD Output Correlations. Research Discussion Paper 05. Reserve Bank of Australia.

In the last regression we always included the four dummy variables together with one of the four determinants of stock market integration in order to see how the single determinants are able to measure the goodness of fit by R-squared, which allows us to define the single determinant, which has superior explanatory power over the other variables.

5. Data description

In order to test the impact of the determinants on stock market integration, which we proposed in section 3.2, we use a data set of monthly observations of the main stock market indices in the China, Japan and South Korea from November 1994 until December 2012. We collect monthly data of the SSE Composite Index, Nikkei 225 Stock Average Index and Korea KOSPI Composite Index in local currency. The monthly observations avoid the noise coming from the daily effect, and since we have a period of 18 years, we focus on the long-term stock markets' co-movement and spillover effects. The rate of inflation, short-term interest rate, bilateral and total exports and imports are monthly data of which the bilateral and total exports and imports are expressed in US dollar. We collected the data from International Monetary Fund and datastream.

We transferred the data frequency by using Eviews. The data frequency of GDP is quarterly data and is measured in US dollar. The frequency for bilateral inward and outward FDI flows is on yearly basis, which is also measured in US dollar. The sample is from 1994 to 2011. To deal with the problem that the FDI data are missing for years between, we take an average between the year before and the year after. For the missing values of inward and outward FDI flows in 2012, we assume the same as the value in 2011. This data was collected from OECD library. In order to obtain the quarterly bilateral FDI intensity, which is calculated by the average of bilateral inward and outward FDI flows divided by GDP, firstly we used the "linear-match last" option when we transferred the data frequency from yearly to quarterly. Secondly we used the transformed data and the quarterly GDP data in order to calculate bilateral FDI intensity. Because there is no clear trend observable when analyzing the graphs we used the “constant-match average” option for transforming the quarterly data to monthly data.

Graph 13 plots the three countries’ indices which we normalized by setting the starting value of the series to 100 at the starting day November 1994. This graphs shows that there are differences in the evolution of the three indices. Chinese stock market has an outstanding over-performance during the years of 2006 and 2007, whereas South Korea and Japan have stable stock market prices over the previous 18 years. Graph 14.1 to 14.3 indicate that regarding the returns of three countries’ indices the KOSPI return is the most volatile one in the period of the 1997 financial crisis. Besides, a mean reversion pattern is observed for the returns of all the three countries’ indices.

Before the empirical studying, we intent to do the following two steps to process the data for the stock indices returns. First, in order to ensure that this time series is stationary, we conduct Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test in order to examine unit root and stationary. The ADF test of three countries’ stock markets indices is shown in the appendix by table 3, which is illustrating that the indices of NIKKEI 225, SSE and KOSPI are non-stationary.

Then we transform the price indices to stock returns by taking logs and differences, the differenced logarithmic stock indices are the continuously compounded stock returns, denoting r_t.

$$r_t = (\log(p_t) - \log(p_{t-1})) = \ln\left(\frac{p_t}{p_{t-1}}\right) = d(\log(p_t)) \quad (32)$$

where p_t stands for the stock index for each country.

From the results of ADF, PP and KPSS test for the three countries’ stock market returns shown in table 4 in the appendix, it can be obtained that there is a consistent confirmation that the returns series of KOSPI, NIKKEI 225 and SSE are stationary. Thus, we can use the stationary data to implement our DCC estimations.kk

Second, we establish the unconditional correlation matrices of these four countries' stock indices and returns to observe the interdependence of stock markets. From table 5 in the appendix, it can be seen that there is a relative high unconditional correlation between the SSE index and KOSPI index. There are negative relative low unconditional correlations in NIKKEI 225 index with KOSPI index and SSE index. With respect to the stock returns found in table 6 in the appendix, the SSE index is almost uncorrelated with NIKKEI 225 and KOSPI. However, the unconditional correlation between the returns of NIKKEI 225 and KOSPI is about 0.49.

In the first two procedures, a general summary of statistical properties for the sample and returns series is presented in table 7 of the appendix. The SSE index has the highest average return when compared to the average returns of the KOSPI index and NIKKEI 225. The mean of NIKKEI 225 return is negative, illustrating that the Japanese stock market has negative returns on average. According to the standard deviation, there exists a higher risk in South Korea and in China, whereas the Japanese stock returns are less risky. The positive skewness of the three indices means that they have long tails to the right, large positive stock indices are more common than large negative stock indices, whereas the negative skewness of the returns of SSE and NIKKEI 225 indicating that large negative stock returns are more common than large positive returns. Besides, the values of kurtosis for our sample stock returns are larger than three and the standard deviation are high. It is illustrating that the SSE, NIKKEI 225 and KOSPI returns have fatter tails and higher peaks, which means that there exists stock market volatility and stability in China, Japan and South Korea. The statistics of Bera-Jarque test reject the null hypothesis of normality, thus the distribution of returns is non-normal, indicating that the three stock markets are more likely to have large positive or negative shocks.

According to table 8 summarizes the descriptive statistics of the four determinants of stock market integration. We recognize that there is multicollinearity between explanatory variables in table 9 because these macroeconomic variables are related to each other, e.g. interest rate and inflation, which means that over time they move in the same direction, however they measure different things. There is a trade off between adjusting the data set in order to address multicollinearity problem and the interpretation of the explanatory variables since it is very difficult to interpret the differentiated determinants in our linear regression framework. We therefore opted for the interpretational power of the explanatory variables since the correlations between the determinants in table 19 and the R-squared in our estimated regressions were not close to 1.

6. Empirical results

We use Excel and Eviews for our empirical studies. We first estimate the DCC model in order to obtain the conditional variance and correlation of each country's stock market. To specify, we acquire the conditional variance by constructing a univariate GARCH (1,1) model to analyze the varying volatilities across markets. Then, we impose a GARCH-like equation for conditional correlation, so as to observe the dynamic integration between stock markets. After this, we compute the log-likelihood function and maximize it with respect to the parameters under certain restrictions to ensure the stationarity of the conditional variance, by referring to the statistics values of coefficients in DCC model, we are able to investigate the spillover effects and stock markets integration between countries.

Then in order to investigate the influence of the external shocks, special events and the determinants on the stock market integration we regress the time-varying correlations with and without dummy variables by using the linear equation framework introduced in section 4.2 and lastly we analyze and compare the results.

6.1 Results of DCC estimation

In table 10 we summarized the results from the estimation of the DCC – MGARCH model. For the mean equation all the coefficients are insignificant. The result for the variance equation shows that the ARCH effect denoted by the α's is much lower than the GARCH effect denoted by the β's. The high positive values of the β's implies that there is a high degree of volatility clustering and persistence in the changes of stock indices. Since $\alpha_i + \beta_i$ is always lower than 1 we ensure that the dataset is stationary and that the pattern of the dynamic conditional correlation is mean reverting. The results of the γ's in the GARCH-like equation indicates that there is a high persistence in the conditional correlation process between the indexes of the countries in our sample and the coefficient estimates γ's are significant. In other words, the correlation heavily depends on its past conditional correlation in our pairwise countries: China and Japan, Japan and South Korea, China and South Korea, the percentage accounts for about 98.7777%, 93.0668% and 80.5092% respectively. The highest persistence in the conditional correlation process is between the indexes of China and Japan, whereas the China and South Korea indices have the lowest persistence in the conditional correlation. The κ's are always slightly negative except for the relationship between the KOSPI and NIKKEI 225 index, which is implying that there are negative short-run volatility impacts on the conditional correlation in the pairwise countries. For China and Japan, China and South Korea, these conditional correlations are negatively depending on the previous standardized residuals, which approximately occupied -5.0567% and -6.984% respectively. However the coefficient estimates κ's are not at a significant level, except for the pair China-Japan.

By using the Ljung–Box Q statistic test we examine the residual serial correlation with the null hypothesis that there is no serial correlation. The result is presented by table 11 in the appendix. For the series of SSE, KOSPI and NIKKEI 225 return, the p-values of Q1 statistics accept the null until lag 8, which means that there is no serial correlation in the standardized residuals. However, except for the KOSPI, the p-values of Q2 statistics for SSE and NIKKEI 225 returns reject the null, which shows that there is no serial correlation in the squares of the standardized residual for the KOSPI returns.

The result of heteroskedasticity by Engle' ARCH effect test for the returns of KOSPI, NIKKEI 225 and SSE shown in table 12 indicates that we accept the null hypothesis significantly, which means that there is no ARCH effect in the three return series respectively.

The development of the correlations shown in the graphs 15 to 17 confirms our findings from the DCC model estimations that there is a relatively low level of volatility and that there is a high level in the persistence of volatility shocks. Regarding the dummy variables and their impacts on the evolution of the correlation we can see that for the pair of China and South Korea in graph 15 that there has been an increased stock market integration after the end of the Asian crisis, the same for the dummy variable 2 since there has been a positive effect after the bursting of the dot-com bubble, which however sharply decreased from 2003 until 2004 and then increased again from 2004 until 2005. In recent years the correlation declined and in 2012 is slightly negative. Graph 16 shows the evolution of the correlation between Japan and South Korea. It was steadily increasing after the Asian crisis and after the dot-com bubble. After the 2008 financial crisis the correlation was shooting up from 0.45 to 0.65 which lets us to conclude that there has been an outstanding significant positive effect resulting from the trilateral summit for these two countries. However after reaching the peak point in early 2009 the correlation significantly reduced during the period from 2009 until 2011 before it recovered and increased once again to its current level of 0.5. From graph 17 we can see that the correlation between China and Japan sharply increased after the Asian crisis and also sharply increased after the end of the dot-com bubble and also after the 2008 financial crisis. However since 2010 there has been a sharp decline in the correlation and currently there is a slightly negative correlation between the stock markets of China and Japan. Overall we conclude that there is weak stock market integration between the three most dominant economic players in Asia. Furthermore we cannot support the finding by Wang et al. (2008) and Chiang (2007) that the stock market correlation is continuing to stay at a higher level after the end of a financial crisis. Because the first trilateral summit was held in December 2008, only two months after the collapse of Lehman Brothers, it is not clear if the short-term increase in the correlation was caused by the political and economical cooperation between the three countries or if it was the impact of the 2008 financial crisis since dummy variables 3 and 4 overlap. However it can be stated that the increased political cooperation starting since 2009 fails to contribute to increased stock market integration between China, Japan and South Korea and that since the three countries are in different economic states there is a low stock market integration persisting today. However since it is not clear cut if the increase in stock market integration in 2008 was caused by the financial crisis or the political event we cannot really support the findings of Wang et al. (2008), who states that political events, represented by the joining of the EU by Poland and Czech Republic, increased stock market correlation between two countries with EU market.

The stock markets of the pairs China-South Korea and China-Japan are very independent on each other since China-Japan has a coefficient very close to 0 in 2012 and China-South Korea has a slightly negative coefficient close to -10% in 2012. This means that for investors in Japan and South Korea China is a very attractive market to invest in, in order to diversify their investments. In this way Japanese and South Korean investors are able to benefit from the diversification effect, which has been documented by Markowitz (1959) and his asset allocation theory, since their stock markets are very independently correlated with the Chinese stock market, which makes their diversified portfolios less risky. Our results are consistent with Jeong (2012), who also found that Chinese stock markets are a very attractive market for Asian investors to invest in, in order to benefit from the diversification effect since China is not as heavily influenced by global markets compared to Japan and South Korea.

As graph 19 indicates because of globalization and increased international economic linkages between countries since the mid 1990s it has become more difficult for investors to diversify their portfolios. For example the correlation of European stock markets with the UK and the U.S stock markets has reached a very high level since the mid 1990s. During the recession because of the triggering of the dot-com financial crisis at the beginning of the 2000s the correlation between EU stock markets and UK and U.S stock markets reached a correlation of 0.92, which is very close to a perfect correlation. The numbers in graph 19 confirm that the correlation of stock markets during a recession period is higher compared to an economic boom period.

From the graphs 20 to 21 which show the dynamical conditional variances of the three countries' returns. As can be seen the volatilities in the different stock markets are varying in different periods. South Korea suffered from unprecedented volatility during 1998 and 2000, after this the major volatile was alleviated to the level of 0.5%

to 1%. The similarly situation can be observed in the case of China, but not as severe as South Korea. Comparatively, Japan did not experience such severe stock market volatility at that time. From 2008 until 2010, there has been an increase in the volatility of stock market returns of the three countries. For Japan, South Korea and China, the highest volatile period appears in 2009, with values up to the level of 1.3%, 1.5% and 2.2% respectively.

6.2 Results from linear equation framework

6.2.1 Results for regression including bilateral FDI intensity, inflation, interest rate and bilateral trade intensity (calculated by formula 1) with and without dummy variables.

Table 13 summarizes the results of the coefficients for each determinant without dummy variables from the linear equation estimations. The second column of table 13 for the pair China-Japan can be read as followed:

1) Bilateral FDI intensity: The pairwise correlation between China and Japan decreases by 2555.61 basis points for every unit increase in bilateral FDI intensity.

2) Inflation: The pairwise correlation between China and Japan increases by 1.9261 basis points for every unit increase in inflation.

3) Interest rate: The pairwise correlation between China and Japan decreases by 1.4243 basis points for every unit increase in the short-term interest rate.

4) Bilateral Trade Intensity 1: The pairwise correlation between China and Japan decreases by 130.6841 basis points for every unit increase in bilateral trade intensity.

For the pair China-South Korea in column three of table 13 all of the coefficients are negative however they are not significant, except for the intercept, which is significant and positive. Contrary to this for the pair Japan-South Korea all of the coefficients are significant and bilateral FDI intensity has a positive coefficient as expected by theory. However for the other two pairs this is surprisingly not the case.

In table 14 the results for the regressions including dummy variables can be found. As can be seen from table 14 for the pair of China-Japan all the coefficients are significant, except for dummy1. Dummy3, dummy4, inflation and bilateral trade intensity are significant coefficients in the regression result for the pair China-South Korea. Only three coefficients (dummy1, dummy3 and interest rate) are significant for the pair of Japan-South Korea.

When comparing the regression results with the dummy variables we can see that all the coefficients for the determinants bilateral FDI intensity and bilateral trade intensity are negative except for the pair Japan-South Korea. However these positive coefficients for the pair Japan-South Korea are not significant. In both regressions the R-squared for China-South Korea is the lowest one, the R-squared for China-Japan is the second highest one and the pair Japan-South Korea has the highest R-squared.

6.2.2 Results for regression including bilateral FDI intensity, inflation, interest rate and bilateral trade intensity (calculated by formula 2) without and with dummy variables

Table 15 summarizes the results for the regression excluding dummy variables, in which we use a different formula for calculating trade intensity. The second column of table 16 for the pair China-Japan can be read as followed:

1) Dummy1: The correlation coefficients were on average 6.7119 basis points lower than usual during the Asian financial crisis.

2) Dummy2: The correlation coefficients were on average 19.9557 basis points higher than usual during the dot-com financial crisis.

3) Dummy3: The correlation coefficients were on average 11.9086 basis points lower than usual during the 2008 financial crisis.

4) Dummy4: The correlation coefficients were on average 8.8995 basis points lower than usual during the period of the trilateral summits from 2008 until 2012.

5) Bilateral FDI intensity: The pairwise correlation between China and Japan decreases by 2284.659 basis points for every unit increase in bilateral FDI intensity.

6) Inflation: The pairwise correlation between China and Japan increases by 2.0072 basis points for every unit increase in inflation.

7) Interest rate: The pairwise correlation between China and Japan decreases by 1.7169 basis points for every unit increase in the short-term interest rate.

8) Bilateral Trade Intensity 2: The pairwise correlation between China and Japan decreases by 25.0555 basis points for every unit increase in bilateral trade intensity.

For the pair China-Japan all of the coefficients are significant except for dummy1, interest rate and bilateral trade intensity. The only significant coefficients for the pair China-South Korea are dummy3, dummy4 and bilateral FDI intensity. Dummy1, dummy3, and interest rate are the only significant coefficients for Japan and South Korea. When it comes to R-squared again Japan-South Korea has the highest R-squared amongst the three pairs, China-Japan has the second highest value and China-South Korea has the lowest one.

6.2.3 Results for regression including only one explanatory variable (using both formulas for bilateral trade intensity)

In order to find the determinant which has superior explanatory power we regressed the four dummy variables with only one determinant and compared the R-squared to the R-squared in tables 14 and 16. The result can be found in table 17 and 18. When comparing table 14 and table 17 we find that there are two single determinants which can explain stock market correlation between China and Japan since bilateral FDI intensity and interest rate are significant coefficients, which have an R-squared of 31.39% and 29.40% respectively. These values are very close to the R-squared of 36.92% for the regression including all four determinants and all four dummy variables. For the pair China-South Korea we find that bilateral FDI intensity, interest rate and bilateral trade intensity are significant coefficients. Bilateral trade intensity has an R-squared of 23.94%, whereas bilateral FDI intensity has an R-squared of

22.67%, which are very close to the overall R-squared of 27.54% in table 14. Therefore bilateral trade intensity and bilateral FDI intensity are the best determinants for the stock market correlation between China and South Korea. For the pair Japan-South Korea we get a significant coefficient for all four variables. Interest rate is the outstanding determinant in explaining stock market correlation between the two countries because it has an R-squared of 62%, which is very close to the overall R-squared of 62.73% in the regression including all four variables and all four dummies in table 14. The same observation can be made by comparing table 18 with table 16. Table 19 summarizes the key determinant(s) for each pair.

When comparing the graphs 15 to 17 with the results from the regressions we observe that for the pair Japan-South Korea, which has the highest correlation amongst the three pairs is also the only pair which has a positive coefficient for bilateral trade intensity and bilateral FDI intensity in both regressions including dummy variables and different formulas for trade intensity in table 14 and 16. Furthermore in the regressions including dummy variables and only one determinant, where bilateral trade intensity is calculated by formula 2 in table 18 the pair Japan-South Korea is the only one which has a positive coefficient for bilateral FDI intensity and bilateral trade intensity. For the other two pairs we get negative coefficients for bilateral trade intensity and bilateral FDI intensity, which contradicts to theory of stock market integration since it states a positive relationship between the two determinants and stock market integration.

When looking at the results for the dummy variables in table 14 and 16 we observe that in both regressions for the pair China-Japan only dummy variable 2 had a positive effect on the stock market correlation between the two countries. For the other two pairs the dummy variables which stand for three financial crises and a political event have a positive effect on the integration of stock markets between the country-pairs. This is in accordance with the theory in stock market integration, which states that financial crises and political events lead to an increase in stock market correlation. We have fourteen significant dummy variables out of twenty-four coefficients for the four dummy variables.

6.3 Comparison of linear regression results with previous research results

Table 20 summarizes the findings of previous researchers, who used the same fundamental factors that influence the stock market correlation as in our regressions. Other researchers also found negative coefficients for bilateral trade intensity, e.g. Shi et al (2010) who use the same formula for the calculation of bilateral trade intensity, however they use a different methodology (Geweke feedback measure). Chee-Wooi et al (2009) also state a negative coefficient for bilateral trade intensity however they study the stock market correlation of trading blocs and use panel regression in their methodology. For the determinants short-term interest rate and inflation many previous studies, e.g. Bracker et al (1999) and Pretorius (2002), get a negative coefficient, which however is insignificant. Regarding interest rate our regression results in table 14 and 16 indicate mixed evidence since we have almost all the time a negative coefficient which is in accordance with theory of stock market integration however the coefficients are not always significant (three significant coefficients out of six regressions). In table 13 and 15 we have two significant coefficients out of six regressions, both of them for the pair Japan-South Korea. For the explanatory variable inflation we have three significant negative coefficients out of six regressions in tables 14 and 16 and for tables 13 and 15 four coefficients are negative and significant out of six regressions. The determinant bilateral FDI intensity has not often been used so far. As far as we know there are only two articles, which used a different measure for variable: Forbes et al. (2004) use bilateral foreign investment and get an insignificant coefficient. Shi et al. (2010) calculate bilateral FDI flows, which turns out to be a positive significant coefficient.

Our findings of negative and positive effects on stock market integration by the impact of financial crises and political events represented by dummy variables is in accordance with the results of pervious studies on stock market correlation, which also conclude that there is mixed evidence regarding the impact of financial crises and political events, e.g. Syllignakis et al. (2011) finds negative and positive impacts by the Asian crisis on Central Eastern European countries. Furthermore Syllignakis found that there is a negative, as well as a positive effect on the stock market correlation by the dot-com crises and a significant positive effect for the dummy representing the 2008 stock market crash. Wang et al (2008), and Pretorius (2002) both get a positive significant coefficient for the Asian crisis on stock market integration. The same result is obtained by Chee-Wooi (2009) regarding the Asian crisis; however he finds a significant negative coefficient for the dot-com bubble.

7. Conclusion

In this study we analyzed the dynamic evolution of the conditional correlation between the stock markets of China, Japan and South Korea by using the DCC-MGARCH model and we also investigated the key determinants of regional stock market integration by using a linear equation framework. We find that there is weak stock market correlation between the three most important industrial countries in East Asia. There is an independent co-movement between the stock markets of China and South Korea, as well as between China and Japan. For the pair Japan-South Korea there is a correlation of 0.5 at the end of 2012. We therefore think that Chinese stock markets are a very attractive market since it allows investors from Japan and South Korea to benefit from the diversification effect by investing a part of their money in China. According to the asset allocation theory put forward by Markowitz (1959) this will lead to a decrease in the systematic risk of the portfolio. Contrary to previous research we find that the stock market correlation was not continuing to stay at a higher level after the end of all three financial crises represented by dummy variables and that the impact of the trilateral summits had only a positive impact on the stock market integration between China and South Korea.

Regarding the regional determinants of stock market integration between the three countries we find that for China and Japan interest rate and bilateral FDI intensity are the single key determinants explaining the R-squared to a very large extent. For China-South Korea bilateral FDI intensity and bilateral trade intensity are the key determinants for explaining stock market correlation, whereas for Japan-South Korea interest rate is the single key explanatory variable. In all four regressions the pair

Japan-South Korea had the highest R-squared, followed by China-Japan and the lowest R-squared was observed for China-South Korea. Furthermore we find that the coefficients for bilateral trade intensity and bilateral FDI intensity are almost all negative in the four regressions which is not consistent to the theory of stock market integration, however the coefficients for the absolute differential values for inflation and interest rate are almost all the time negative which is in accordance with the theory. Overall we think that the current weak stock market correlation, especially between the pairs China-Japan and China-South Korea results from the weak economic integration and the different monetary policies which the countries adopt, which leads to a divergence in the business cycles of the respective countries and in the end results in a weak stock market integration.

Appendix:

Table 3: ADF test for unit roots of KOSPI, Nikkei 225 and SSE index

Test			KOSPI		NIKKEI_225		SSE	
ADF			t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
Critical values	1% level	-3.460453						
	5% level	-2.874679						
	10% level	-2.573850	-0.586445	0.8697	-1.790449	0.3846	-2.487804	0.1199
H_0: series contains a unit root.			Accept null		Accept null		Accept null	

As this table shows, the series of three countries, stock market indices contain a unit root.

Table 4: ADF, PP and KPSS tests for stationarity of the returns of KOSPI, Nikkei 225 and SSE index

Test			Return KOSPI		Return NIKKEI 225		Return SSE	
ADF			t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
Critical values	1% level	-3.460596						
	5% level	-2.874741						
	10% level	-2.573883	-12.26046	0.0000	-13.30308	0.0000	--8.402471	0.0000
H_0: series contains a unit root.			Reject null		Reject null		Reject null	
PP			t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
Critical values	1% level	-3.460596						
	5% level	-2.874741	-12.20613	0.0000	-13.31057	0.0000	-14.44198	0.0000

	10% level	-2.573883			
H_0: series contains a unit root.			Reject null	Reject null	Reject null
KPSS			LM-Stat.	LM-Stat.	LM-Stat.
Critical values	1% level	0.739000			
	5% level	0.463000			
	10% level	0.347000	0.149225	0.047573	0.080939
H_0: series is stationary.			Accept null	Accept null	Accept null

As this table shows, all the series of three indices' returns are stationary.

Table 5: Unconditional Correlation of Stock Indices

	SSE	NIKKEI 225	KOSPI
SSE	1.000000	-0.261445	0.672539
NIKKEI_225	-0.261445	1.000000	-0.305311
KOSPI	0.672539	-0.305311	1.000000

Table 6: Unconditional Correlation of Stock Returns

	Return _SSE	Return NIKKEI_225	Return _KOSPI
Return SSE	1.000000	0.003723	-0.049664
Return NIKKEI 225	0.003723	1.000000	0.492886
Return KOSPI	-0.049664	0.492886	1.000000

Table 7: Descriptive statistics of the three countries' stock indices and the returns

	SSE	NIKKEI 225	KOSPI	Return SSE	Return NIKKEI 225	Return KOSPI
Mean	1878.966	13675.97	1108.772	0.005529	-0.003432	0.002580
Median	1634.210	13229.48	919.2000	0.006238	-0.001223	0.003424
Maximum	5954.770	22455.49	2228.960	0.278055	0.138082	0.367948
Minimum	537.3500	7280.150	305.6400	-0.282779	-0.281743	-0.263444
Std. Dev.	969.2648	3931.207	507.9352	0.084850	0.061465	0.086543
Skewness	1.438780	0.292198	0.528358	-0.075282	-0.462717	0.227385
Kurtosis	5.761648	1.837202	2.018781	4.085654	3.993841	4.951657
Jarque-Bera	144.4891	15.38371	18.88824	10.86188	16.67418	36.30937
Probability	0.000000	0.000457	0.000079	0.004379	0.000239	0.000000
Sum	409614.6	2981362.	241712.3	1.199793	-0.744668	0.559754
Sum Sq. Dev.	2.04E+08	3.35E+09	55985597	1.555093	0.816030	1.617758

Table 8: Descriptive statistics of determinants in linear regression equation

	Bilateral FDI Intensity			Inflation		
	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea
Mean	0.009582	0.008224	0.003944	3.571111	2.950926	3.555185
Median	0.009014	0.008686	0.004182	2.100000	2.100000	3.510000
Maximum	0.025693	0.016118	0.008681	23.60000	18.90000	8.410000
Minimum	0.002452	-0.001391	0.000921	0.010000	0.000000	0.300000
Std. Dev.	0.005005	0.004528	0.001933	4.130973	3.221772	1.405875

Skewness	1.327160	-0.353609	0.130915	2.609837	2.545881	0.549453
Kurtosis	4.828576	1.937990	2.130393	10.95405	10.58340	3.947272
Jarque-Bera	93.50189	14.65220	7.422943	814.6078	750.9055	18.94424
Probability	0.000000	0.000658	0.024442	0.000000	0.000000	0.000077
Sum	2.069763	1.776303	0.851853	771.3600	637.4000	767.9200
Sum Sq. Dev.	0.005385	0.004409	0.000803	3668.962	2231.660	424.9440

	Interest Rate			Bilateral Trade Intensity 1		
	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea
Mean	4.026065	1.556852	2.469213	0.289794	0.216845	0.192619
Median	2.950000	1.330000	2.400000	0.289771	0.237144	0.195668
Maximum	9.940000	5.440000	4.500000	0.324883	0.290967	0.270748
Minimum	2.490000	0.080000	0.950000	0.245888	0.114938	0.150273
Std. Dev.	2.327319	1.526538	1.117207	0.017457	0.055995	0.026734
Skewness	1.562414	1.308270	0.591381	-0.190947	-0.282079	0.490849
Kurtosis	3.755426	3.719310	2.535333	2.262570	1.466544	2.775129
Jarque-Bera	93.01692	66.27323	14.53358	6.206814	24.02786	9.128672
Probability	0.000000	0.000000	0.000698	0.044896	0.000006	0.010417
Sum	869.6300	336.2800	533.3500	62.59554	46.83849	41.60563
Sum Sq. Dev.	1164.529	501.0183	268.3528	0.065522	0.674109	0.153657

	Bilateral Trade Intensity 2		
	China-Japan	China-South Korea	Japan-South Korea
Mean	0.033590	0.046669	0.033484
Median	0.033004	0.047119	0.033552
Maximum	0.050922	0.090599	0.043937
Minimum	0.017112	0.013563	0.020083
Std. Dev.	0.007019	0.021456	0.003859
Skewness	0.134557	0.127307	-0.129272
Kurtosis	2.436005	1.553895	3.077832
Jarque-Bera	3.514610	19.40444	0.656123
Probability	0.172509	0.000061	0.720319
Sum	7.255356	10.08052	7.232562
Sum Sq. Dev.	0.010592	0.098974	0.003201

Table 9: Unconditional correlation of determinants in linear regression equation

Determinants		Bilateral FDI Intensity			Inflation			Interest Rate			Bilateral Trade Intensity 1		
		China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea
Bilateral FDI Intensity	China-Japan	1.000000	0.331563	-0.164244	0.753844	0.394983	0.133727	0.676630	0.760371	0.370566	-0.061321	-0.147648	0.397214
	China-South Korea	0.331563	1.000000	0.623278	0.186539	-0.225166	-0.124697	-0.197543	0.037481	-0.462727	0.271072	0.752695	-0.542817
	Japan-South Korea	-0.164244	0.623278	1.000000	-0.200304	-0.416896	-0.238387	-0.607835	-0.345092	-0.794687	0.257569	0.731046	-0.612077
Inflation	China-Japan	0.753844	0.186539	-0.200304	1.000000	0.636809	0.249635	0.580281	0.668327	0.295623	-0.153861	-0.258962	0.434498
	China-South Korea	0.394983	-0.225166	-0.416896	0.636809	1.000000	0.506709	0.538026	0.483664	0.459922	-0.370819	-0.564824	0.401267
	Japan-South Korea	0.133727	-0.124697	-0.238387	0.249635	0.506709	1.000000	0.294955	0.231609	0.297970	-0.008042	-0.280480	0.062881
Interest Rate	China-Japan	0.676630	-0.197543	-0.607835	0.580281	0.538026	0.294955	1.000000	0.914587	0.833478	-0.392360	-0.691779	0.551829
	China-South Korea	0.760371	0.037481	-0.345092	0.668327	0.483664	0.231609	0.914587	1.000000	0.538842	-0.244262	-0.468332	0.394707
	Japan-South Korea	0.370566	-0.462727	-0.794687	0.295623	0.459922	0.297970	0.833478	0.538842	1.000000	-0.483591	-0.801162	0.610225
Bilateral Trade Intensity 1	China-Japan	-0.061321	0.271072	0.257569	-0.153861	-0.370819	-0.008042	-0.392360	-0.244262	-0.483591	1.000000	0.506234	-0.111139
	China-South Korea	-0.147648	0.752695	0.731046	-0.258962	-0.564824	-0.280480	-0.691779	-0.468332	-0.801162	0.506234	1.000000	-0.709275
	Japan-South Korea	0.397214	-0.542817	-0.612077	0.434498	0.401267	0.062881	0.551829	0.394707	0.610225	-0.111139	-0.709275	1.000000

Determinants		Bilateral FDI Intensity			Inflation			Interest Rate			Bilateral Trade Intensity 2		
		China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea
Bilateral FDI Intensity	China-Japan	1.000000	0.331563	-0.164244	0.753844	0.394983	0.133727	0.676630	0.760371	0.370566	0.100076	-0.097329	0.043545
	China-South Korea	0.331563	1.000000	0.623278	0.186539	-0.225166	-0.124697	-0.197543	0.037481	-0.462727	0.519767	0.785712	0.389630
	Japan-South Korea	-0.164244	0.623278	1.000000	-0.200304	-0.416896	-0.238387	-0.607835	-0.345092	-0.794687	0.353081	0.781163	0.510403
Inflation	China-Japan	0.753844	0.186539	-0.200304	1.000000	0.636809	0.249635	0.580281	0.668327	0.295623	-0.027053	-0.143500	0.184627
	China-South Korea	0.394983	-0.225166	-0.416896	0.636809	1.000000	0.506709	0.538026	0.483664	0.459922	-0.360854	-0.492863	-0.178481
	Japan-South Korea	0.133727	-0.124697	-0.238387	0.249635	0.506709	1.000000	0.294955	0.231609	0.297970	-0.259203	-0.227080	-0.123036
Interest Rate	China-Japan	0.676630	-0.197543	-0.607835	0.580281	0.538026	0.294955	1.000000	0.914587	0.833478	-0.423313	-0.615191	-0.303795
	China-South Korea	0.760371	0.037481	-0.345092	0.668327	0.483664	0.231609	0.914587	1.000000	0.538842	-0.367804	-0.356665	-0.147635
	Japan-South Korea	0.370566	-0.462727	-0.794687	0.295623	0.459922	0.297970	0.833478	0.538842	1.000000	-0.379265	-0.794198	-0.431126
Bilateral Trade Intensity 2	China-Japan	0.100076	0.519767	0.353081	-0.027053	-0.360854	-0.259203	-0.423313	-0.367804	-0.379265	1.000000	0.636281	0.530122
	China-South Korea	-0.097329	0.785712	0.781163	-0.143500	-0.492863	-0.227080	-0.615191	-0.356665	-0.794198	0.636281	1.000000	0.554837
	Japan-South Korea	0.043545	0.389630	0.510403	0.184627	-0.178481	-0.123036	-0.303795	-0.147635	-0.431126	0.530122	0.554837	1.000000

Table 10: Estimations from the DCC-MGARCH Model:

Dependent	Japan		China		South Korea	
Independent	China	South Korea	Japan	South Korea	China	Japan
Mean equation:						
μ	-0.001214 (0.7548)	-0.001214 (0.7548)	0.002143 (0.6666)	0.002143 (0.6666)	0.005604 (0.2014)	0.005604 (0.2014)
Variance equation:						
ω	0.000779 (0.3248)	0.000779 (0.3248)	0.000398 (0.2929)	0.000398 (0.2929)	0.000397 (0.2370)	0.000397 (0.2370)
α	0.110268 (0.3610)	0.110268 (0.3610)	0.122457* (0.0818)	0.122457* (0.0818)	0.165922* (0.0644)	0.165922* (0.0644)
β	0.683752** (0.0186)	0.683752** (0.0186)	0.820095*** (0.0000)	0.820095*** (0.0000)	0.782959*** (0.0000)	0.782959*** (0.0000)
R-squared	-0.001308	-0.001308	-0.001600	-0.001600	-0.001227	-0.001227
Log-Likelihood	299.9748	299.9748	238.5225	238.5225	244.9440	244.9440
GARCH-like equation:						
κ	-0.050568** (0.0496)	0.030472 (0.2381)	-0.050568** (0.0496)	-0.069841 (0.3036)	-0.069841 (0.3036)	0.030472 (0.2381)
γ	0.9877768*** (0.0000)	0.930673*** (0.0000)	0.987776*** (0.0000)	0.8050920** (0.0240)	0.8050920** (0.0240)	0.930673*** (0.0000)
Log-Likelihood	-612.0272	-579.7079	-612.0272	-612.8143	-612.8143	-579.7079

Note: This table summarized the values of coefficients and the number in parentheses is the p-value. In the following tables, * for significant at 10% level. ** for significant at 5% level. *** for significant at 1% level

Table 11: The Ljung–Box Q Statistic Test for serial correlation

Lag	Return SSE				Return KOSPI				Return NIKKEI 225			
	Q1-Stat	Prob	Q2-Stat	Prob	Q1-Stat	Prob	Q2-Stat	Prob	Q1-Stat	Prob	Q2-Stat	Prob
1	0.9751	0.323	0.1451	0.703	3.8085	0.051*	0.0487	0.825	1.8354	0.175	0.1018	0.750
2	5.8832	0.053*	0.7420	0.690	4.0806	0.130	1.2897	0.525	2.1576	0.340	0.8922	0.640
3	5.8834	0.117	3.3007	0.348	6.1330	0.105	1.9713	0.578	3.3375	0.342	0.9126	0.822
4	7.7084	0.103	3.7075	0.447	6.5008	0.165	2.3408	0.673	3.5753	0.467	0.9147	0.922
5	7.8074	0.167	4.0288	0.545	8.5065	0.130	3.0187	0.697	3.7529	0.586	1.8077	0.875
6	8.6756	0.193	4.3710	0.627	9.2202	0.162	3.4017	0.757	9.2565	0.160	2.3613	0.884
7	9.6737	0.208	6.2526	0.511	9.4052	0.225	3.8305	0.799	9.2568	0.235	4.2314	0.753
8	9.6848	0.288	6.2541	0.619	10.161	0.254	4.2065	0.838	10.892	0.208	4.6937	0.790

The Ljung–Box Q statistic test is to exam the residual serial correlation with the null hypothesis that there is no serial correlation. For the series of SSE, KOSPI and NIKKEI_225 return, the p-values of Q1 statistics are not significant and reject the null at lag 8, it is means that there is serial correlation in the standardized residuals. However, the p-values of Q2 statistics are high, we accept the null that there is no serial correlation in the squares of the standardized residual for the three stock indices' returns.

Table 12: Heteroskedasticity Test: ARCH effect

Heteroskedasticity Test: ARCH effect		
Number of lag: 1	F-statistic	Prob. F(1,214)
Return KOSPI	0.047508	0.8277
Return NIKKEI 225	0.099089	0.7532
Return SSE	0.146144	0.7026

As the result of heteroskedasticity by Engle' ARCH effect test for the returns of KOSPI, NIKKEI 225 and SSE shown, it is can be seen that we accept the null hypothesis significantly, therefore there is no ARCH effect in the three return series respectively.

Table 13: Coefficients for the determinants of stock market integration from linear equation estimations of all four determinants using first formula for trade intensity without dummies

Dependent Variable	COR China-Japan	COR China-South Korea	COR Japan-South Korea
C	0.766877*** (0.0061)	0.175809* (0.0900)	1.438020*** (0.0000)
Bilateral FDI Intensity	-25.55610*** (0.0000)	-4.827126 (0.3980)	21.51227** (0.0121)
Inflation	0.019261*** (0.0004)	-0.001598 (0.7483)	0.012383* (0.0893)
Interest Rate	-0.014243 (0.1327)	-0.000589 (0.9618)	-0.088313*** (0.0000)
Bilateral Trade Intensity 1	-1.306841 (0.1618)	-0.535654 (0.3372)	-1.113580** (0.0204)
R-squared	0.209891	0.063475	0.539895
Adjusted R-squared	0.194912	0.045721	0.531173

Table 14 : Coefficients for the determinants of stock market integration from linear equation estimations using FDI, inflation, interest rate and trade intensity (first formula) and all four dummy variables

Dependent Variable	COR China-Japan	COR China-South Korea	COR Japan-South Korea
C	0.664893** (0.0177)	0.416087*** (0.0003)	1.186900*** (0.0000)
DUMMY1	-0.084478 (0.1478)	0.016454 (0.6853)	0.106635*** (0.0037)
DUMMY2	0.191355*** (0.0003)	0.034489 (0.4680)	0.008053 (0.8013)
DUMMY3	-0.125118*** (0.0018)	0.208735*** (0.0000)	0.195925*** (0.0000)
DUMMY4	-0.078000** (0.0386)	0.142026*** (0.0001)	0.005589 (0.8618)
Bilateral FDI Intensity	-22.61223*** (0.0000)	-6.676166 (0.2291)	12.99384 (0.1218)
Inflation	0.019261*** (0.0002)	-0.009518** (0.0384)	0.010039 (0.1685)
Interest rate	-0.018233* (0.0745)	-0.005759 (0.6370)	-0.116197*** (0.0000)
Bilateral Trade Intensity 1	-0.912331 (0.3241)	-1.722551*** (0.0030)	0.543361 (0.3329)
R-squared	0.369212	0.275433	0.627307
Adjusted R-squared	0.344833	0.247430	0.612903

Table 15: Coefficients for the determinants of stock market integration from linear equation estimations of all four determinants using second formula for trade intensity without dummies

Dependent Variable	COR China-Japan	COR China-South Korea	COR Japan-South Korea
C	0.346839*** (0.0008)	0.063867 (0.1637)	1.298904*** (0.0000)
Bilateral FDI Intensity	-28.79820*** (0.0000)	-11.84848 (0.0260)	29.27298*** (0.0009)
Inflation	0.020230*** (0.0000)	0.001131 (0.8125)	0.015210** (0.0367)
Interest Rate	-0.005409 (0.6298)	0.009762 (0.3623)	-0.098956*** (0.0000)
Bilateral Trade Intensity 2	0.993302 (0.7187)	0.629132 (0.6139)	-2.680576 (0.3612)
R-squared	0.203001	0.060504	0.529859
Adjusted R-squared	0.187892	0.042694	0.520946

Table 16: Coefficients for the determinants of stock market integration from linear equation estimations using FDI, inflation, interest rate and trade intensity (second formula) and all four dummy variables

Dependent Variable	COR China-Japan	COR China-South Korea	COR Japan-South Korea
C	0.402502*** (0.0002)	0.171469*** (0.0020)	1.235206*** (0.0000)
DUMMY1	-0.067119 (0.2295)	0.040186 (0.3119)	0.094161*** (0.0037)
DUMMY2	0.199557*** (0.0002)	0.054197 (0.2591)	0.014059 (0.6532)
DUMMY3	-0.119086*** (0.0027)	0.201853*** (0.0000)	0.190049*** (0.0000)
DUMMY4	-0.088995** (0.0193)	0.142652*** (0.0003)	0.001809 (0.9553)
Bilateral FDI Intensity	-22.84659*** (0.0002)	-11.03021** (0.0490)	8.972527 (0.2883)
Inflation	0.020072*** (0.0001)	-0.006606 (0.1380)	0.009144 (0.2063)
Interest Rate	-0.017169 (0.1614)	0.007860 (0.4646)	-0.110668*** (0.0000)
Bilateral Trade Intensity 2	-0.250555 (0.9233)	-2.711674* (0.0522)	1.915934 (0.4948)
R-squared	0.366263	0.257576	0.626455
Adjusted R-squared	0.341771	0.228883	0.612018

Table 17: R-squared for the determinants of stock market integration from linear equation estimations of each determinant, whereas trade intensity is calculated by the first formula

	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea
Determinants	Bilateral FDI Intensity			Inflation		
Coefficients (p-value)	-15.73350*** (0.0000)	-18.75227*** (0.0000)	48.32821*** (0.0000)	-0.004543 (0.2008)	0.004192 (0.2797)	-0.024227*** (0.0023)
R-squared	0.313977	0.226724	0.524380	0.233766	0.134282	0.435108
Determinants	Interest Rate			Bilateral Trade Intensity 1		
Coefficients (p-value)	-0.028343*** (0.0000)	0.016728** (0.0413)	-0.115819*** (0.0000)	-0.101660 (0.9147)	-1.477628*** (0.0000)	-2.603619*** (0.0000)
R-squared	0.294034	0.146573	0.620035	0.227798	0.239453	0.475145

Table 18: R-squared for the determinants of stock market integration from linear equation estimations of each determinant, whereas trade intensity is calculated by the second formula

	China-Japan	China-South Korea	Japan-South Korea	China-Japan	China-South Korea	Japan-South Korea
Determinants	Bilateral FDI Intensity			Inflation		
Coefficients (p-value)	-15.73350*** (0.0000)	-18.75227*** (0.0000)	48.32821*** (0.0000)	-0.004543 (0.2008)	0.004192 (0.2797)	-0.024227*** (0.0023)
R-squared	0.313977	0.226724	0.524380	0.233766	0.134282	0.435108
Determinants	Interest Rate			Bilateral Trade Intensity 2		
Coefficients (p-value)	-0.028343*** (0.0000)	0.016728** (0.0413)	-0.115819*** (0.0000)	1.672934 (0.4671)	-3.950730*** (0.0000)	8.151966** (0.0120)
R-squared	0.294034	0.146573	0.620035	0.229703	0.232143	0.427031

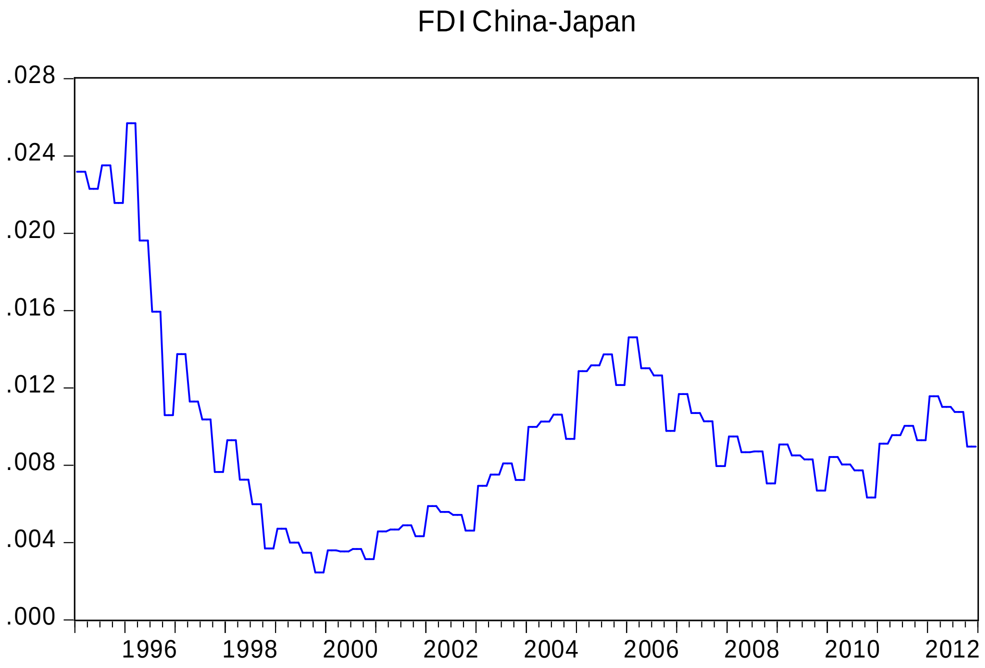
Table 19: Key determinant(s) of stock market integration for all three sample pairs

Pair	China-Japan	China-South Korea	Japan-South Korea
Key determinant	Interest Rate and Bilateral FDI Intensity	Bilateral FDI Intensity and Bilateral Trade Intensity	Interest Rate

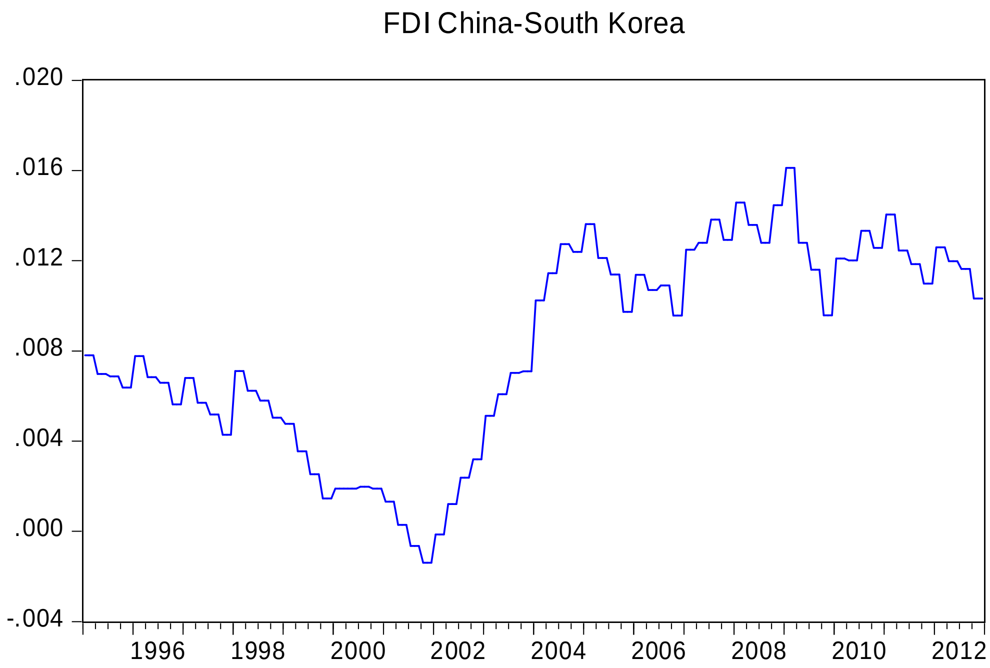
Table 20: The short summary of the same fundamental factors that influence the stock market correlation used as ours in previous studying

Dummies and Determinants	Sign	Main Previous studying
Dummy for Asian crisis 14 October 1997	Significant Positive	Wang, P. and Moore, T. (2008)
Dummy for 1998 regional effect	Significant Positive	Pretorius, E. (2002)
Dummy for Asian crisis 19971121-19981030	In some countries negative/positive	Syllignakis et al. (2011)
Dummy for dot-com bubble 20000310-20020927	In some countries negative/positive	
Dummy for 2008 stock market crash 20080926-20090213	Significant Positive	
Dummy for Asian crisis July 1997-Dec 1998	Significant Positive	Chee-Wooi, H. and Kom-Leng, G. (2009)
Dummy for dot-com bubble March 2000- March 2003	Significant Negative	
Trade intensity	Significant Negative	
Trade openness	Significant Negative	
Trade openness	Significant Positive	Guesmi, K. and Nguyen, D. K. (2011)
Trade openness	Insignificant Negative	Shi et al. (2010)
Imports and exports	Significant Positive/negative	Bracker et al (1999) and Mukherjee, K. N and Mishra, R.K.(2006)
Bilateral trade	Significant Positive	Pretorius, E. (2002)
Bilateral trade flows	Significant	Forbes, K. J. and Chinn, M.D. (2004) Note: the calculation measure is different
Bilateral foreign investment	Insignificant	
Bilateral FDI flows	Significant Positive	Shi et al. (2010)
Total FDI flows	Significant Negative	
Inflation differential	Insignificant	Pretorius, E. (2002)
Interest rate differential	Insignificant	
Interest rate differential	Insignificant Negative	Bracker et al (1999) and Mukherjee, K. N and Mishra, R.K.(2006)
Inflation differential	Insignificant Negative	

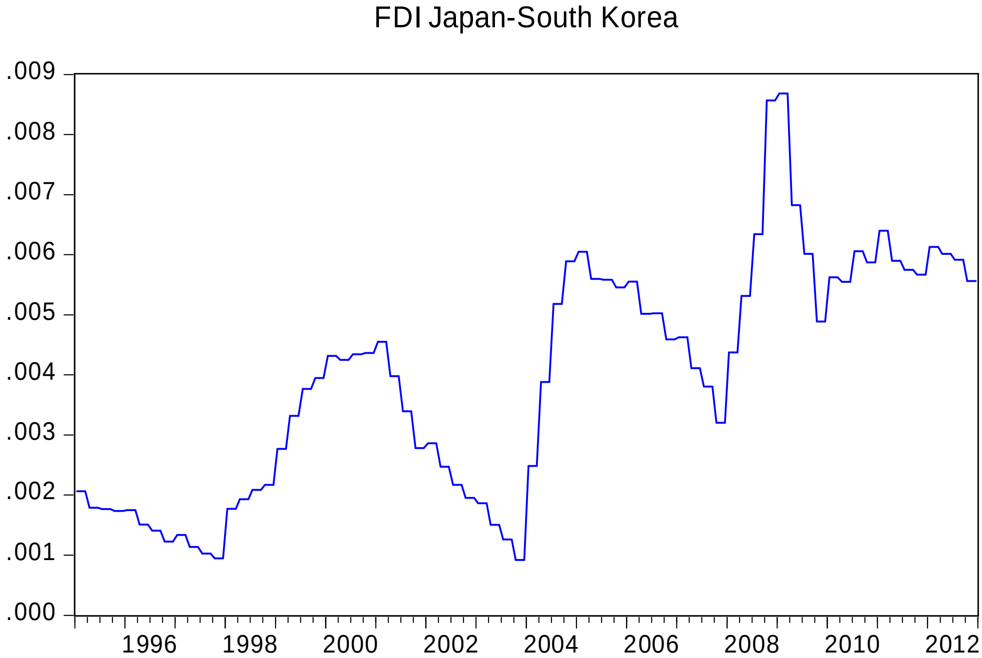
Graph 1: Evolution of bilateral FDI intensity between China and Japan



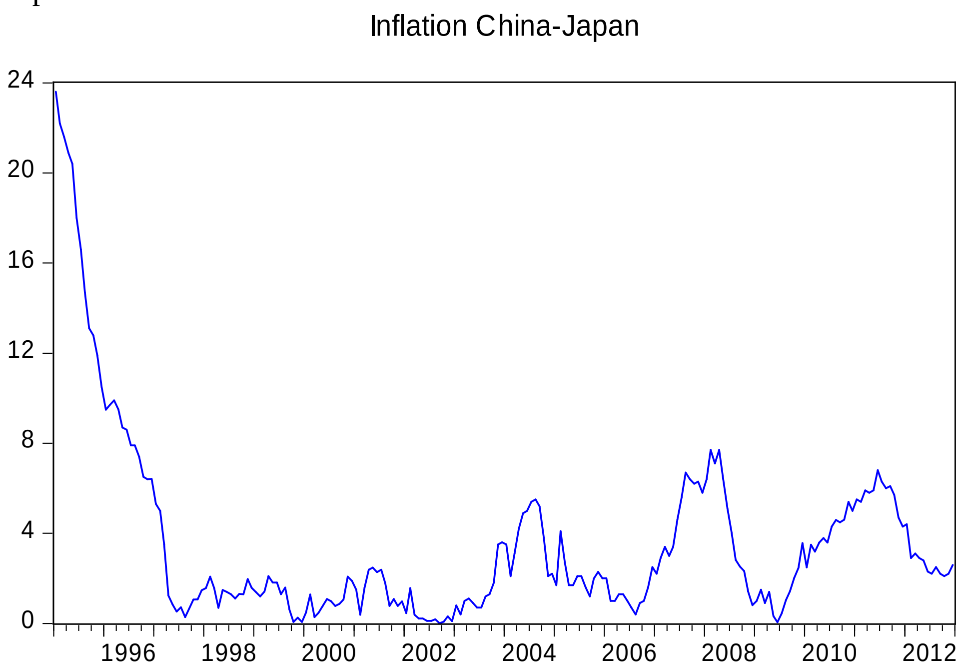
Graph 2: Evolution of bilateral FDI intensity between China and South Korea



Graph 3: Evolution of bilateral FDI intensity between Japan and South Korea

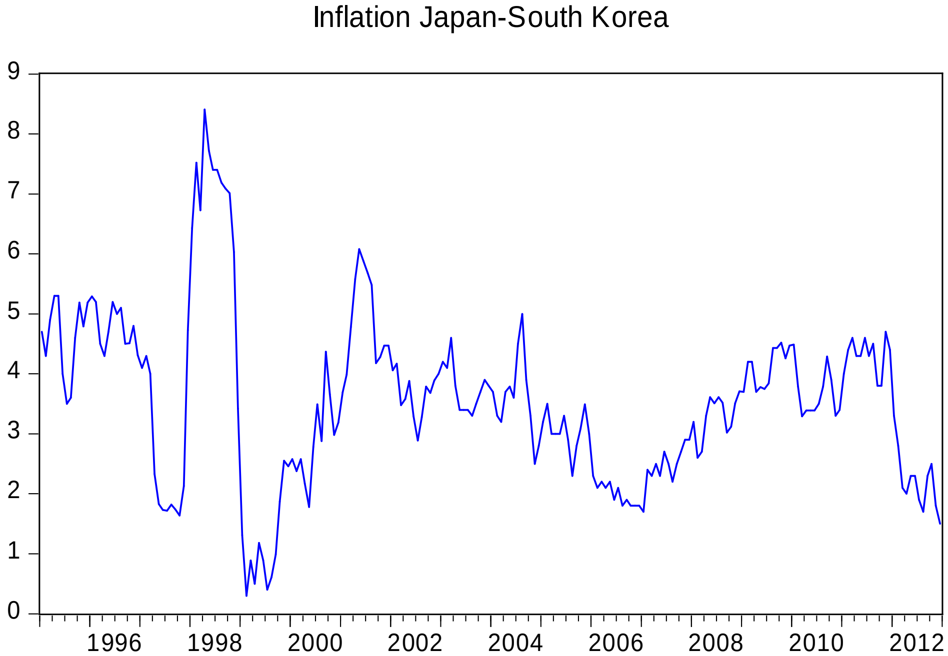


Graph 4: Evolution of the absolute difference between the inflation of China and Japan

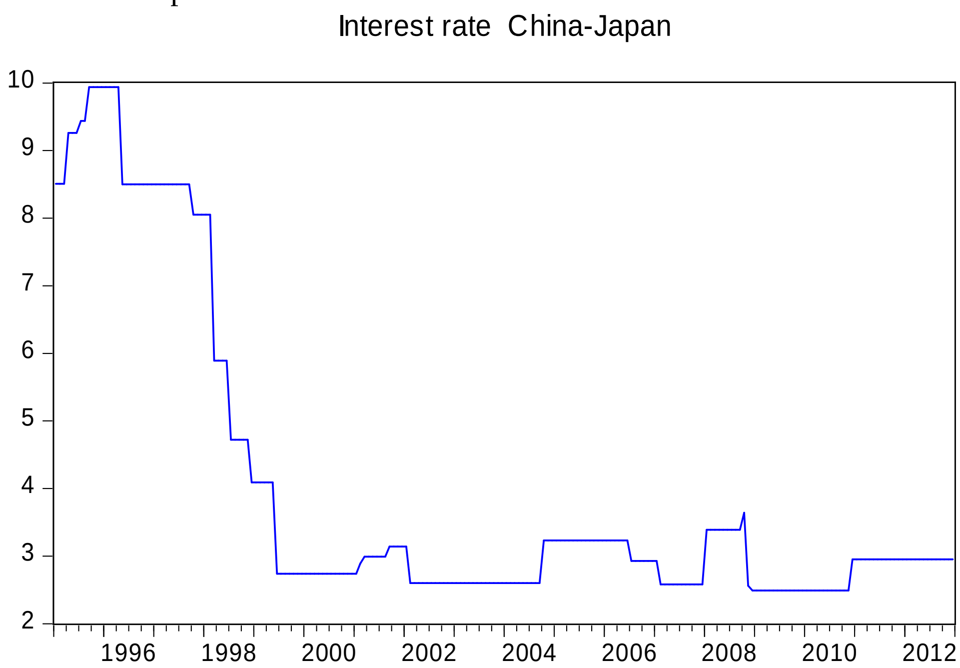


Graph 5: Evolution of the absolute difference between the inflation of China and South Korea

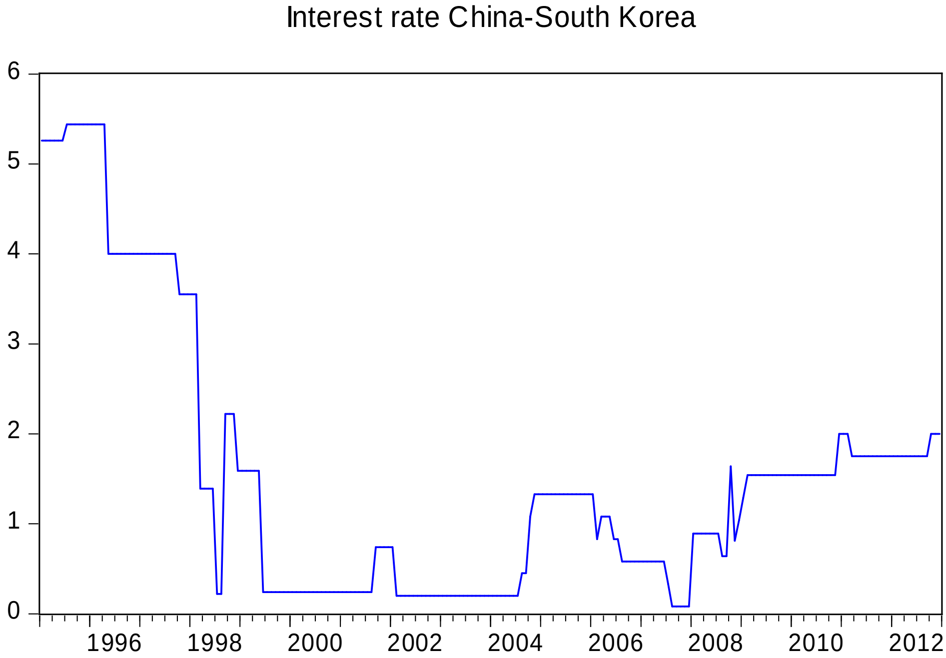
Graph 6: Evolution of the absolute difference between the inflation of Japan and South Korea



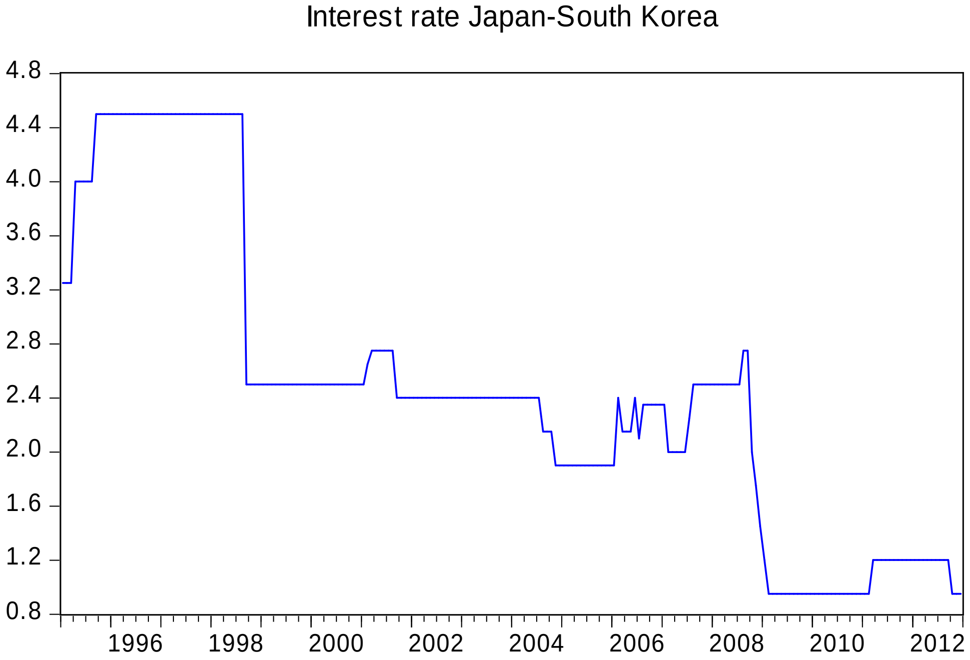
Graph 7: Evolution of the absolute difference between the short term interest rate of China and Japan



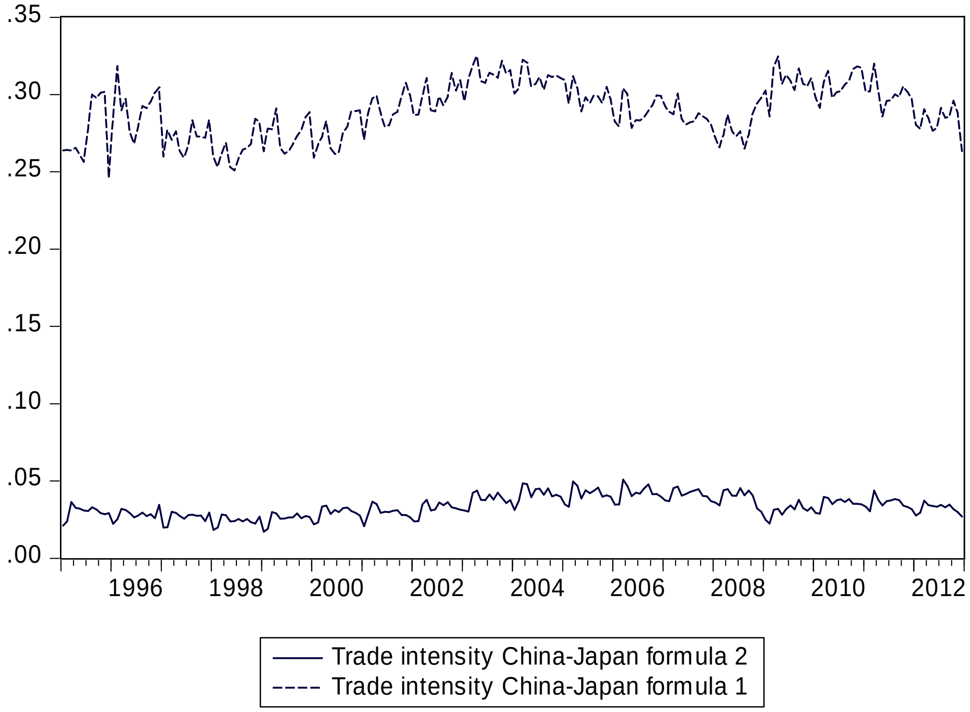
Graph 8: Evolution of the absolute difference between the short term interest rate of China and South Korea



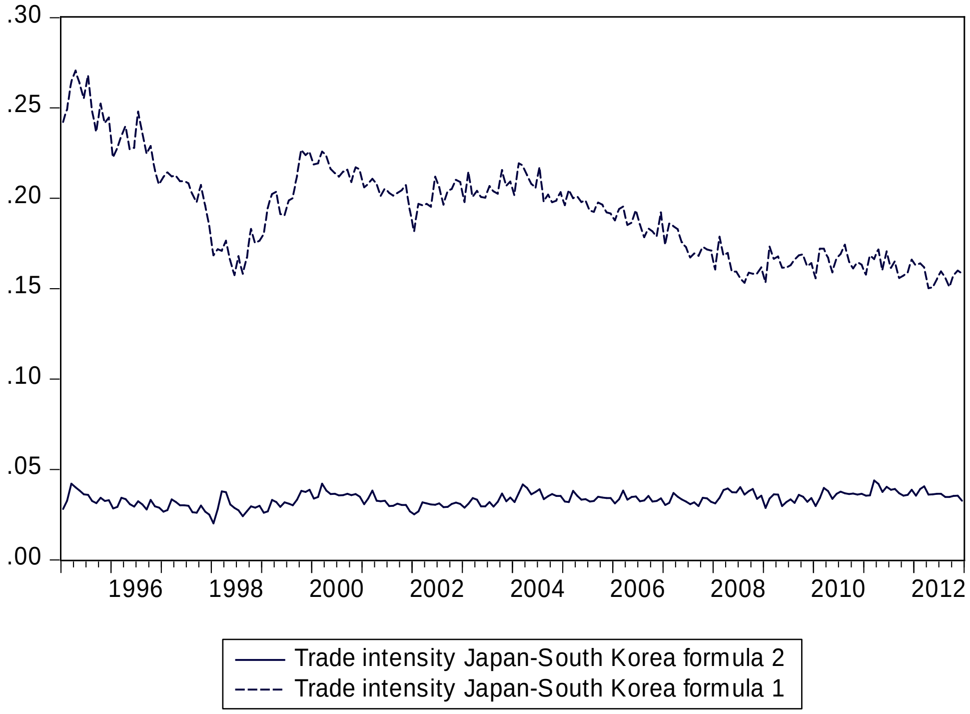
Graph 9: Evolution of the absolute difference between the short term interest rate of Japan and South Korea



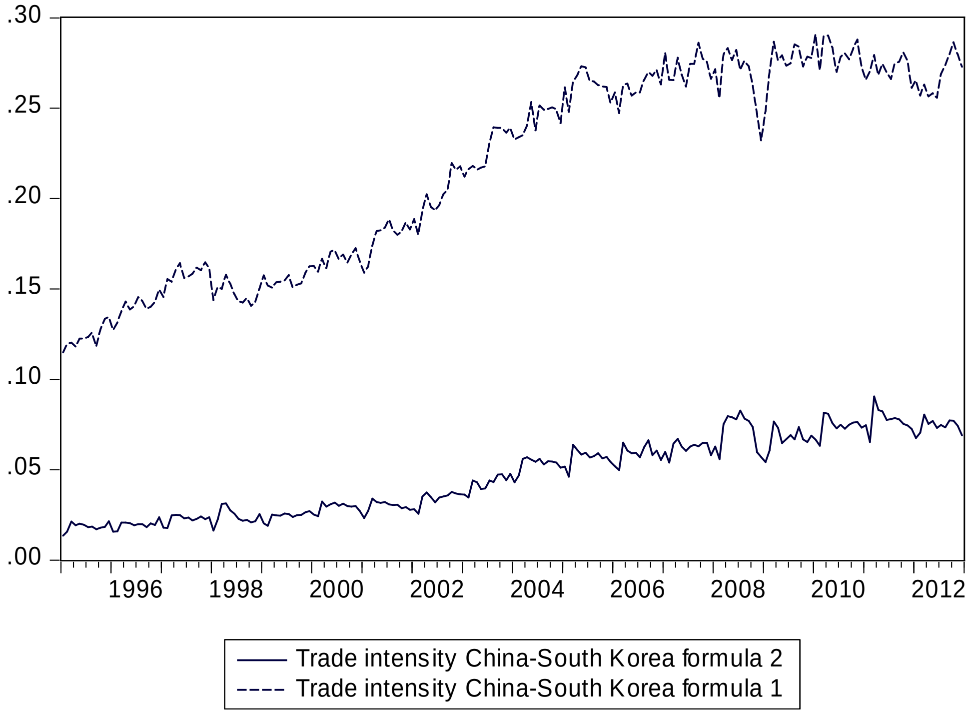
Graph 10: Evolution of bilateral trade intensity between China and Japan using trade intensity formula 1 and 2



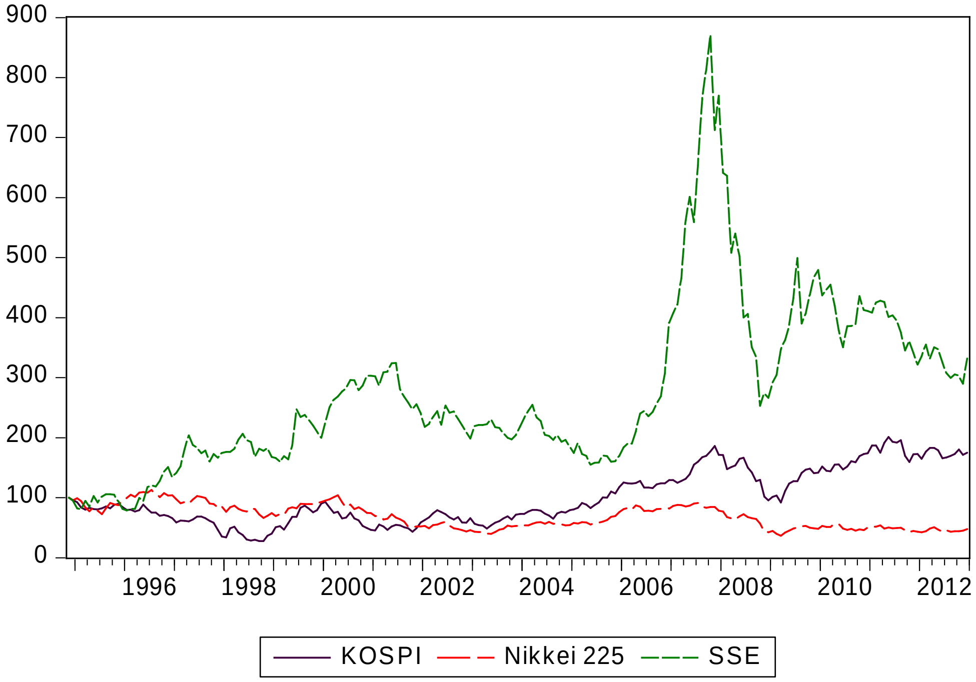
Graph 11: Evolution of bilateral trade intensity between Japan and South Korea using trade intensity formula 1and 2



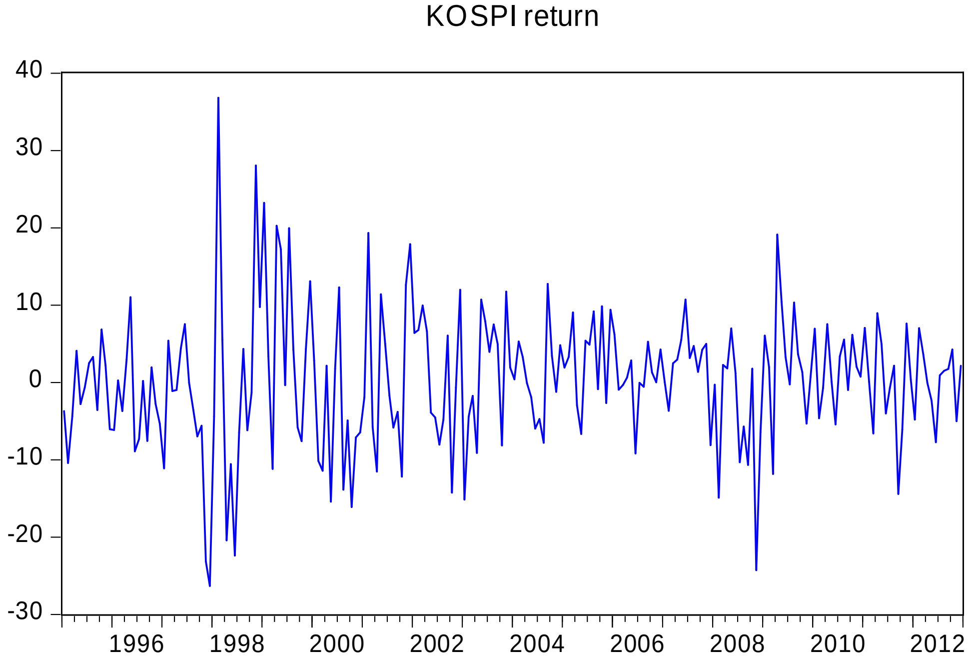
Graph 12: Evolution of bilateral trade intensity between China and South Korea using trade intensity formula 1 and 2



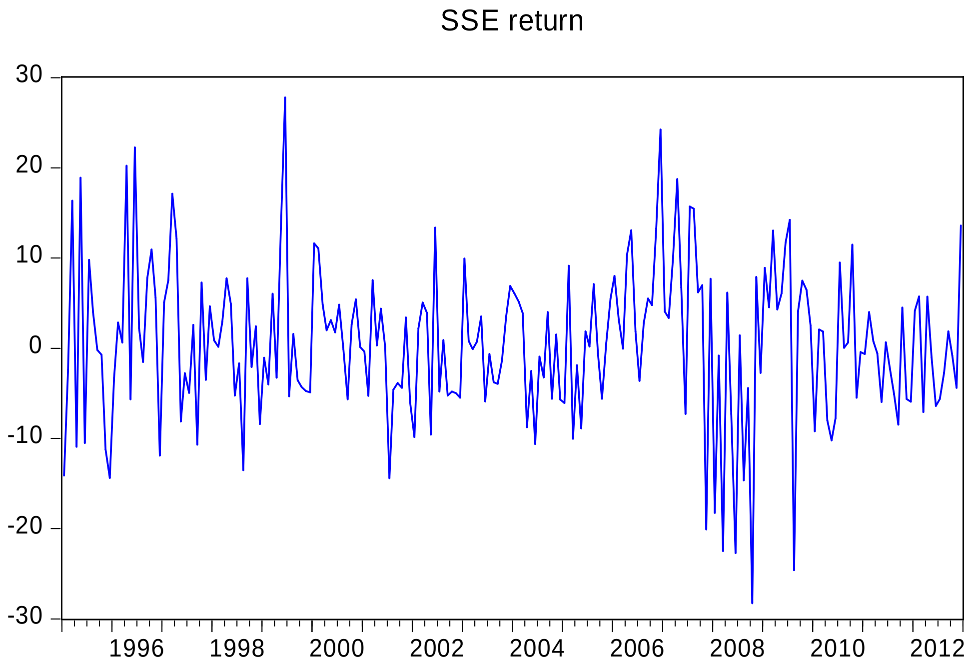
Graph 13: Evolution of South Korea, Japan and China stock index between 1995 and 2012



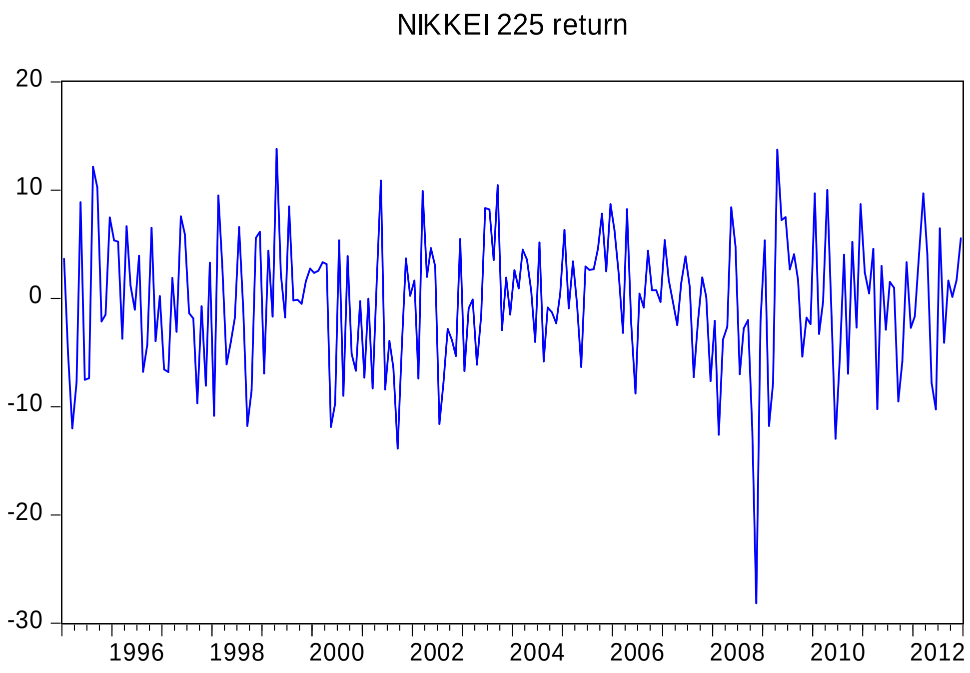
Graph 14.1: Evolution of South Korean stock market returns between 1995 and 2012



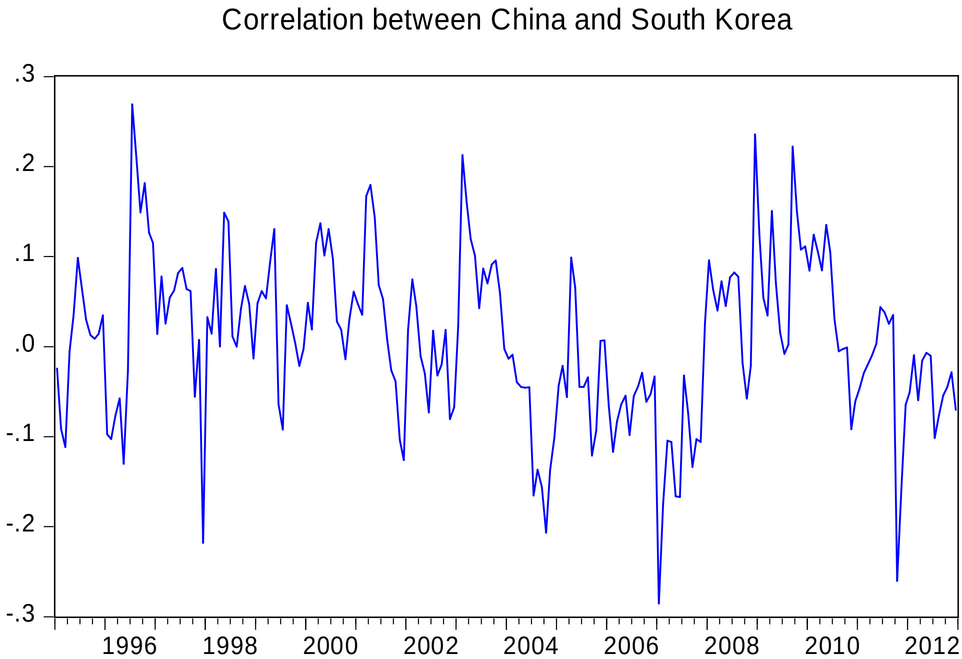
Graph 14.2: Evolution of Chinese stock market returns between 1995 and 2012



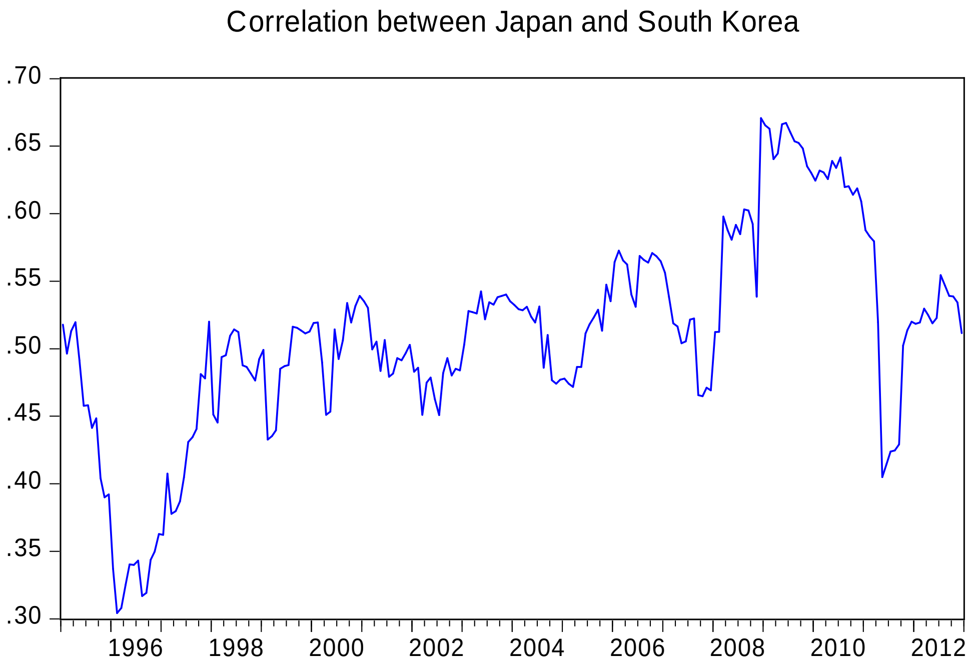
Graph 14.3: Evolution of Japanese stock market returns between 1995 and 2012



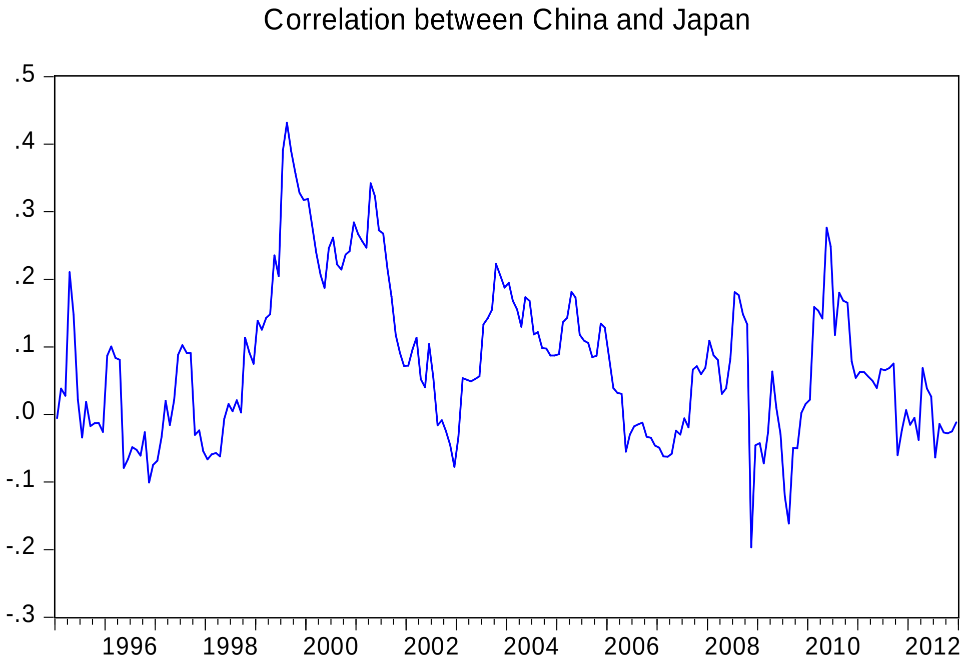
Graph 15: Development of conditional correlation between China and South Korea between 1995 and 2012



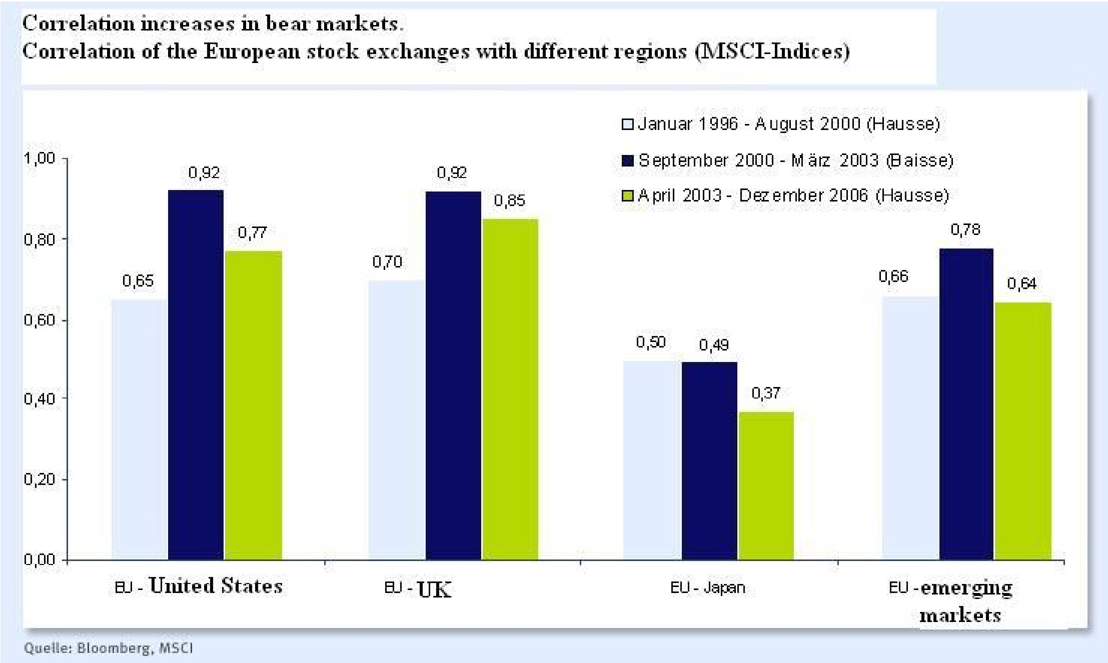
Graph 16: Development of conditional correlation between Japan and South Korea between 1995 and 2012



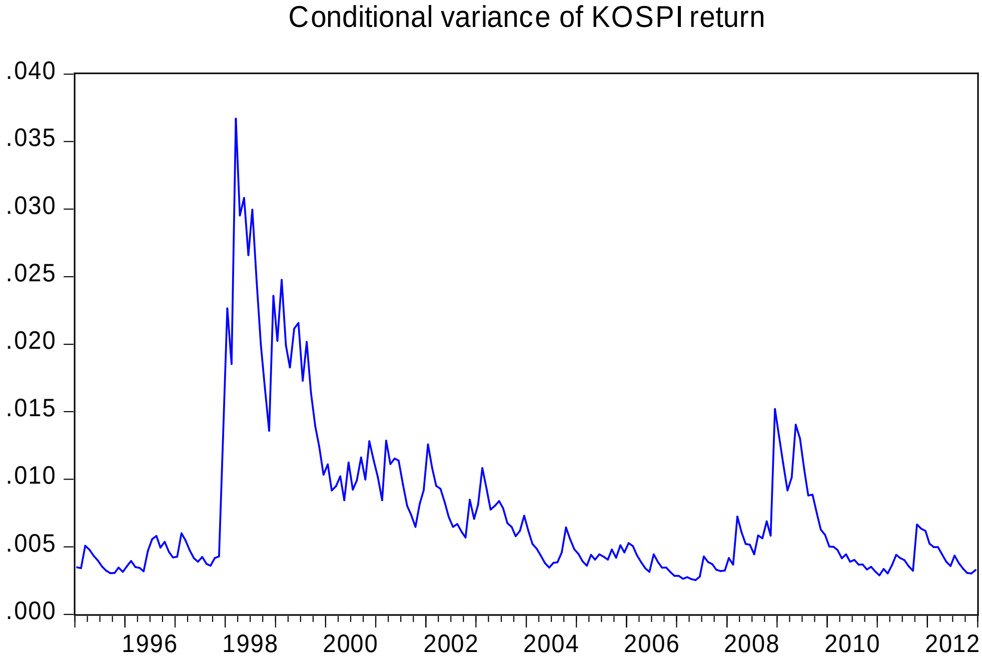
Graph 17: Development of conditional correlation between Japan and China between 1995 and 2012



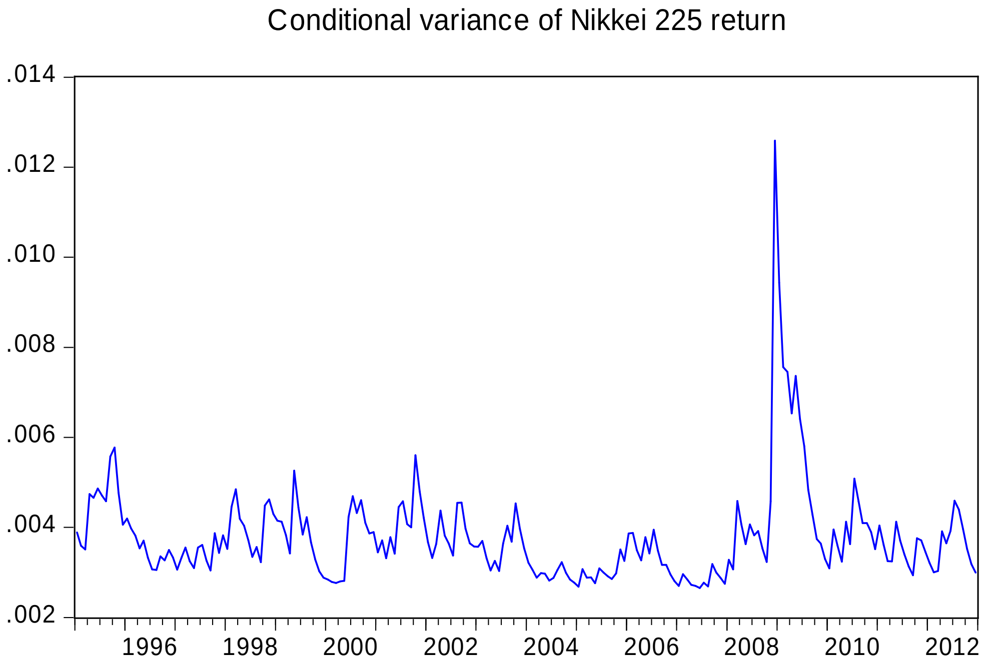
Graph 18: Correlation of European stock exchanges with different regions



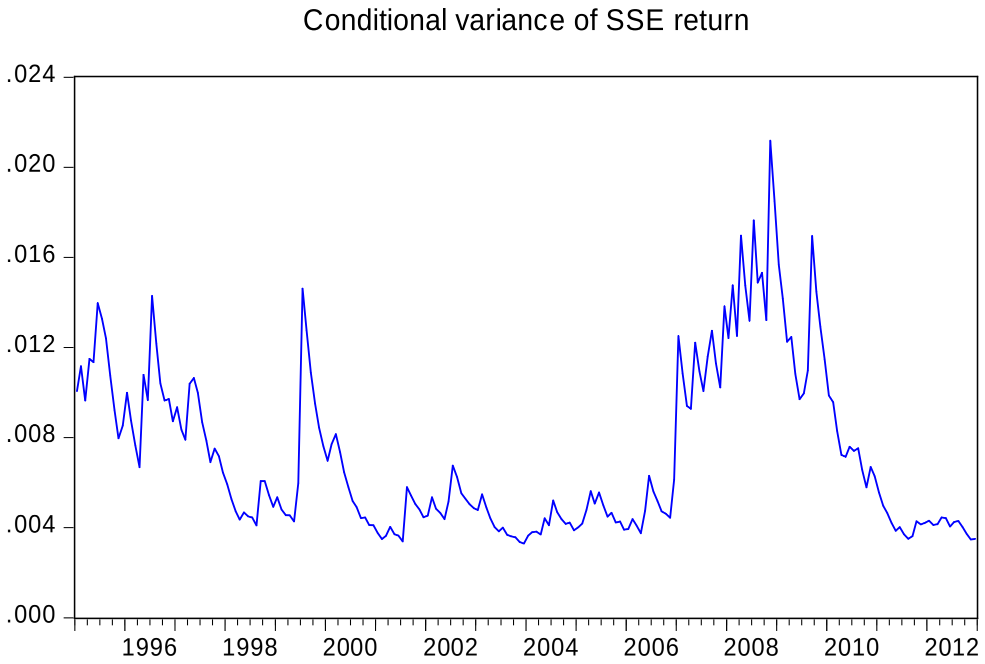
Graph 19: Conditional variance of KOSPI (South Korea) return



Graph 20: Conditional variance of Nikkei_225 (Japan) return



Graph 21: Conditional variance of SSE (China) return



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