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Cointegration between the Chinese and US stock markets

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Abstract: This paper conducts an empirical study on the relationship between the emerging financial market of China and the developed market of the US, both during and after the 2007-2009 financial crisis. Stock indices from the two countries are analysed to examine whether there exist any comovements between the different equity markets. Econometric time series testing of weekly stock values indicate that there is a long term cointegrating relationship during the financial crisis and a short term relationship in both time periods. These results provide Chinese policy makers with vital information for making decisions on future reforms of the Chinese financial market. The understanding of linkage between the stock markets is also important for investors who can use this information to achieve diversification of assets.

Key words: China, cointegration, stock market, time series, US

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1. INTRODUCTION AND RESEARCH QUESTION

One of the main incentives for investing in the global stock market stems from the theory that return on assets on international markets exhibit more diversification and less correlation compared to investing on a single market (Grubel 1968). There is a wide-spread belief among investors that financial markets which are highly developed share common features and are closely linked to each other; and as a result, investors turn to emerging markets under the assumption that these are scarcely correlated with the developed financial markets and thus present an opportunity for asset diversification. This school of thought is supported by empirical studies, which encourage investors that are mainly committed to markets in developed countries to transfer capital into financial markets in emerging economies. Inferring from this, the question at hand is whether the low correlation that has been observed historically between emerging and developing markets will persist over time or if the gradual development of fledgling markets eventually leads to cointegrating movements with international financial markets.

To provide an answer to this question, this paper selects two different Chinese equity markets - one from the emerging financial market of mainland China and one from the more established financial sector of Hong Kong, and compare these to mature Western markets, with the main focus being on the US financial market. This paper conducts an empirical study on these markets over a time interval that spans over two contrasting periods, namely the recent financial crisis and the post crisis period, which will provide insight into whether cointegration is present among these geographically distant markets during different economic periods.

The Chinese stock market has been growing in a very rapid pace since being established in 1990. Since becoming a member of WTO in 2001, China’s financial market has begun to play a more pronounced role on the global scene and attracts more interest from international investors than ever before.
Li and Zhang (2014) argue that the transformation of the financial market in China can be explained by three reforms that was pursued by the country to make its market more integrated globally. The first step in this metamorphosis was the Qualified Foreign Institutional Investor (QFII) reform which was put in effect 2003 and allows foreign investors that hold a license to sell and buy RMB-denominated A-shares. The second step was the Chinese government’s implementation of a reform to eliminate non-tradable shares (NTS) 2005 which affected the stock pricing and successfully increased the volume of stocks traded on the financial market (Bortolotti and Beltratti 2006). The final step was the Qualified Domestic Institutional Investor (QDII) reform that was stipulated 2007 and allow domestic financial firms to gain access to financial markets abroad. All of these financial reforms have played a pivotal role in the liberalization of the Chinese financial market and helped to make it both easier for Chinese investors to access foreign assets, and at the same time also allowing international investors increased opportunity to speculate on the Chinese market.
This transition of the Chinese financial market also implies that it can no longer stay immune to financial or economic turbulence that occur externally or outside of the domestic market.

When taking these factors into account, it is possible that the historical observations of non-cointegration between the Chinese and US stock market no longer hold true. It is likely that the financial crisis, which reverberated across all of the world's financial markets, could have created a stronger bond between Chinese and international equity markets and made the cointegration between these entities more pronounced.

Inferring from these remarks, the research question of this thesis is thus to investigate the relationship of the Chinese and US stock markets both during and after the financial crisis, to determine whether or not the financial markets show any evidence of cointegration.

Looking at the market capitalization, number of listed shares and volume of trade, it is clear that the US financial market is one of the largest and most developed in the world; whereas China's market, which is still under constant change and has yet to reach a state of matureness, is now the biggest emerging market in the world. This makes for a very representative combination in studying the linkage between a developed and emerging financial market. Any evidence of a stronger bond between the two markets after the financial crisis is highly interesting information, especially for China who after joining the WTO wants to prove that the country is now an integrated part in the world economy (Blancher and Rumbaugh 2004). Investors are another group that can benefit from understanding the comovements between two enormous markets that China and the US comprise. Owing to the benefits that can be reaped by asset diversification on international markets, Schmukler (2004) argues that one of the most important factors that investors take into consideration when deciding to invest is whether or not there is any financial integration between the markets. This paper will shed light upon this and provide useful information that perhaps can guide investors to make sound financial decisions. The pattern of cointegration between the Chinese and US financial markets, along with understanding how impulses or shocks from one market might affect the other can also be of interest to policymakers in China who can implement precautionary policies accordingly.

Even though the Chinese economy is playing an increasingly important role on the Asian and world market, it has received comparably little interest in the literature written about stock market integration. A plausible reason for this could be the relative novelty of the Chinese stock markets, considering the fact that the two main stock exchanges, Shanghai and Shenzhen, are less than 30 years old. Notwithstanding, the economic linkages between China and its neighbouring countries, as well as the US, has deepened during the recent years as a result of increased foreign direct investment and import and export. The Asian markets have also shown signs of integration between them. Jorion (1989) argues that the shared culture in Greater China (Confucianism) can induce interdependencies between the stock markets in mainland China and a vast area of East Asia, particularly Taiwan, Hong Kong and Singapore. In summary, as Johnson and Soenen (2003) suggest, the extent of influence that one country can exert on another in strongly related to the countries expectations of economic development. On this note, different stock markets could also show the same pattern in response to economic shocks and thus creating comovements and spill-over effects between stock prices.

2. BACKGROUND

2.1 The development of the financial system in China

China's economic reformation began in the end of the 1970s, and as a result the financial sector of the country has gradually developed into becoming a modern financial system which is now able to allocate financial capital from investors and attract capital from abroad. A vital component in this development has been the unfolding of a dynamic equity market. China's rapid economic growth began in 1978 and China has now become the second largest economy in the world. There are strong indications that it could surpass the US and become the largest one in a matter of years based on Purchasing Power Parity (PPP) (Allen et al. 2005). Even though China's role on the world stage has increased significantly recently, its financial system albeit subject to an array of structural reforms, has lagged behind other parts of the economy juxtaposed to the overall transition that has taken place from central planning to market orientation, and is in this respect rather underdeveloped. To understand this course of events it is imperative to take a closer look at the history and development of China's financial system.

2.2 Financial reforms and establishment of a stock market in China

By the beginning of the 1990s there was a crucial need to develop a functional stock market in China. The state-owned enterprises (SOEs) faced serious problems with liabilities and a severe lack of working capital. The government realised that it had to establish stock markets that could provide a stable supply of long-term funding for the SOEs. The reforms that had been made in the agricultural and urban sector led to calls for a revision of property and ownership rights. These changes were deemed possible by the sale of shares in SOEs to specific institutions such as local and provincial governments, private individuals, and banks. Given all these circumstances, it is evident that the emergence of a stock market was vital for a multitude of reasons. (Xu and Lillai 2011) identify the four most pressing purposes which helped to promote the emergence of the Chinese equity market.

1. Stock markets are able to provide additional capital and induce higher growth rates for companies which otherwise would have struggled a to raise funds on their own.

2. Stock markets instigate a schism in the management and ownership relationship of firms which can lead to higher performance incentives.

3. Stock markets relieve the burden of nonperforming loans in state-owned banks and lead to a diversification in risk of credit.

4. In providing different options for return on assets, stock markets can provide better investment opportunities than depositing in banks with low interest rates.

It is important to keep in mind that the reformation process in China was not merely aimed at liberating a defunct financial system, but rather a progression of developing a market-orientated system by reforming the institutional framework of the financial sector. However, even today the Chinese government still holds control over the flows of capital and interest rates, but are at the same time promoting competition in line with its socialist market economy approach.

2.3 Development phases of the stock market

China's financial reform programs took place at a particular time in the context of a unique economic history. As such, China had to develop its own characteristic approach to financial reforms and development which Western scholars usually ascribe the epithet 'gradualism' (Harrold 1992). It has been argued that the lack of a general reformation theory has been one of the hallmarks of China's financial transformation. Another point of view is also that the reform philosophy of China is to not plan any reforms, but to merely guide reforms in a rational manner when so demanded or permitted by the social and economic climate (Park 2004).

The development of the Chinese stock market is succinctly illustrated and captured in its overall reformation strategy as mentioned earlier, and can be interpreted as an endogenous adjustment process which reacts to changes in political constraints as well as to economic growth. The goals of these reforms have been to limit the role of the Chinese government in capital markets, strengthen property rights, induce private investments, and to increase the share of private ownership in companies. This process of development of the Chinese stock market can be divided into five phases (Xu and Lillai 2011).

- *Phase one (1984-1990): Shares as a source of capital*

  By departing from a central planned system into a becoming a decentralized market, the introduction of shares was first introduced for state-owned enterprises and provided an alternative way of obtaining funds other than loans from the banking sector or through fiscal funding.

- *Phase two (1991-1996): Trade share commences and premature government initiative*

  With a regulatory framework in place and a functional nationwide infrastructure, the stock exchanges in Shanghai and Shenzhen opened up for electronic trading. An initial public offering (IPO) system was introduced but did not function properly due to complex and intricate share structures. Neither legal person nor state-owned shares could be traded or listed on any of the two stock exchanges. Attempts by the government to publicly trade its share of state-owned shared came to an abrupt end when the stock exchange in Shanghai plunged 80% in 1994, and had to be abandoned as panic arose in fear of a huge sell-off of state-owned shares.

- *Phase three (1997-1999): Regulation enforcement*

In the aftermath of the Asian financial crisis the Chinese government implemented strict supervision and regulation of the equity market in the end of the 1990s to keep financial contagion in check and avoid another crisis. The measures that were taken included a host of security laws as well as implementation of a segmented financial system in which the insurance, banking, securities and trust sectors were separated from commercial bank funds that were taken off the stock market.

- *Phase four (1999-2001) IPO acceleration and second government attempt at SOE sell-off*

With the onset of the 1999 recession, the amount of nonperforming loans in the Chinese banking sector increased exponentially. To be able to maintain high GDP growth through the economic slump, the policy from the Chinese government was to expand the stock market. This led to a quick acceleration in initial public offerings on the market and resulted in 90% of the SOEs becoming corporatized. The Shanghai Composite Index reacted positively to this measure and double its value and hit a record high in 2001. Later during the same year attempts by the government to secure social security funds were initialised by reduction of state holdings in the companies listed on the stock market. This, however, led to concerns of rapid market capitalization expansion and caused a plummeting market.

- *Phase five (2002-2005): Reduction of state holdings and emergence of new actors*

During this phase the Chinese government were finally successful in reducing its holdings in listed firms. It also witnessed the emergence of new important actors such as institutional investors.

Understanding the underpinnings of the development of the Chinese equity market provides a good insight into its unique characteristic and behaviour which can provide vital information in the ability to make a comprehensive interpretation of the underlying reasons for comovements between China and different stock markets. In the following section, literature that has been written about cointegration between financial markets is presented.

2.4 Literature review

Previous research has identified two theories as to why stock markets might exhibit co-movement. The first one, which is related to economic fundamentals, argue that there exist common fundamental variables at a macroeconomic level that exert influence on the equity markets which in turn can spread across different economies (Solnik 1974; Stultz 1981). Ross (1989) suggest that information flows such as public information is embedded it the volatility of financial markets and hence induce cointegrating movements. This is supported in a study by Connolly and Wang (2003) which present empirical evidence that the release of macroeconomic news can explain linkage between the financial markets in Britain, Japan and America.
The second theory explain the co-movements of stock markets as a result of financial contagion. King and Wadhwani (1990) concludes that the trading of stocks on one market will

affect the price of stocks on another one. They also find that the market contagion theory for co-movement is more applicable in the short run compared to the macroeconomic approach which is better in determining long term cointegration.
The body of literature regarding cointegration between stock markets is growing continuously. Daily closing values of the S&P500 and the Nikkei index were used in a cointegration study by Becker, Finnery and Friedman (1995), in which they found strong evidence for correlation between the Japanese and US stock markets. Blackman, Holden and Thomas (1994) examined the linkage between the stock markets in 17 countries and found that co-movements were scarcely present during the 1970s, but became more pronounced in the 1980s. The cointegration of the stock markets in the Pacific Rim region were investigated by Janakiramanan and Asjeet (1998) in which they provided evidence that the US stock market exerts influence on the trends and movements of other stock markets in the region, while no result indicated that the other countries had any significant impact on the stock markets in the US. The same region was also studied by Tay and Zhu (2002), in which they discovered that information that give rise to volatility in the financial market of one area can be spread quickly throughout the region and result in significant cointegrating movements between regional markets. Cha and Seeking (2000) observed that four emerging Asian economies, South Korea, Singapore, Taiwan and Singapore, had developed a stronger linkage with the US and Japan after the US stock market crash in the end of the 1980s, and continued to increase even more after the financial crisis in Asia 1997. Chan, Lien and Weng (2008) studied the financial markets of Hong Kong and the US and found that there is a one-way causality during the period after the financial crisis and post 9/11 from the US to the Hong Kong market.

Although the integration of stock markets has been widely studied, research on the international linkage for the mainland Chinese stock exchanges is somewhat limited. However, with the rapid development of the Chinese financial market, scholars and academics have gradually included China in their research. One of the first studies that was conducted on the topic was Bailey (1994) who found that there was little or no inter-correlation between the returns on Chinese stock shares and international equity returns. Huang, Yang and Hu (2000) utilized daily closing values for the stock markets in Hong Kong, China, Taiwan, US from 1992 to 1997 and concluded that there was no cointegration present between the Chinese and the other stock markets. Hsiao, Hsiao and Yamashitac (2003) present evidence that financial linkages between the US and Asia-Pacific has been strengthened by the recent information technology revolution. Their results also show that a slump in the US stock price indices will create a stock market recession in Taiwan, Korea and Japan, but not in China.

Wang and Firth (2004) examined the correlation of volatility and return among the four stock exchanges in Greater China (Shanghai, Shenzhen, Taipei and Hong Kong) and three major international equity markets (New York, London and Tokyo). The authors found that China's two mainland stock exchanges are relatively segregated and were mainly influenced by the development of the regional markets in Hong Kong and Taipei. Li (2007) investigated the relationship between the stock markets of the US, Hong Kong and mainland China and also found that there is a unidirectional spill-over from Hong Kong to mainland China, whereas the relationship between the Chinese and US equity markets do not provide any evidence of being linked to each other. Lin, Menkveld and Yang (2009) studied the period from 1992 to 2006 and found no relevant indications that there is any correlation between the Western markets and mainland China.

Lucey and Zhang (2010) analyse the impact of cultural distance in respect to the integration of financial markets. Their results from examining 46 stock markets indicate that countries with smaller cultural differences display a higher degree of linkage. Lai and Tseng (2010) investigates the regular and extreme dependences between the G7 and Chinese stock markets. They find that Chinese stock market has not only been working as a hedge, but function as a safe haven for G7 stock markets, making it a target for international investors and global stock fund managers who are seeking to hedge their portfolios during tumultuous financial periods. Wang, Chen and Huang (2011) probed into the dependence structure between the Chinese stock market and other major world markets. They found consistent evidence of the Chinese market displaying the highest levels of dependence, but also the greatest variability in dependence with the Pacific and Japanese markets. In studying the co-movements for the US and Chinese stock market during the period from 2004 to 2012, Li and Zhang (2014) found that there was no cointegrating relationship, but discovered indications that the impact of the US market on the Chinese one is particularly strong in times of economic turbulence.

There is much evidence from previous research that China's stock markets have remained rather isolated from international markets since being established. The degree of integration, however, has changed over the course of time. After the Asian financial crisis 1997, the stock exchanges of Shanghai and Shenzhen have become more linked with regional equity markets such as Taipei and Hong Kong, while the integration with the markets in the West have continued to be weak.

One important aspect that has not been thoroughly investigated in much of the previous conducted research is whether the structural change in the cointegration between international stock markets and China exhibited any changes during the financial crisis or not. Yang, Kolari and Min (2003) proved that equity markets become strengthened during times of economic crisis and generally also become more integrated with one another after the crisis than before it.

This paper aims to fill the research gap of whether there is any cointegration between Chinese and US stock indices in two distinctly separate time spans, namely the financial crisis and the post crisis period.

3. METHODOLOGY

This paper employs econometric time series tools to analyse the presence of comovements between the stock indices, but also to investigate the short and long run effects of their relationship. The methods and theory behind these econometric models will be thoroughly described in this section of the thesis.

3.1 Stationarity and unit root testing

If a time series that is non-stationary were to be tested with another series that is stationary, it is very likely that a regression involving these two would become spurious (Nielsen 2005). Therefore, when dealing with time series consisting of financial data such as stock indices which often exhibit non-stationary behaviour, it is imperative to perform unit root tests to be able to determine the order of integration for the series. This paper employs two stationarity tests to examine for unit roots in the data, namely the Augmented Dickey-Fuller (ADF) and Kwiatkowsi, Philips, Schmidt and Shin test (KPSS).

3.1.1 Augmented Dickey-Fuller test (ADF)

The Augmented Dickey-Fuller test was developed by Dickey and Fuller (1979) as a method for testing stationarity in statistical data. The test can be estimated in three different ways to examine whether there are unit roots in the data (Brooks 2002):

1. Unit root test:

$$\Delta y_t = \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta y_{t-i} + u_t$$

2. Unit root test with drift:

$$\Delta y_t = \beta_0 + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta y_{t-i} + u_t$$

3. Unit root test with a deterministic trend and drift:

$$\Delta y_t = \beta_0 + \varphi^* y_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta y_{t-i} + \beta_1 t + u_t$$

In the above equations, y_t denotes the stock market indices in levels; β_0 the drift term; t the linear trend term; u_t the error term.
The null hypothesis of the test is the presence of a unit root:

H_0: $\varphi^* = 0$ existing unit root (the data is non-stationary).
H_0: $\varphi^* < 0$ no unit root (the data is stationary).

H_0 is rejected if the ADF test statistic is larger in absolute value when comparing it to the critical value for every level of significance ($|\text{T stat}| > |\text{T critical}|$).

Before running the Dickey-Fuller test, there are important parameters that need to be taken into consideration as these can drastically alter the outcome of the test. Namely, should the regression of the variables include a trend, trend and constant, or neither? One possible solution would be to apply a general specification to the test which includes both a trend and a constant, and from this starting point examine whether any of these entities impose any statistical significance on the regression. However, by including irrelevant regressors in the model, the power of the test could be greatly diminished and consequently affect the interpretation of the null hypothesis. To mitigate this problem, and in adherence to the method proposed by Verbreek (2004), model specification for the Dickey-Fuller test will be based on graphical inspection of the time series. Following this school of thought, the time series should include a constant in the regression if there is not an explicit origin or beginning of the series. In addition, should the graphs of the data indicate any trend in its movements through the course of time, a trend should be included.

In visually assessing the time series graphs of the financial data in this paper (see Appendix), it is evident that the series in levels display both downward and upward trends with no clear-cut starting point or origin of the data. Looking at the graphs in first differences indicate that there are no trends, but a clearly an intercept (constant). According to these observations a constant and trend will be included when testing the data in levels, while only a constant will be a part of the model when testing the data in first differences.

Another important matter that has to be addressed before performing the tests is the determination of lag length. Overestimating the number of lags could lead to misspecifications of the model and consequently affect the assessment of the null hypothesis. On the other hand, a model with too few lags could possibly lead to over-rejection of the null hypothesis.

To determine the correct lag length, this paper use two information criteria (IC) models, SBIC (Schwartz Bayesian Criterian) and AIC (Akaike Information Criterion) which estimates and minimizes the information that is lost in the approximation of the models.
It can generally be said that SBIC selects the correct model with less lags than AIC. Therefore, as this paper is dealing with highly volatile weekly data, SBIC will be the criterion of choice should there arise any conflicting results from the information criteria models.

Some researchers have raised critical remarks regarding the power and reliability of the Dickey-Fuller test when estimating unit roots that are close or near to non-stationarity. In these instances, the test could incorrectly indicate that the data is stationary when it is not (Brooks 2002). To be sure that the data used for the analysis is stationary, an additional unit root test is therefore applied.

3.1.2 Kwiatkowski-Philips-Schmidt-Shin test (KPSS)

Another model for testing the data for stationarity is the Kwiatkoswki, Philips, Schmidt and Shin (KPSS) test which takes a different approach in testing the data compared to the ADF test. It works as a Lagrange multiplier (LM) and calculates the test statistic by performing a regression on the response variable (y_t) with a constant, or both a trend and a constant. By saving the residual (ε_t) from the regression the partial sums (S_t) from the equation can be calculated (Verbreek 2004).

$$KPSS\ LM = \sum_{t=1}^{t} \frac{S_t^2}{\hat{\sigma}_\varepsilon^2}$$

$S_t = \sum_{s=1}^{t} \varepsilon_s$ and $\hat{\sigma}_\varepsilon^2$ are the regression error variances from

$y_t = \alpha + \beta_t + \varepsilon_t$ or $y_t = \alpha + \varepsilon_t$

The null hypothesis of the test is that stationarity is present in the data.

In utilizing both the KPSS and ADF test in examining for stationarity, the results of the unit root tests are deemed to be very reliable. Should there arise a situation when the both test give contradictory reading, the KPSS test will be prioritized due to the shortcomings of the Augmented Dickey-Fuller test as described earlier.

3.2 Cointegration

The term cointegration was coined by Engle and Granger (1987) in one of the most influential works that has been written for econometrics and time series analysis during the last decades. Their theory and method for examining cointegration between time series provide researcher with a powerful tool that can be utilized in investigating linkages between different time series and is now used throughout all fields of economics (Diebold 2004). Two tests are available to test for cointegration between time series: 1) The Engle-Granger test which can test for cointegration in bivariate series. Consequently, this method can only detect one cointegrating relationship, and it usually requires that the data consist of a large number of observations to give reliable results. 2) The Johansen test which is capable of testing cointegration for more than two variables. It also allows for examination of the long-run relationship between the cointegrating variables.

3.2.1 Engle and Granger test (EG)

The Engle and Granger method is a single equation residual-based univariate approach that measures cointegrating parameters between two variables. The first step in examining whether or not there is cointegration is to confirm that the variables are stationary. Using non-stationary variables in a regression will produce spurious results that more often than not look too good to be true. Thus, care has to be taken to ensure that the time series have a unit root and are integrated in the first order, $I(1)$. The series are said to be cointegrated if there is a linear combination between them that is $I(0)$. Namely:

$$(\mathrm{y}, \mathrm{x}) \sim I(1), \text{ if there is } (\theta_1, \theta_2) \text{ that hold for } \theta_1 y_t \ + \ \theta_1 x_t \ = \ u_t \sim I(1)$$

After making sure that the variables to be tested for cointegration are $I(1)$ by running a stationarity test such as Dickey-Fuller, an OLS is performed to estimate the cointegrating regression:

$$\Delta y_t = C + \beta x_t + u_t$$

Next step is to save the residuals ($\hat{u}_t$) from the regression and test for stationarity by using a unit root test:

$$\hat{u}_t = \psi \hat{u}_{t-1} + \upsilon t$$

If the residuals are found to be stationary, the variables are considered to be cointegrated according to the Engle and Granger theory. This approach is quite straightforward but it also has its limitations. Being a single equation model, it is only capable of estimating one cointegrating relationship. Furthermore, the EG method is not applicable in investigating a long-term relationship for the cointegrating variables. Thus, in order to test for these relationships, the Johansen multivariate approach which is based on a vector autoregressive model will also be used as it is capable of finding cointegration between more than two variables and can also provide information about the short and long term relationship between the time series.

3.2.2 Vector Autoregressive Models (VARs)

Vector autoregressive models (VARs) are utilized to capture the interdependency and dynamics of multivariate time series. Its use in econometrics was popularised by Sims (1980) as being a natural generalisation of the univariate autoregressive model. Taking on more than one dependent variable, the vector autoregressive model can be said to be a systems regression model that is considered to be a hybrid between the simultaneous equation and time series model. In its most rudimentary form as a bivariate VAR only two variables are present, y_{1t} and y_{2t}, whose values are dependent on error terms and different combination of values of k. The equations can be written as follows (Brooks 2002).

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \cdots + \beta_{1k}y_{1t-k} + \alpha_{11}y_{2t-1} + \cdots + \alpha_{1k}y_{2t-k} + u_{1t}$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \cdots + \beta_{2k}y_{2t-k} + \alpha_{21}y_{1t-1} + \cdots + \alpha_{2k}y_{1t-k} + u_{2t}$$

in which u_{1t} denotes white noise disturbance with E(u_{1t}) = 0 and E($u_{1t}u_{2t}$) = 0.

The above system can also be expanded to incorporate g variables, y_{1t}, y_{2t},..., y_{gt}. Where each value is treated as an equation in its own right which makes for a very compact system. The above equations where $k = 1$ can be rewritten as:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \alpha_{21} & \beta_{21} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

in which each variable is only dependant on the previous values of y_{1t} and y_{2t} as well as the error term.

VAR models are very flexible and are able to capture time series data more succinctly than the simpler autoregressive model (AR) due to fact that VARs do not solely depend on its own lags or white noise term. The main advantage of VARs, however, is that all variables are treated as endogenous. This greatly facilitates the interpretation of the data as assumptions about exogeneity or endogeneity can be avoided.

Some of the shortcomings about the model is that it is a-theoretical and therefore difficult to interpret. This arises from the lack of theoretical information used in the system regarding the relationship of the variables used, and could result in misspecification of the model. There is some debate whether the components of the VAR should be stationary or not. Stationary ensures that the estimated regression is not spurious and thus produces more reliable results. On the other hand, as the purpose of VAR estimation lies in examining relationship between the time series, differencing the data would render the long-time information nonsensical. As financial time series typically exhibit non-stationarity, a solution is to use a combination of first difference and level data, which is possible by transforming the VAR model into a VECM (Vector Error Correction Model) (Brooks 2002).

In determining the optimal lag length for the VAR there are generally two methods which are used: information criteria (IC) or a cross-equation restriction approach such as least likelihood ratio test (LR). The latter being limited to pairwise connections while also assuming that the errors are normally distributed from each equation makes it unsuitable for financial data. This paper will use information criteria to select the most suitable lag length, and as for reasons mentioned earlier SBIC is preferred.

3.2.3 The Johansen test

As previously mentioned, the Engle and Granger method is used for testing cointegration for bivariate series. However, Johansen (1991) generalized the testing procedure to allow for multivariate cases involving more than two variables. The Johansen test also allows for examining the long run equilibrium relationship for the variables involved. Thus, when examining if there exist any cointegration between the four stock indices that are a part of the analysis, the Johansen test will be the method of choice.

Johansen's methodology originates from the vector auto-regression model (VAR) of order p, as given by the following equation (Hjalmarsson and Österholm 2007):

$$y_t = \Phi d_t + \Pi_1 y_{t-1} + \cdots + \Pi_p y_{t-p} + \varepsilon_t$$

where y_t is an nx1 vector composed of variables that are integrated in the first order, $I(1)$; d represents deterministic terms; and ε_t denotes an nx1 vector of innovations.

This type of VAR model, however, is not optimal for further analysis as the cointegrating relationships contained in y_t are ambiguous. To apply the Johansen test, the above VAR model should therefore be transformed into a Vector Error Correction Model (VECM) in the following fashion:

$$\Delta y_t = \Phi d_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

where $\Pi = \Pi_1 + \cdots + \Pi_p - I_g$ and $\Gamma_k = -\sum_{j=k+1}^{p} \Pi_j , k = 1, \dots , p-1$

As Πy_{t-1} is the only term that includes the variables that potentially are $I(1)$ it thus contains the cointegrating relations (if there are any). Thus, the object of interest in the Johansen test lies in the interpreting the rank of the Π matrix, which indicates the number of linear combinations between the variables (Huyghbaert and Lihong 2010).
This can be further explained by examining the two following cases:

$$rank(\Pi) = 0$$

This implies that $y_t \sim I(1)$ and that there is no cointegration, and consequently the VECM is reduced to a VAR in first differences.

$$\Delta y_t = \Phi d_t + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

However, if the rank is not zero:

$$0 < rank(\Pi) = r < n$$

this means that $y_t \sim I(1)$ has $n-r$ common unit roots (stochastic trends), and r linearly vectors that are cointegrated.
With Π having rank r. It can be written as a product of α and β.

$$\Pi = \alpha\beta'$$

where both α and β are nxr matrices $(rank(\alpha) = rank(\beta) = r)$. The elements of the α matrix represent the speed of adjustment coefficients and β the long-run relationship between the variables. In this case, the VECM is written:

$$\Delta y_t = \Phi d_t + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

where $\beta' y_{t-1} \sim I(0)$ because β' is a matrix of cointegrating vectors.

It is important to keep in mind that further restrictions to the models should be imposed in order to calculate the unique values for α and β'. This can be achieved by normalizing the value of β'. I.e. if $\beta = (\beta_1, \beta_2)'$, normalization of the beta value renders the equation:

$$\Pi = \alpha\beta' = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} (1 - \beta) = \begin{pmatrix} \alpha_1 - \alpha_1\beta \\ \alpha_2 - \alpha_2\beta \end{pmatrix}$$

the VECM for the cointegrating vectors, Δy_t, can thus be written:

$$\Delta y_t = \alpha\beta' y_{t-1} + \varepsilon_t$$

3.2.4 Test statistics for cointegration

Since the cointegration between the y variables is estimated by examining the rank of the Π matrix through its eigenvalues (roots), the Johansen approach utilizes two likelihood ratio (LR) statistics for cointegration in which the rank of the matrix can be determined by the number of eigenvalues, denoted as λ_i, that differ from zero.
If the variables in the equation are not cointegrated, then the rank of the Π matrix will not differ significantly from the value of zero ($\lambda_i \approx 0$) (Brooks 2002).

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i)$$

and

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$$

r denotes the number of cointegrating vectors under the null hypothesis and $\hat{\lambda}_i$ represents the ith ordered estimated eigenvalue of the Π matrix.

λ_{trace} test the null hypothesis: $[H_0(r_0 = 0)\ vs\ H_1(r_0 > 0)]$
λ_{max} test the null hypothesis: $[H_0(r_0) : r = r_0)\ vs\ H_1(r_0) :\ r_0 = r_0 + 1)]$
Rejection of the null means that there is at least one cointegrating vector.

If the two tests were to give different results, this paper will abide by the research of Helmut and Pentti (2001) which indicate that the trace test give more reliable readings.

3.2.5 Deterministic components for the Johansen test

Johansen (1995) demonstrated that the deterministic terms of the test can be restricted to the form:

$$\phi d_t = \mu_t = \mu_0 = \mu_1 t$$

By enforcing restrictions on the deterministic terms, the behaviour of y_t is altered due to changes in trends and intercepts. When running the Johansen test, five options concerning restriction of deterministic components are possible to apply in the VECM equation (Harris and Sollis 2003):

1. No constant: $u_t = 0$

$$\Delta y_t = \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

with no deterministic trends or intercepts in both VAR and cointegrating equations (CE).

2. Restricted constant: $u_t = \mu_o = \alpha p_0$

$$\Delta y_t = \alpha(\beta' y_{t-1} + p_0) + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

with no deterministic trends or intercept in VAR and intercept in CE

3. Unrestricted constant: $u_t = \mu_o$

$$y_t = \mu_o + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

with intercept in VAR and CE and no trends in VAR or CE

4. Restricted trend: $u_t = \mu_o + \alpha p_1 t$

$$\Delta y_t = \mu_o + \alpha(\beta' y_{t-1} + p_1 t) + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

with intercept in VAR and intercept and linear trend in CE.

5. Unrestricted constant and trend: $u_t = \mu_o + \mu_1 t$

$$y_t = \mu_o + \mu_1 t + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots \Gamma_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t$$

with intercept and a quadratic deterministic trend in both VAR and CE.

As first and the last model are rarely used and are not applicable for the kind of financial data used in this study, only model one to three will be elaborated and tested on.

The selection of trends and intercepts highly influence the result of the test. Therefore, Johansen (1995) suggested that the deterministic components and rank order should be tested by using the Pantula principle to reach a parsimonious model. This means that the models above are tested in order of restrictiveness. The most restrictive model (model 2) is tested first, and lastly the least restrictive model (model 4). The critical values and eigenvalue test statistics are monitored throughout the process, and when a model is reached when the null hypothesis can be rejected, a parsimonious model has been established.

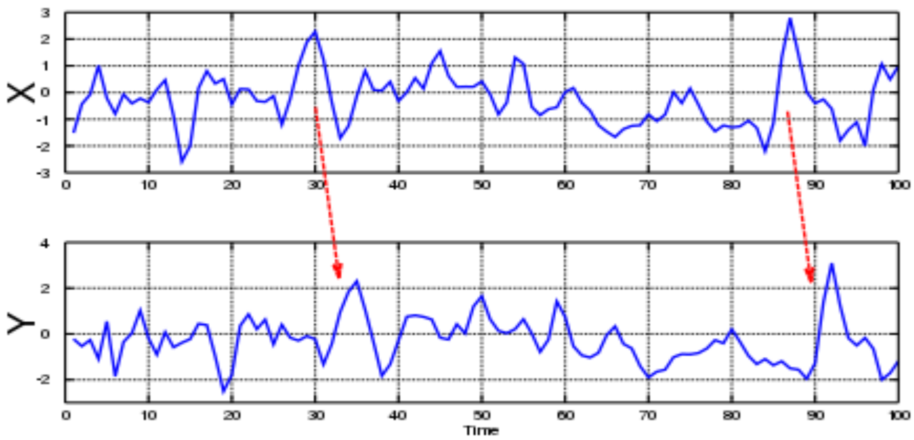
3.3 Granger causality test

The Granger causality test is a statistical hypothesis test that is useful for determining if one time series can be used to forecast the behaviour of another. Granger (1969) argued that the prior values of one time series could be used to predict the future values for another time series. The Granger test will be used in this paper to investigate if there is any causality between the variables in the time series. The method gives a probabilistic[1] account of causality when examining correlating patterns.

Although the test is referred to as being a causality test, the test actually only calculates preceding values of one variable and compares it with another. True causality would mean that one variable X is the cause of Y or vice versa. The figure below illustrates the idea of the Granger test:

[1] Probabilistic is the opposite of deterministic and means that randomness is involved in the prediction of future events.

Figure 1. Granger causality



Source of figure: Liu and Bahadori (2012).

When looking at the figure above it is clear that the Y variable is affected by the preceding value of X. Hence, X Granger-causes Y.

Testing for Granger causality corresponds to estimating a VAR model such as the following (Brooks 2002):

$$\Delta y_t = \alpha + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \sum_{j=1}^{n} \tau_j \, \Delta y_{t-j} + \mu_t$$

$$\Delta x_t = \theta + \sum_{i=1}^{p} \phi_i \Delta x_{t-i} + \sum_{j=1}^{q} \psi_j \, \Delta y_{t-j} + \eta_t$$

However, if the series are cointegrated, the equations need to include an error correction term as regressing on first difference variables that are cointegrated would likely lead to misspecifications.

$$\Delta y_t = \alpha + \delta(y_{t-1} - \gamma x_{t-1}) + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \sum_{j=1}^{n} \tau_j \, \Delta y_{t-j} + \mu_t$$

$$\Delta y_t = \theta + \delta(y_{t-1} - \gamma x_{t-1}) + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \sum_{j=1}^{n} \tau_j \, \Delta y_{t-j} + \mu_t$$

The null hypothesis for the test is that the variation in one variable (y) cannot be explained by lagged values in another (x). By examining the OLS coefficients for the above equations the relationship between y_t and x_t can be formulated in four different hypotheses (Brooks 2002):

1. Unidirectional Granger-causality from x_t to y_t: $\sum_{j=1}^{n} \tau_j \neq 0$ and $\sum_{j=1}^{q} \psi_j = 0$ (X Granger causes Y).
2. Unidirectional Granger-causality from y_t to x_t: $\sum_{j=1}^{n} \tau_j = 0$ and $\sum_{j=1}^{q} \psi_j \neq 0$ (Y Granger causes X).

3. Bidirectional causality: $\sum_{j=1}^{n} \tau_j \neq 0$ and $\sum_{j=1}^{q} \psi_j \neq 0$ (Both X and Y Granger causes each other).

4. Independence between y_t and x_t: $\sum_{j=1}^{n} \tau_j \neq 0$ and $\sum_{j=1}^{n} \tau_j = 0$ (no Granger causality in any direction).

3.4 Impulse response functions

The Granger causality test does not provide the complete story of cause-and-effect as it only examines the variables in a given point of time. However, impulse response functions (IRFs) can be utilized to examine the duration of the movements of the effects and also how long they last. Thus, IRFs are a valuable tool in econometrics that are able to measure the dynamic effect of an unanticipated shock to the system. Impulse responses analyse how each of the dependant variables in a VAR model react to shocks or impulses from the explanatory variables. To create impulses, the error term is impacted with a unit shock while the effects over time in the VAR system is recorded for every impulse. An unstable system will result in a time path that looks explosive, whereas a stable one will decline to the value of zero on any given shock (Lin 2006). By writing the VAR as a vector moving average (VMA) the impulses can be generated for variables in the system (g variables can produce g^2 impulses).

To illustrate this, consider a basic bivariate VAR(1) model setup (Brooks 2002):

$$y_t = A_1 y_{t-1} + u_t \text{ where } A_1 = \begin{pmatrix} 0.2 & 0.1 \\ 0.0 & 0.3 \end{pmatrix}$$

this gives the following equation:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 0.2 & 0.1 \\ 0.0 & 0.3 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

and measuring a unit shock at $t = 0$ for y_{1t} gives:

$$y_0 = \begin{pmatrix} u_{10} \\ u_{20} \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$y_1 = A_1 y_0 = \begin{pmatrix} 0.2 & 0.1 \\ 0.0 & 0.3 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0.2 \\ 0.0 \end{pmatrix}$$

$$y_2 = A_1 y_1 = \begin{pmatrix} 0.2 & 0.1 \\ 0.0 & 0.3 \end{pmatrix} \begin{pmatrix} 0.2 \\ 0.0 \end{pmatrix} = \begin{pmatrix} 0.04 \\ 0.0 \end{pmatrix}$$

This can continue for y_2, y_3 ...; and given that the system is stable, the shocks will consequently fade out over time. As the variable y_{1t-1} has the value of zero, y_{2t} will hence always be zero. However, the same calculation can of course be made with a unit shock to y_{2t} instead of y_{1t}. This would also render two separate time paths as the dependent variable will be influenced by both of the independent variables.
The results of these equations can be plotted as impulse responses which give a more intuitive interpretation of the data compared to only looking at the VAR model.

4. DATA

The data used in this paper has been obtained from Morningstar, Inc. which is an investment management and investment research company based in the United States. Morningstar, Inc. provides a range of financial services such as stock quotes, financial reports, and offer historical data of stock indices which can be parsed and downloaded.
In order to examine the cointegration between the financial markets of China and the US, three major stock indices were selected to represent the two countries. In addition, to serve as a reference for the analysis, a Swedish stock market index is also included to help in measuring the level of cointegration for all the indices involved in the study.

S&P500 (Standard & Poor's 500) is an American stock market index comprised of the market capitalizations of 500 large companies that have their stocks listed on the NASDAQ or NYSE. The weightings and composition of the index are determined by the S&P Dow Jones Index, which originally developed and now also maintains the S&P500. The S&P500 is considered to be a bellwether for the US economy as well as the being one of the best representations for the entire stock market in the US. Having a very diverse weighting methodology and constituency, S&P500 differs in many ways from other stock indices in the US (Arnott et al. 2005). All these factors make it an optimal choice for representing the US equity market.

HSI (Hang Seng Index) is a Hong Kong based capitalization-weighted freefloat adjusted stock market index that includes the 50 largest companies from the Hong Kong stock market (58% of the Hong Kong Stock Exchange capitalisation). It serves as the main indicator for the overall performance of the Hong Kong market. It was created 1969 as an idea of creating a Dow Jones index for Hong Kong and is currently owned by a subsidiary of the Hang Seng Bank (Kwan 2009).

SSE (Shanghai Stock Exchange) is based in Shanghai and is beside the Shenzhen Stock Exchange the only stock exchange that operates freely within the People's Republic of China. Measured by market capitalization, it is the world's third largest stock market. Unlike the stock exchanges in Hong Kong, the Shanghai Stock Exchange is forced to abide by regulations stipulated by the central government of China which leads to tight control of its capital as well as restricted access for foreign investors to operate on the market. The exchange itself is run by a non-profit organization which is under direct control of the China Securities Regulatory Commission (CSRC).

OMXS30 (The OMX Stockholm 30) is a capitalization-weighted index based in Sweden that is comprised of the 30 most traded stock classes on Nasdaq Stockholm. The index functions as an indicator for the Swedish stock market and is a benchmark for a wide array of financial products such as futures, options and funds.

4.1 Structural breaks and functional form

In order to avoid misrepresentative or skewed data when testing historical stock values for cointegration, it is important to look at the historical movements of the international global financial markets to examine whether there are any time periods that exhibited unusual behaviour or exceptions to the normal trends. Visual inspection of historical values of stock prices indicate that the financial period between 2007 and 2009, also dubbed the financial crisis, clearly displays extraordinary and turbulent behaviour. As the purpose of this paper is to measure the cointegration between the stock markets during the financial crisis and post crisis, structural breaks are imposed in the data to isolate these two periods of time. Thus, the first structural break of the data is set during the financial crisis. Interpretation of the data indicates that the stock markets exhibit most turbulence between August 2007 until 1st July 2009. The second structural break is set after the crisis and cover the period from January 2010 to the 31th of March of 2018.

Table 1. Structural breaks

Period	**Interval**
Crisis	1 August 2007 – 1 July 2009
Post crisis	1 January 2010 – 31 March 2018

To be able to capture the often volatile and short-time movements on the stock market the data in the time series is based on weekly closing values. To avoid what Frank Cross (1973) calls the ‘Monday effect’, namely that stock markets follow a trend from the previous Friday which will continue throughout the weekend and impact the closing values of the next Monday, all the data is based on Wednesday closing values.
The functional form of the data is transformed into levels (log-log) in order to smooth the appearance of the graphs, but also to be able to succinctly capture the pronounced elasticity that is prevalent in financial time series.

Table 2. Overview of data

Location	**Stock index**	**Abbreviation**	Transformation
USA	Standard & Poor’s 500	S&P500	Logarithm
Hong Kong	Hang Seng Index	HSI	Logarithm
China	Shanghai Stock Exchange	SSE	Logarithm
Sweden	OMX Stockholm 30	OMXS30	Logarithm

4.2 Preliminary analysis

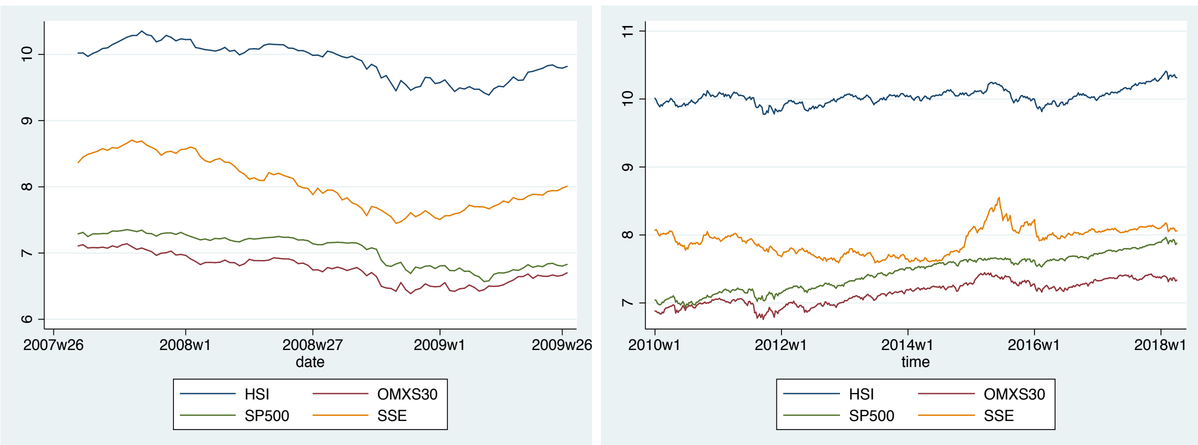
The descriptive overview of the stock indices below presents a comparison of the variables. It is peculiar, and somewhat surprising that SSE have a higher mean during the financial crisis than afterwards. This might be due to the fact that SSE was not as closely linked to the global financial market compared to the other indices and thus not impacted in the same degree. However, SSE also has the highest standard deviation during the crisis, which indicates volatile movement. Normality testing (from the VAR) indicate that there are a few problems with normality in the series.

Table. 3 Descriptive overview of the stock indices

Variable	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	p-value
Crisis							
S&P500	101	7.048451	.2392108	-.78414	5.3368	32.670	0.00000
OMX	101	6.764741	.2184447	-.06887	3.2188	0.276	0.87123
HSI	101	9.899981	.2710678	-.08483	4.1181	5.275	0.07153
SSE	101	8.049051	.3805072	.27557	3.0384	1.259	0.53284
Post crisis							
S&P500	430	7.447391	.2686655	-.64637	4.7897	86.925	0.00000
OMXS30	430	7.151772	.1771745	-.03844	4.2505	27.991	0.00000
HSI	430	10.03234	.1163871	.0179	3.1654	0.511	0.77465
SSE	430	7.90942	.1988093	-.62463	6.9412	304.841	0.00000

Ocular inspection of the figure below which presents an outline of the movements of the indices during and after the crisis gives some clues about the cointegration of the series (see Appendix). S&P500 and OMXS30 seem to exhibit the same pattern of movements and follow each other's ups and downs in both of the charts, whereas the time series for HSI and SSE appear to move in a more individual manner compared to the other indices. Especially HSI show signs of erratic movement during the post crisis. Cointegration cannot, however, be determined by graphs alone and analysis of the data will be performed in the following section.

Figure. 2 Overview of the indices during and post crisis



5. RESULTS AND ANALYSIS

5.1 Stationarity and unit root testing

The first task before investigating if there exist any linkage between the stock indices is to perform tests for stationarity and unit roots. The Augmented Dickey-Fuller test (ADF) and the Kwiatkowski, Philips, Schmidt and Shin (KPSS) test are used to determine whether the time series are stationary or not. The null hypothesis of the ADF test is that the data is non-stationary, contrary to the KPSS which test the null hypothesis of stationarity (presence of a unit root). Hence, the KPSS test is performed as a confirmatory measure to verify the results of the ADF test. Should both tests give contradictory conclusion regarding the rejection of unit roots, the results from the KPSS test will be opted for.
The testing is first performed on the series in the functional form of levels, and then the same procedure is repeated in first differences to be able to determine the order of integration of the time series. If a time series exhibit non-stationarity in levels but is stationary in first differences, its integrated in the first order.

When eye-balling the time series (see Appendix), there are no pronounced starting-points for the series in the logarithmical functional form, but there are discernible upward and downward trends throughout the graphs. In first differences, however, there is a clearly an intercept in the data, but no obvious trends. Thus, both a constant and a trend will be a part of the stationarity testing in levels, while only accounting for an intercept when testing in first differences.
As mentioned before, information criteria are used to find the appropriate lag length of the data. When consulting AIC and SBIC, some contradictory results were presented. The recommendation from SBIC is preferred as it recommends the correct lag length with fewer lags. In this instance, all the time series in levels have lag length 1 except for OMX30 which has 2; and in first differences 0 lags are recommended for all series with the exception of OMXS30 for which 1 lag is proposed.

The results from the tables below present strong evidence that the time series are non-stationary when testing in levels. The null hypothesis cannot be rejected for the ADF test and the null hypothesis of non-stationarity for the KPSS test can be rejected. When comparing the test statistics for the indices during the crisis and post crisis, it is evident that the time series from the crisis exhibit very non-stationary behaviour in contrast to the post crisis which sometimes are very close to the 5% critical value of the test.
Interpretation of the same tests for stationarity in first differences clearly indicate that the time series indeed are stationary when the functional form is changed. The null hypothesis for the ADF test can be strongly rejected for all indices. These results are also confirmed by the KPSS test. Thus, unit roots are present in all the time series when testing in first differences, but not in levels, which means that the data is integrated in order of one, $I(1)$. With this knowledge, it is now possible to proceed for further testing of cointegration between the variables.

Table 4. ADF test in levels and first differences

Index	Lags	Specification	T-stat	5% crit.	Null	Obs.
Crisis		in levels				
OMXS30	1	intercept with trend	-0.937	-3.451	not rejected	99
SP500	1	intercept with trend	-1.829	-3.451	not rejected	99
HSI	1	intercept with trend	-1.567	-3.451	not rejected	99
SSE	1	intercept with trend	-0.068	-3.451	not rejected	99
Post crisis		in levels				
OMXS30	2	intercept with trend	-2.647	-3.423	not rejected	427
SP500	1	intercept with trend	-3.273	-3.423	not rejected	428
HSI	1	intercept with trend	-2.548	-3.423	not rejected	428
SSE	1	intercept with trend	-2.366	-3.423	not rejected	428
Crisis		first difference				
OMXS30	0	constant, no trend	-10.965	-2.891	rejected	99
SP500	0	constant, no trend	-9.311	-2.891	rejected	99
HSI	0	constant, no trend	-10.460	-2.891	rejected	99
SSE	0	constant, no trend	-9.705	-2.891	rejected	99
Post crisis		first difference				
OMXS30	1	constant, no trend	-15.439	-2.873	rejected	427
SP500	0	constant, no trend	-22.805	-2.873	rejected	428
HSI	0	constant, no trend	-20.295	-2.873	rejected	428
SSE	0	constant, no trend	-18.875	-2.873	rejected	428

Table 5. KPSS test in levels and first differences

Index	Lags	Specification	T-stat	5% crit.	Null	Obs.
Crisis		in levels				
OMXS30	1	intercept with trend	.514	0.146	rejected	99
SP500	1	intercept with trend	.481	0.146	rejected	99
HSI	1	intercept with trend	.426	0.146	rejected	99
SSE	1	intercept with trend	.845	0.146	rejected	99
Post crisis		in levels				
OMXS30	2	intercept with trend	.83	0.146	rejected	427
SP500	1	intercept with trend	1.5	0.146	rejected	428
HSI	1	intercept with trend	.92	0.146	rejected	428
SSE	1	intercept with trend	2.57	0.146	rejected	428
Crisis		first difference				
OMXS30	0	constant, no trend	.2	0.463	not rejected	99
SP500	0	constant, no trend	.123	0.463	not rejected	99
HSI	0	constant, no trend	.168	0.463	not rejected	99
SSE	0	constant, no trend	.405	0.463	not rejected	99
Post crisis		first difference				
OMXS30	1	constant, no trend	.0425	0.463	not rejected	427
SP500	0	constant, no trend	.0239	0.463	not rejected	428
HSI	0	constant, no trend	.1	0.463	not rejected	428
SSE	0	constant, no trend	.167	0.463	not rejected	428

5.2 Engle-Granger test

Since the variables are cointegrated in the first order, it is now possible to perform tests of cointegration for the time series. The first test that is presented is the Engle-Granger test that can be utilized to find cointegration for a bivariate system, in comparison to the Johansen test that can find cointegrating vectors for more than two variables.
The specification of the model in estimated with no intercept and no trend to avoid misspecification of the regression. The Engle and Granger test is highly sensitive to the lag length and the method for selecting the appropriate on is a much debated topic (Agunloye 2014). One possible approach to this it to begin at a given lag, in this case 2 lags have been selected, and then test down in incremental steps until reaching 0 lags. As can be seen, the test statistic produces the highest value for almost all indices when lag is 0. Because the Dickey-Fuller test is performed on the residuals from the regression it is not possible to use the critical values from the usual ADF test. Thus, the critical values provided by Hamilton is used here (Hamilton 1994).

The results of the analysis show that the null hypothesis of no cointegration cannot be rejected for S&P500/OMXS30 during the financial crisis. After the crisis, however, the rejection of no cointegration is possible at 0 lags. It is not completely surprising that there is cointegration between these two indices as much research show that the US stock markets exert strong influence on financial markets in Europe (Bala and Premaratne 2004). It should however be noted that cointegration between the indices only is present after the crisis. During the financial crisis there are not indications of any linkage (not even at 10% critical value).

Somewhat more surprising is the fact that the opposite holds true for the cointegration results for S&P500 and HSI. The results present evidence of cointegration between the indices during the financial crisis at 1 lag (also at 0 lags at 10% critical value), but not after the crisis. This suggest that HSI follows the trends of the S&P500 more during times of financial turbulence than vice versa. These findings are in line with Assidenou (2011) who found that S&P500 display more cointegration with several Asian markets including the HSI during the crisis.

The Engle and Granger cointegration test for S&P500 and SSE does not indicate that there is any cointegration between the indices both during and after the financial crisis. A reason for this could be that SSE mainly concerns itself with mainland financial dealings and is not as integrated on the global financial market compared to the other indices.
It is also noteworthy that SSE and HSI, although both being actors on the Asian financial market present very different results in the test for cointegration between the indices, as the results show that there is no cointegration between the two stock markets. HSI has a much longer history than SSE and has been operating for a much longer period of time while also not being under the strong influence of the Chinese government. These factors are very likely to play in big role in how the stock indices are integrated with other international financial markets.

Table 6. Engle-Granger test for S&P500/OMXS30

Lags	Specification	T-stat	5% crit.	Null	Obs.
Crisis					
2	no intercept, no trend	-0.889	-2.76	not rejected	98
1	no intercept, no trend	-1.251	-2.76	not rejected	99
0	no intercept, no trend	-1.679	-2.76	not rejected	100
Post crisis					
2	no intercept, no trend	-2.364	-2.76	not rejected	427
1	no intercept, no trend	-2.284	-2.76	not rejected	428
0	no intercept, no trend	-2.781	-2.76	**rejected**	429

Table 7. Engle-Granger test for S&P500/HSI

Lags	Specification	T-stat	5% crit.	Null	Obs.
Crisis					
2	no intercept, no trend	-1.697	-2.76	not rejected	98
1	no intercept, no trend	-2.761	-2.76	**rejected**	99
0	no intercept, no trend	-2.636	-2.76	not rejected	100
Post crisis					
2	no intercept, no trend	-1.981	-2.76	not rejected	427
1	no intercept, no trend	-2.028	-2.76	not rejected	428
0	no intercept, no trend	-2.181	-2.76	not rejected	429

Table 8. Engle-Granger test for S&P500/SSE

Lags	Specification	T-stat	5% crit.	Null	Obs.
Crisis					
2	no intercept, no trend	-0.966	-2.76	not rejected	98
1	no intercept, no trend	-1.349	-2.76	not rejected	99
0	no intercept, no trend	-1.287	-2.76	not rejected	100
Post crisis					
2	no intercept, no trend	-1.726	-2.76	not rejected	427
1	no intercept, no trend	-1.606	-2.76	not rejected	428
0	no intercept, no trend	-1.559	-2.76	not rejected	429

Table 9. Engle-Granger test for HSI/SSE

Lags	Specification	T-stat	5% crit.	Null	Obs.
Crisis					
2	no intercept, no trend	-1.772	-2.76	not rejected	98
1	no intercept, no trend	-1.812	-2.76	not rejected	99
0	no intercept, no trend	-2.001	-2.76	not rejected	100
Post crisis					
2	no intercept, no trend	-1.835	-2.76	not rejected	427
1	no intercept, no trend	-1.717	-2.76	not rejected	428
0	no intercept, no trend	-1.704	-2.76	not rejected	429

5.3 Johansen test

The limitation of the Engle-Granger test of lies in its capability of only being able to measure cointegration between two variables. To be able to test all the four indices together and also examine the long-run relationship for the variables, the Johansen test is applied.

Before running the test, the appropriate lag length for the underlying VAR model must be chosen. The table of lag length selection below indicates that there are conflicting recommendations from the different information criteria. AIC suggests 4 lags whereas SBIC opts for 1 lag for the data during the financial crisis. Post crisis, AIC recommends 2 lags and SBIC 1 lag. A consensus is yet to be reached among researchers regarding which IC that produce the most consistent and dependable results. It is noteworthy that the difference between the IC recommendations during the crisis of 1 lag and 4 lags is very wide. For reasons discussed in the methodology section in this paper, SBIC is the IC of choice.

Table 10. Selection of lag length financial crisis

S&P500, OMXS30, HSI, SSE	**VAR(1)**	**VAR(2)**	**VAR(3)**	**VAR(4)**
Crisis				
LL	748.067	764.031	784.929	803.15
AIC	-15.0117	-15.0109	-15.1119	**-15.1577***
SBIC	**-14.4808***	-14.0554	-13.7317	-13.3528
Post crisis				
LL	4291.99	4313.71	4320.14	4325.85
AIC	-20.0563	**-20.0832***	-20.0382	-19.9899
SBIC	**-19.866***	-19.7405	-19.5433	-19.3427

Now that appropriate lag lengths have been selected the Johansen test can be performed to investigate whether there are any cointegrating vectors among the indices. VAR models can be sensitive to problems within the residuals, so testing for kurtosis, skewness and normality of the variables should be conducted to ascertain that the data can be used in the Johansen test. The results from these test (see Table 3) indicate that the variables in the VAR does not exhibit any problematic deviations with the exception of S&P500 which has some problem with normality and kurtosis.

The Johansen test is conducted by using the Pantula principle in which the models 2 to 4 are tested in sequential order. The least restrictive model (4th model) is the preferred model as it is less restrictive than the other ones. The results from the test show that there is one cointegrating vectors between the indices for both model 3 and model 4. This means that there is one cointegrated relationship among all the variables, and it is thus possible to proceed with testing for the long term effects among the indices. Table 11 show the general results of the test, more detailed results for all the models are in the Appendix.

Table 11. Johansen test

S&P500, OMXS30, HSI, SSE	Lags	Trace statistic	5% crit.	Cointegrating vectors
Crisis				
Model 2	1	50.7047	53.12	0
Model 3	1	21.4872	29.68	**1**
Model 4	1	37.8793	42.44	**1**
Post crisis				
Model 2	1	39.9496	53.12	0
Model 3	1	33.9269	47.21	0
Model 4	1	58.4387	62.99	0

5.3.1 Vector Error Correction Model

The Johansen test confirmed that there are cointegrating relationships between the four stock indices S&P500, OMXS30, HSI, SSE during the crisis. Thus, by using a vector error correction model, it is now possible to calculate the long-run relationship as well as the speed of adjustment of the cointegrating indices.

Normalization of the Beta coefficients enable long run forecasting of the other indices. Table 12 below represent the results of the long run effects on the different indices when the Beta of S&P500, HSI and SSE is normalized to 1. Due to the normalization, the signs are reversed meaning that a negative number is interpreted as a being positive.

Summary of the statistically significant results from the VECM normalization table below:

- 1% unit increase in HSI leads to a 0.56% increase of S&P500 in the long run.
- 1% unit increase in SSE leads to a -0.30% decrease of S&P500 in the long run.

- 1% unit increase in S&P500 leads to a -3.35% decrease of SSE in the long run.
- 1% unit increase in HSI leads to a 1.90% increase of SSE in the long run.

- 1% unit increase in S&P500 leads to a 1.77% increase of HSI in the long run.
- 1% unit increase in SSE leads to a 0.53% increase of HSI in the long run.

Interestingly, a unit increase in HSI and SSE results in different behaviour for S&P500 in the long run. These effects are substantiated in how SSE is affected in the long run by HSI and S&P500. HSI increases in the long run by a unit increase in both SSE and S&P500. This could indicate that there is an indirect (lagged) spill-over effect from HSI in two steps. Namely the long run effect from S&P500 on HSI is passed on to the mainland Chinese market. This might not be noticeable by merely looking at the long run cointegrating relationship between S&P500 and SSE due to the delayed and intricate behaviour of the effect.

The interpretation of the Alpha coefficient, which represents the speed of adjustment to equilibrium, indicate that HSI and SSE correct a previous period of disequilibrium to S&P500 at a speed of 2-5%. This is considerably slower than the opposite case in which S&P500 adjust to equilibrium at a speed of ~30% to SSE and HSI, indicating that the duration of the cointegrating relationship does not last for very long and that the US, not surprisingly, is more pronounced in the relationship.

Table 12. VECM estimation for Beta and Alpha during the financial crisis

Beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
S&P500	1					
OMXS30	-.4783563	.0931097	-5.14	0.000	-.6608479	-.2958646
HSI	-.563472	.0543017	-10.38	0.000	-.6699013	-.4570427
SSE	.2985311	.0377101	7.92	0.000	.2246207	.3724415
Alpha	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
S&P500	-.0833587	.1177358	-0.71	0.479	-.3141166	.1473991
OMXS30	.2681432	.1328687	2.02	0.044	.0077254	.5285609
HSI	.3274282	.1732356	1.89	0.059	-.0121073	.6669638
SSE	-.2937549	.1619198	-1.81	0.070	-.6111119	.0236021

Beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
SSE	1					
OMXS30	-1.602367	.2725996	-5.88	0.000	-2.136652	-1.068081
HSI	-1.887482	.2867815	-6.58	0.000	-2.449563	-1.3254
S&P500	3.349735	.3869806	8.66	0.000	2.591267	4.108203
Alpha	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
SSE	-.087695	.0483381	-1.81	0.070	-.1824359	.0070459
OMXS30	.0800491	.0396654	2.02	0.044	.0023063	.1577919
HSI	.0977475	.0517162	1.89	0.059	-.0036144	.1991094
S&P500	-.0248852	.0351478	-0.71	0.479	-.0937736	.0440032

Beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
HSI	1					
OMXS30	.8489442	.1851671	4.58	0.000	.4860233	1.211865
SSE	-.5298064	.0726263	-7.29	0.000	-.6721513	-.3874616
S&P500	-1.774711	.1411196	-12.58	0.000	-2.0513	-1.498122
Alpha	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
HSI	-.1844966	.0976134	-1.89	0.059	-.3758154	.0068221
OMXS30	-.1510912	.0748678	2.02	0.044	-.2978293	-.004353
SSE	.1655227	.0912373	1.81	0.070	-.0132991	.3443445
S&P500	.0469703	.0663408	-0.71	0.479	-.0830553	.1769959

5.4 Granger causality

It has been proven that there is a long-run cointegrating relationship between several of the indices, but it is also important to examine whether there exists any relationship in the short run. Therefore, by applying the Granger causality test it is possible to see if there is any causal linkage between the indices. The conclusions that can be derived from this test are very useful to be able to forecast and determine future predictions about how one variable will be affected in the short run by the impact of another variable.

The table below bears witness to the fact that several of the indices exert statistically significant influence on the future values of one another, and that there is more Granger causality during the financial crisis than after the crisis. This is in line with the previously stated hypothesis that that the financial crisis created a pronounced domino effect on the financial markets globally that made the indices become more closely interwoven and affected by each other. The US stock market, especially, became a strong influence on the other stock markets which is apparent from looking at table 13. The S&P500 also has a stronger short-term impact on all the other indices than the opposite. The explanation for this is likely that the US financial market is largest in the world and deemed by many to be the driver of the world economy (Hart and Spero 2010). In this role, the movements and trends that appear on the US financial market send out ripples around the globe which have strong financial impacts on markets world-wide.

HSI Granger-causes both S&P500 and SEE during the financial crisis. The reason why HSI Granger-causes SSE while S&P500 does not is likely due to the common features and geographical proximity that HSI and SSE share. HSI is a much more mature index than SSE and also allows foreign investment, which in turn leads to HSI asserting stronger influence on SSE than the other way around. The Engle-Granger test proved that there is cointegration between HSI and SSE, but the results presented here confirm statistically significant short run effects. HSI has long been one of the great financial hubs in Asia and spill-over effects to mainland China are likely to occur.

To summarize the findings: during the financial crisis S&P500 Granger causes both HSI and OMXS30, while itself being Granger-caused by HSI. HSI is the only index that Granger-causes SSE. Interestingly, after the crisis SSE is Granger-caused by S&P500 and OMX, which could be a sign that the Chinese mainland financial market is becoming more and more linked with the Western markets. This is in line with recent research on the topic which show that the Chinese mainland financial markets are becoming more and more open and integrated with the stock markets in Europe and the US (Chen et al. 2014). In addition, mainland China’s stock markets have developed rapidly during the last decade and have under the pressure from WTO been pressured to further liberalize its financial markets and open up for foreign investors (Imbruno 2016).

Table 13. Granger causality financial crisis

Null hypothesis	Prob > chi2	Conclusion
OMXS30 does not granger cause S&P500	0.701	
HSI does not granger cause S&P500	0.020	HSI → S&P500
SSE does not granger cause S&P500	0.868	
All indices do not granger cause S&P500	0.188	
S&P500 does not granger cause OMXS30	0.018	S&P500 → OMXS30
HSI does not granger cause OMXS30	0.218	
SSE does not granger cause OMXS30	0.996	
All indices do not granger cause OMXS30	0.150	
S&P500 does not granger cause HSI	0.001	S&P500 → HSI
OMXS30 does not granger cause HSI	0.972	
SSE does not granger cause HSI	0.462	
All indices do not granger cause HSI	0.003	OMXS30, SSE, S&P500 → HSI
S&P500 does not granger cause SSE	0.397	
OMXS30 does not granger cause SSE	0.236	
HSI does not granger cause SSE	0.043	HSI → SSE
All indices do not granger cause SSE	0.039	OMXS30, HSI, S&P500 → SSE

Table 14. Granger causality post crisis

Null hypothesis	Prob > chi2	Conclusion
OMXS30 does not granger cause S&P500	0.157	
HSI does not granger cause S&P500	0.980	
SSE does not granger cause S&P500	0.720	
All indices do not granger cause S&P500	0.579	
S&P500 does not granger cause OMXS30	0.097	S&P500 → OMXS30
HSI does not granger cause OMXS30	0.808	
SSE does not granger cause OMXS30	0.816	
All indices do not granger cause OMXS30	0.453	
S&P500 does not granger cause HSI	0.458	
OMXS30 does not granger cause HSI	0.350	
SSE does not granger cause HSI	0.315	
All indices do not granger cause HSI	0.178	
S&P500 does not granger cause SSE	0.077	S&P500 → SSE
OMXS30 does not granger cause SSE	0.025	OMXS30 → SSE
HSI does not granger cause SSE	0.800	
All indices do not granger cause SSE	0.137	

5.5 Impulse response functions

The Granger causality test provided information about the how the future behaviour of one stock index can be affected by previous trends of another one in the short run, but does not reveal anything about the movements and length of these effects. Impulse response functions can be utilized to measure and illustrate in what way a stock index respond to a shock or impulse impacting the system. As can be seen in the figure on the next page, impulse response function graphs allow for a very intuitive interpretation of how the system reacts both in its movements and trends but also for what duration of time that a one unit shock prevails in the system. The unit shock is measured in steps from 1 to 5 where every step, as explained in the methodology section, equals the value of $t = 1,2,3$ ... in the VAR equation.

The impulse responses for the financial crisis show, as been prevalent throughout the analysis, that the effects and integration between the indices are more pronounced than during the post crisis period. An impulse on HSI creates almost the same response from S&P500 and HSI, namely a positive rise of the curve which then slowly fades out. The response from SSE goes in a negative direction and it lasts longer, continuing throughout the graph.
As expected, the impulses from S&P500 results in the most distinct responses compared to the shocks produced by any of the other indices. It is interesting to notice how the responses it creates from HSI and SSE are almost identical, except for the fact that SSE lags behind HSI with two steps. This indicates that HSI respond more quickly to shocks from the US market while it takes SSE longer time to react before it is affected by what is happening on the stock market in the US, which suggest that the short term relationship and integration between S&P500 and HSI are stronger than S&P500 and SSE.
HSI, OMXS30 and S&P500 do not show any response at all when shocked by SSE, which is a strong indication that the financial market in mainland China does not exert any influence over the movements of the other indices.

Looking at the table for the post crisis, it is evident that these impulse responses do not present the same kind of up and downward movements. The indices do not seem to exert any influences of higher magnitude on each other after the financial crisis with the exception of S&P500. When hit by shock from the S&P500, the impulse function of HSI, SSE and OMXS30 present statistically significant responses. HSI and SSE both present positive upward movements initially and then levelling out in step 3.

Figure 3. Impulse responses financial crisis

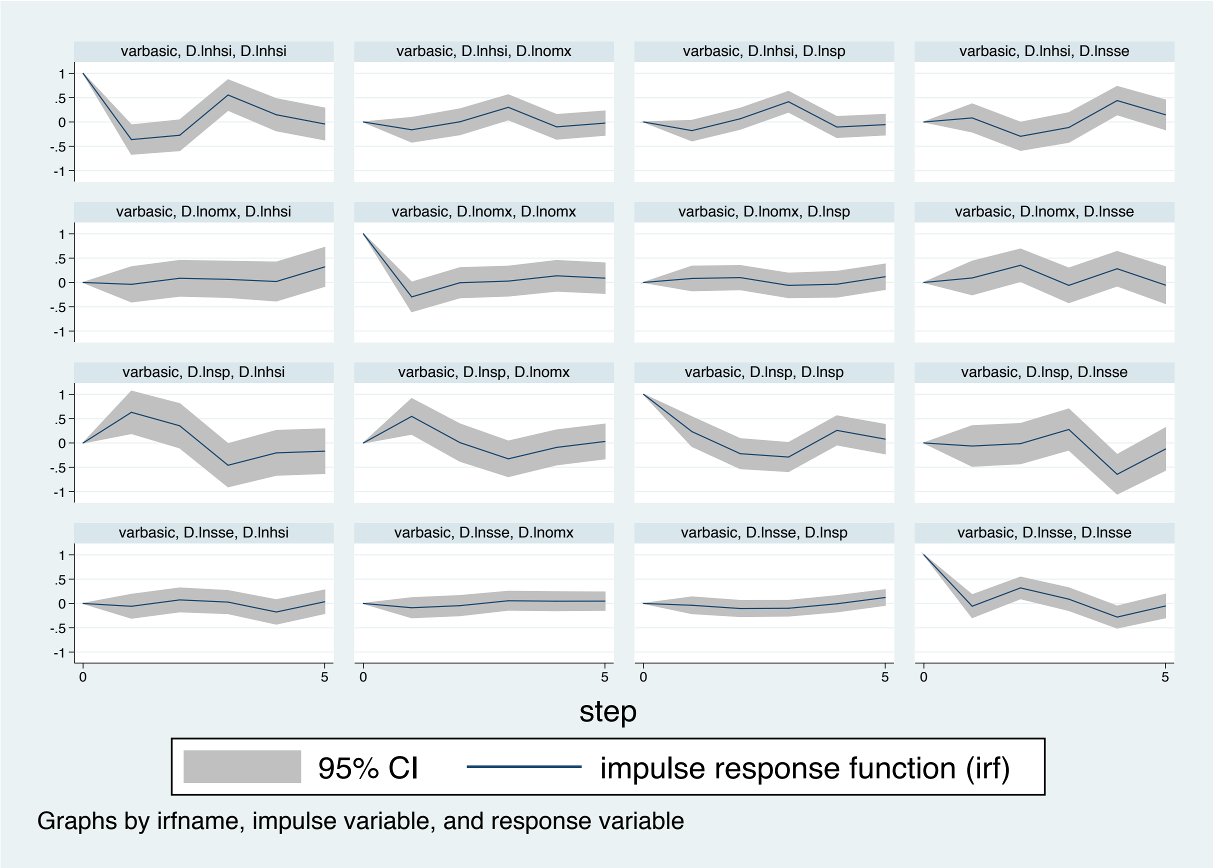
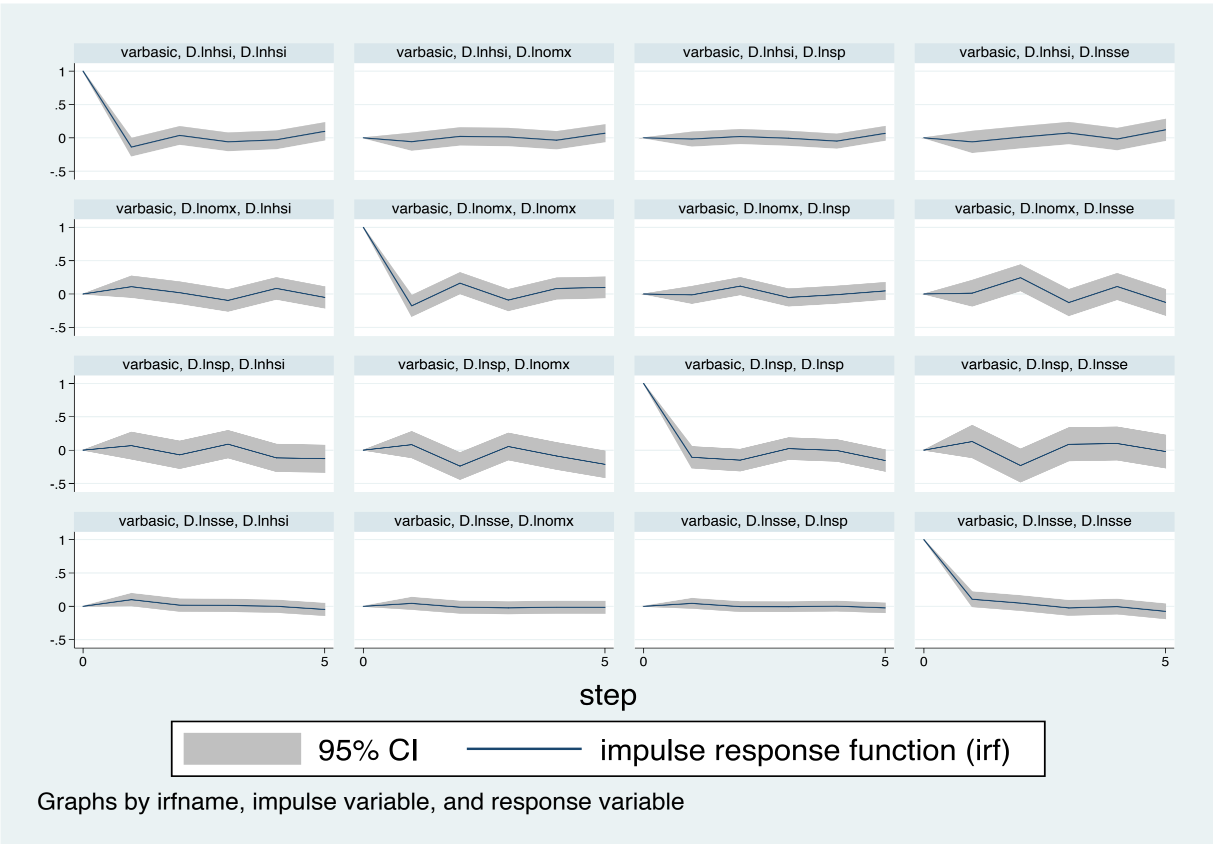


Figure 4. Impulse responses post crisis



6. CONCLUSIONS AND FURTHER RESEARCH

This paper investigates if there exist cointegrating relationships between the Chinese and US equity markets during two different time periods. Based on the results obtained through econometric testing of the stock indices, the linkage between US and Hong Kong financial markets is stronger than that of US and mainland China.

Bivariate cointegration tests did not present any evidence of cointegration between the stock market in mainland China and the US. There is evidence, however, that Hong Kong and the US stock market were cointegrated during the financial crisis. This is in line with previous research that show strong correlations between mature markets during turbulent periods (Assidenou 2011). It is peculiar, however, that the correlation results for OMXS30 and S&P500 present the opposite, being cointegrated only during the post crisis.
Economic theory can explain two reasons for there being no correlation between mainland China and the US, namely: (1) Looking at it from an economic-fundamental point of view, it is evident that the macroeconomic movements and trends between the countries are very dissimilar. This is also confirmed by Xu and Lillai (2011) who found that the growth rate correlation between the countries are very weak due to different economic structures. (2) Cultural and institutional idiosyncrasies for the two countries play a big role in the behaviour of the financial markets. China and the US do not share the same values in these aspects and this might also affect the financial integration between the two countries.

The results from multivariate testing provide evidence for cointegration between all four indices only during the financial crisis period. The different stock markets influence each other in the long run, but the effects from the US market on the Chinse lasts much longer than vice versa. Impulse responses also indicate that the Chinese stock markets respond to impulses from the US with greater magnitude than from any of other the indices. These findings that correlation only is present during the financial crisis is good news for the investor who can achieve diversification by investing in China during less turbulent financial periods.

In the short run, the Chinese market is highly susceptible to trends and shocks that occur on the US stock market both during and after the crisis. This creates difficulties for Chinese policymakers who want the financial market of China to remain stable. However, policies aimed at preventing financial crisis contagion from the US to spread to China would at the same time prevent financial liberalization of the domestic market. As China has adopted a general approach of economic reforms under its recent ‘open-up’ polices it is difficult so see how it is possible to remain isolated from international financial trends.
It is beyond the scope of this thesis to provide any recommendations for what policies the Chinese government should adopt in this question. However, by using of the results presented here, further research should be done to investigate what steps and measures Chinese policy makers can implement to keep the financial markets stable while at the same time continuing its liberalization process.

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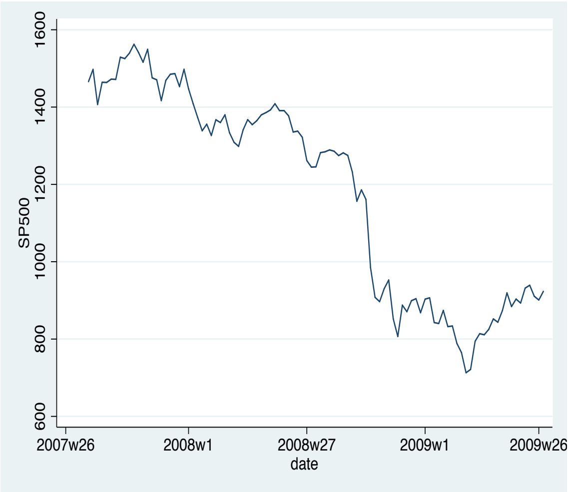
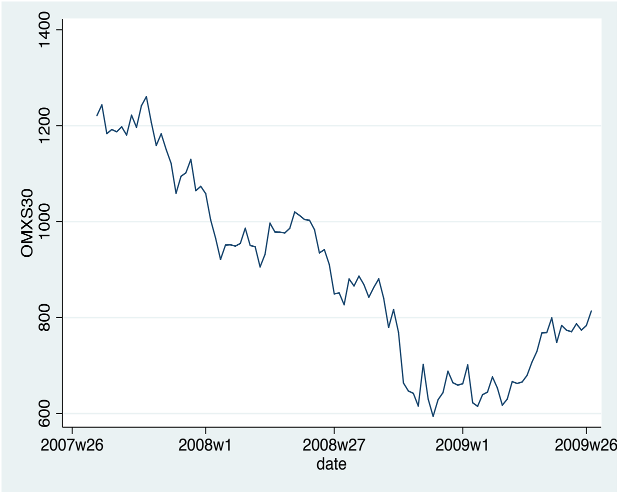
APPENDIX

Stock indices financial crisis

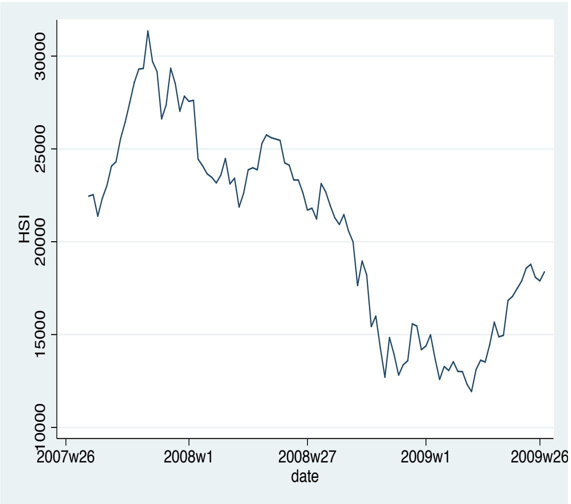
Log S&P500



Log OMXS30

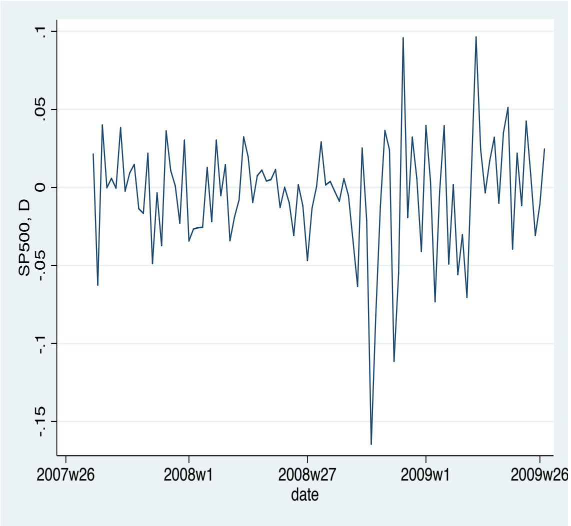


Log HSI

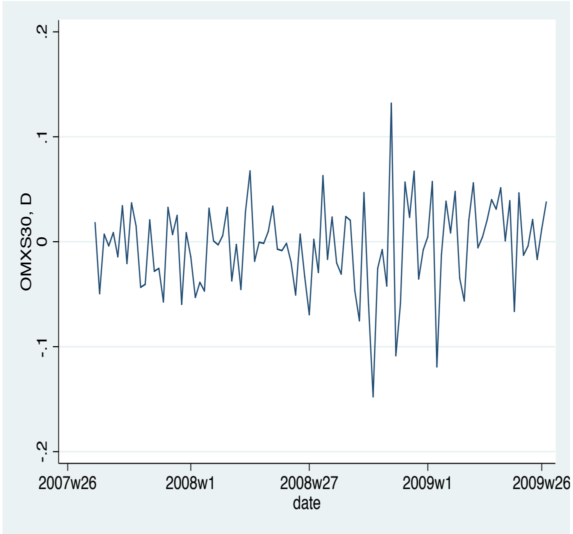


Log SSE

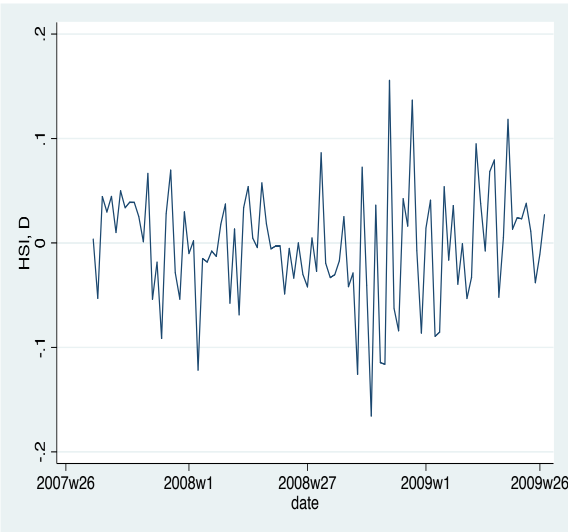
Differentiated S&P500



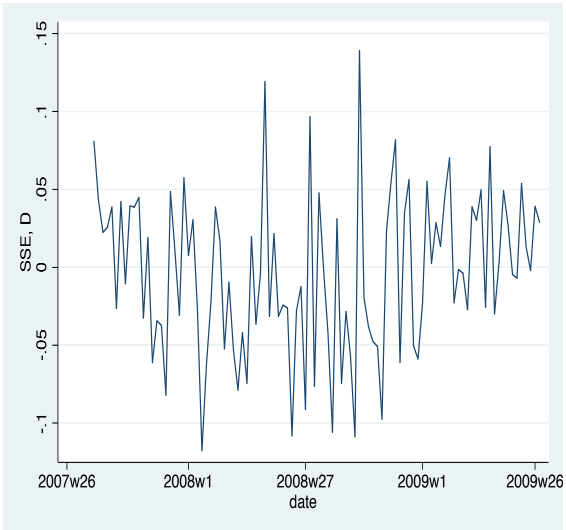
Differentiated Dif. OMXS30



Differentiated HSI

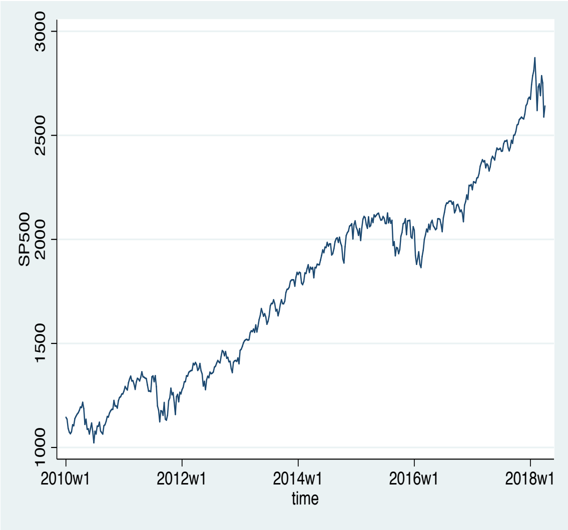


Differentiated SSE

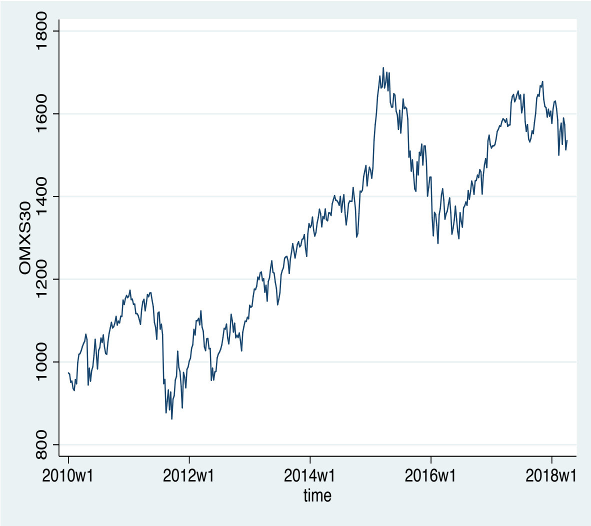


Stock indices post crisis

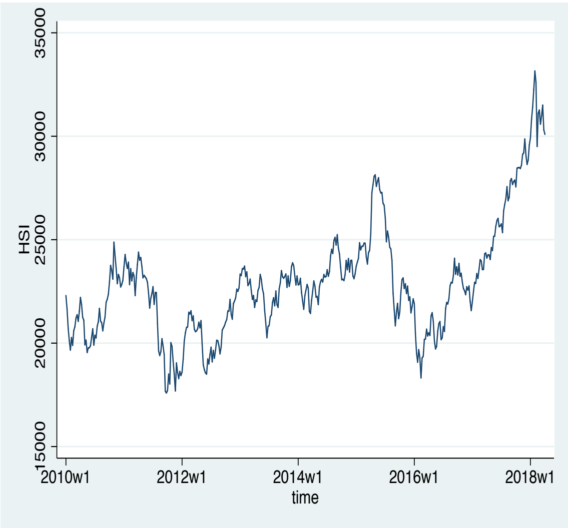
Log S&P500



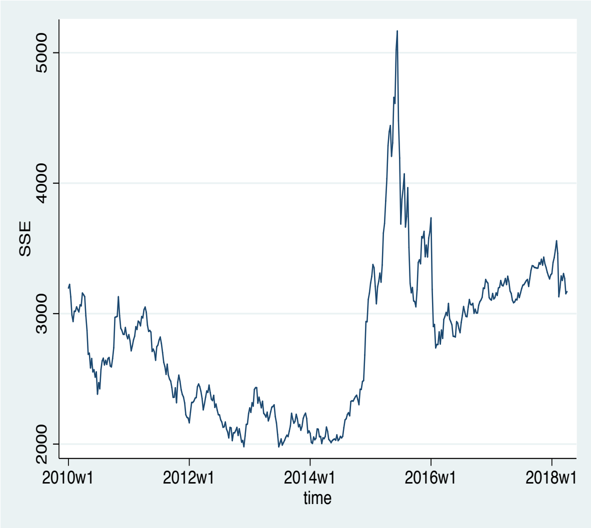
Log OMXS30



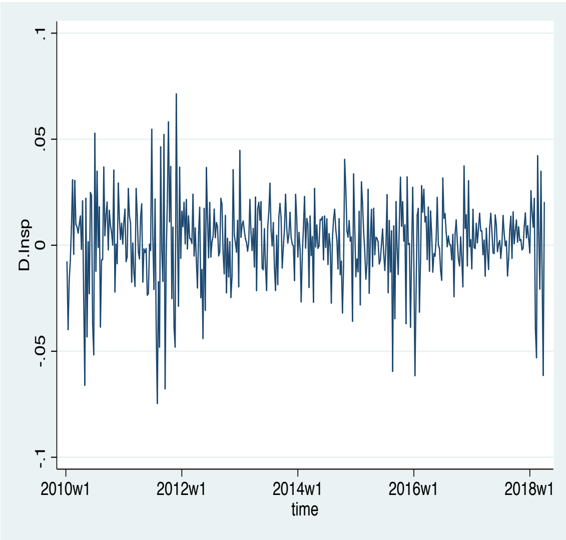
Log HSI



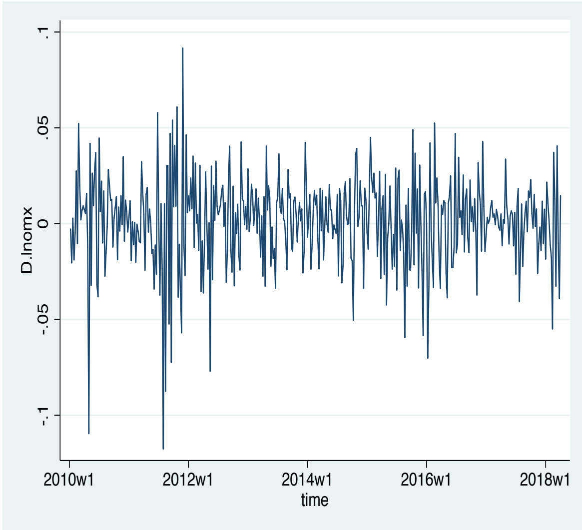
Log SSE



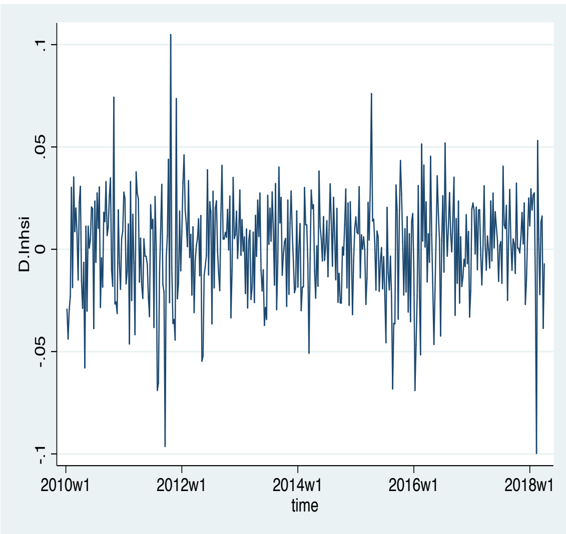
Differentiated S&P500



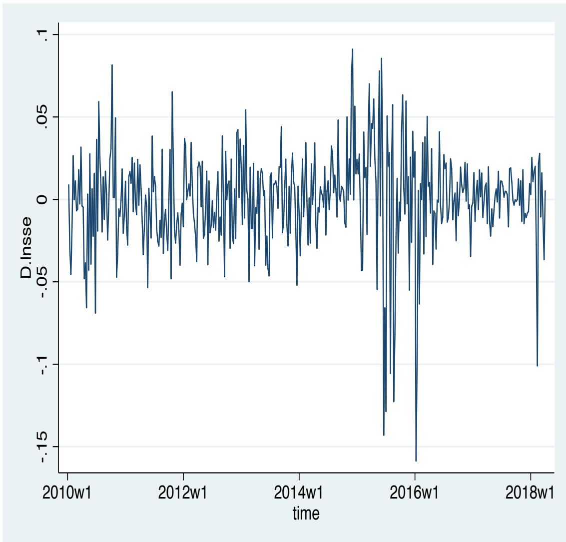
Differentiated S&P500



Differentiated HSI



Differentiated SSE



Johansen test

Pantula principle S&P500, OMXS30, HSI, SSE financial crisis

No of cointegration	Model 2	Model 3	Model 4
0	50.7047*	48.0328	69.2885
1	23.9887	21.4872*	37.8793*
2	12.6534	10.3358	12.6670
3	4.1073	4.0857	4.1018

Pantula principle S&P500, OMXS30, HSI, SSE post crisis

No of cointegration	Model 2	Model 3	Model 4
0	39.9496*	33.9269*	58.4387*
1	18.2831	12.2659	29.2259
2	8.5271	3.2974	10.0233
3	2.5887	0.6420	2.5767