The dynamic interdependence of international financial markets: An empirical study on twenty-seven stock markets

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ABSTRACT

In this paper, we aim to investigate the dynamic interdependence of international financial markets. Based on the data regarding daily returns of each market during the period 2006–2015 from Yahoo finance, we mainly focus on examining 27 markets from three continents, including Asia, America and Europe. By checking the dynamic interdependence between those markets, we find that markets from different continents have strong correlation at specific time shift. We also obtain that markets from different continents not only have a strong linkage with others at same day, but at a delay of one day, especially between Asia, Europe and Asia, America. In addition, we further analyze the time-varying influence strength between each two continents and observe that this value has abnormal changes during the financial crisis. These findings can provide us significant insights to understand the underlying dynamic interdependency of international financial markets and further help us make corresponding reasonable decisions.

1. Introduction

With the rapid growth of globalization, one financial market may be highly associated with turbulence in other markets [1,2]. The impacts of interdependent financial markets, especially stock markets, become more and more evident in turmoil market conditions [2,3]. For example, in the 1987 US market crash, the 1997 East Asian crises, the 1998 Russian collapse, and 2008 financial crisis, evidences have been found that dramatic movements in one financial market can have a powerful impact on other financial markets of very different sizes and structures across the globe [2–6]. This has generated a great deal of interest among the academic community on the interdependence of individual markets over time and across different markets [4,7].

Studies regarding interdependence of financial markets, originating from the seminal work of Markowitz [8], posit that investors and policymakers can improve the performance of their portfolios by allocating their investments into different classes of financial securities according to the market linkages across countries [7,9]. Correlation estimates are the crucial ingredient and the corresponding correlation measures are frequently employed in this domain [2]. By using these measures, existing work has investigated the potential benefits of international diversification and the superiority of portfolios [7,10]. These findings demonstrate that market interdependence evolves both developed and developing countries. In the past few years, there has been an increase interest in correlation analysis on financial markets in turbulent conditions. Several
researchers have found that financial asset returns are more highly correlated during bear markets but less so during bull markets and extreme market downturns [11–14]. Moreover, some researches have demonstrated that diversification across different markets and regions can result in more efficient portfolios [15], while, correlation also plays a critical role in analysis of financial time series [16–19]. The aforementioned studies are mostly based on financial time series data in the small volume and the approaches employed in this studies cannot be extended easily to analyze the large-scale financial information due to the inherent high computation complexity.

To further understand the underlying correlations and the complex interplay in the huge volume of time series and other corresponding information of financial markets, more recently, researchers attempt to apply the complex network analysis to financial issues [20–26]. This approach can reveal the internal structure of various financial markets around the world at a large scale and in turn can help the international portfolio diversification and enhance global financial systems [27]. However, most of existing studies mainly focus on examining the interdependency of financial markets on a snapshot. While, it is known that the opening time of stock markets from different continents have a time delay. Therefore, the shock in one financial market may be transmitted to other in different areas and impact them at one or more days delay.

To solve the above challenges, in this work, we aim to employ the complex network analysis and corresponding correlation measures to investigate the underlying dynamic interdependence of financial markets from different continents. Based on the data regarding daily returns of each market during the period 2006–2015 from Yahoo finance, we examine 27 stock markets from three continents, including Asia, America and Europe. By constructing the network of international stock markets, we test the dynamic interdependency of stock price returns from different continents both at the same day and at the specific time lag [28]. In our study, one vertex represents one stock index, while one edge or one link indicates the relation between two stock indices. This work can complement the existing literatures by programming the correlation structure and dynamic interdependence of international financial indices with the network-based methods, which can provide us significant insights to understand in depth the underlying dynamic interdependency of international financial markets.

The remainder parts of the paper are structured as follows. Section 2 introduces the dataset used in this paper. Section 3 presents the main approaches and corresponding measures used in our analysis. Section 4 gives the main empirical results, including the results of influence strength analysis and dynamic interdependence analysis. In the Section 5, we conclude this paper and discuss the future work.

2. Data

In this work, we use the daily price returns, obtained from Yahoo Finance API, to investigate the dynamic interdependence between various stock markets. Our dataset consists of 27 indices from 24 countries, which are located in Asia, Europe and America respectively. The time interval ranges from January 2006 to December 2015. We chose 27 indices according to the main financial markets recommended in Yahoo Finance. The 27 indices from three regions and their corresponding symbols are listed in Table 1. Specially, in our dataset, the Australia stock market is classified into Asian stock market by Yahoo Finance since the opening time of Australia stock market is very close to that of Asian stock markets. The prices of 27 indices are denominated in local currencies. The return \( r_i(t) \) of index \( i \) on day \( t \) is calculated by taking the log difference of the stock prices on two consecutive trading days,

\[
r_i(t) = \ln(p_i(t)) - \ln(p_i(t - 1)),
\]

where \( p_i(t) \) is the daily price of the country index \( i \) on day \( t \). Each return series in our dataset contains 2537 observations.

3. Methodology

To examine the interdependence of indices, we calculate the pairwise cross-correlations of the chosen indices by comparing the daily return of each index. Note that the cross-correlation is used to measure the degree of the linear relationship between two indices at various time lags. We use the measure \( c(t_l) \), which is calculated as follows,

\[
c(t_l) = \sum_{i=1}^{n} r_i(t) * r_j(t - t_l),
\]

(2)

to observe whether there exists a lag response between indices from different continents. The \( t_l \) represents the time shift \( l \) used to calculate the cross-relation, \( n \) represents all trading days during the period used for analysis. In our study, \( n \) is equal to 2537. A high correlation at a specific lag indicates that these two trends have close strength to influence other indices. To investigate whether there exists an obvious correlation between indices from different continents at a time delay, we use Pearson Product–moment Correlation Coefficient (PPCC) to calculate the correlation coefficients between any two daily returns in the dataset of 27 financial markets and measure the influence strength of each index. The correlation coefficient \( \rho_{ij} \) between index \( i \) and \( j \) is computed as follows [29]:

\[
\rho_{ij} = \frac{\sum_{i=1}^{n}(r_i - \bar{r}_i)(r_j - \bar{r}_j)}{\sqrt{\sum_{i=1}^{n}(r_i - \bar{r}_i)^2} \sqrt{\sum_{j=1}^{n}(r_j - \bar{r}_j)^2}}.
\]

(3)
Table 1
27 indices and corresponding continent, country.

<table>
<thead>
<tr>
<th>Continent</th>
<th>Symbol</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>America</td>
<td>MERV</td>
<td>Argentina</td>
</tr>
<tr>
<td></td>
<td>BVSP</td>
<td>Brazil</td>
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<td></td>
<td>GSPTSE</td>
<td>Canada</td>
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<td></td>
<td>GSPC</td>
<td>USA</td>
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<td>USA</td>
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<td></td>
<td>IXIC</td>
<td>USA</td>
</tr>
<tr>
<td></td>
<td>MXX</td>
<td>Mexico</td>
</tr>
<tr>
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<td>ATX</td>
<td>Austria</td>
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<tr>
<td></td>
<td>BFX</td>
<td>Belgium</td>
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<tr>
<td></td>
<td>DAX</td>
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<td>FCHI</td>
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<td></td>
<td>OSEAX</td>
<td>Norway</td>
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<td></td>
<td>OMXSPI</td>
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<td>Switzerland</td>
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<td></td>
<td>IBEX</td>
<td>Spain</td>
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<td></td>
<td>FTSE</td>
<td>UK</td>
</tr>
<tr>
<td>Asia</td>
<td>AORD</td>
<td>Australia</td>
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<tr>
<td></td>
<td>KS11</td>
<td>Korea</td>
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<tr>
<td></td>
<td>N225</td>
<td>Japan</td>
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<tr>
<td></td>
<td>SHANG</td>
<td>China</td>
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<td></td>
<td>TWII</td>
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<td></td>
<td>JKSE</td>
<td>Indonesia</td>
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<tr>
<td></td>
<td>TA100</td>
<td>Israel</td>
</tr>
<tr>
<td></td>
<td>KLSE</td>
<td>Malaysia</td>
</tr>
</tbody>
</table>

In statistics, PPCC is a measure of the linear correlation between two variables X and Y, giving a value between +1 and −1 inclusive, where 1 means total positive correlation, 0 indicates no correlation, and −1 represents total negative correlation.

We use influence strength to investigate how strongly one vertex influences other vertices in the financial network. The influence strength $S_i$ of vertex $i$ is defined as the sum of correlation coefficient of the given vertex $i$ with all other vertexes it links. A large value of $S_i$ in the network corresponds to a great influence of index $i$ on other indices. Then we can obtain a influence strength matrix $S$ and transform the correlation matrix into a distance matrix $D$ with elements $d_{ij}$, which is defined as

$$d_{ij} = \sqrt{2(1 - \rho_{ij})},$$

where the distance $d_{ij}$ between the two indices $i$ and $j$, and $d_{ij}$ ranges from 0 to 2. We use the distance matrix $D$ to determine the minimum spanning tree (MST) network and further examine the closest indices between each two continents.

4. Empirical results

4.1. Influence strength analysis

During the influence strength analysis, we firstly use Augmented Dickey–Fuller test to detect whether the time series financial indices are stationary or contain a unit root (non-stationary) [30]. The results indicated all of them were stationary. (See S1 and S2 Tables for details, Appendix A).

To detect the dependence of each two indices from different continents, in this study, we use the measure $L(t_l)$ to calculate the degree of the relations between two markets at the time lag $t_l$. The unit of the time lag is day. In all cross-correlation plots, all lags are limited to the scale from −18 to 18 due to the insurance that the sample size is big enough so that the samples obey normal distribution. Each time lag in each table is selected to provide the highest correlation among the paired cross-correlation values and time lags. We use confidence interval to detect the values which are greater than others. For example, the cross-correlation coefficient of the index $i$ and $j$ is 0.65(0) and 0.45(−1), it indicates that at the time shift 0 and −1 the correlation coefficient of $i$ and $j$ is obviously greater than values at other lags so the daily return $r_i(t)$ has strong correlation with $r_j(t)$ and $r_j(t - 1)$.

Since $L(t_l)$ may be greater or smaller than zero, we calculate,

$$L(t_l) = \frac{\text{abs} \left( \sum_{i=1}^{n} r_i(t) r_j(t - t_l) \right)}{\text{abs} \left( \sum_{i=-18}^{18} \sum_{i=1}^{n} (r_i(t) r_j(t - t_l)) \right)},$$

(5)
Table 2
Descriptive statistics of mean correlation coefficients between indices of different continents. The values out of intervals represent the times shifts whose correlation coefficients are out of the 95% confidence interval. The mean correlation coefficient is: America–Asia: 0.26141(−1), 0.21702(0). America–Europe: 0.10905(−1), 0.4004(0). Asia–Europe: 0.3298(0), 0.19737(1).

<table>
<thead>
<tr>
<th>Index</th>
<th>America–Asia</th>
<th>America–Europe</th>
<th>Asia–Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.02537</td>
<td>0.02602</td>
<td>0.02611</td>
</tr>
<tr>
<td>Standard deviation (std)</td>
<td>0.05371</td>
<td>0.06591</td>
<td>0.06034</td>
</tr>
<tr>
<td>95% confidence intervals</td>
<td>[0.00278,0.04346]</td>
<td>[0.00408,0.04824]</td>
<td>[0.00579,0.08645]</td>
</tr>
<tr>
<td>Out of intervals</td>
<td>−1,0</td>
<td>−1,0</td>
<td>0,1</td>
</tr>
</tbody>
</table>

Fig. 1. The influence strength (left) and MST (right) results of Asia and America. The influence strength of the index \( i \) from Asia is calculated by the sum of correlation coefficients regarding the index \( i \) with all indices from America. Similarly, the influence strength of the index \( i \) from America is calculated by the sum of correlation coefficient of all indices from Asia. The weight on each edge of MST represents the distance between the corresponding two vertexes \( i \) and \( j \). Indices from the same continent are marked the same color. In this figure, the red represents Asian indices, and the blue indicates American indices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

To measure the linear of index \( i \) and index \( j \), where lag values indicate that the number of time steps which are shifted from the day \( t \). To generalize the overall of linear relations between indices of different continents, we use the mean of correlation coefficient. Table 2 describes the three measures, including mean, standard deviation and 95% confidence intervals of the correlation coefficients. The values out of intervals demonstrate that there exist linear relations and strong correlations between these indices.

For each of the three correlation coefficients, the values at two lags are notably greater than others. This demonstrates that American indices have strong correlations with Asian and European indices at the lags of \( −1 \) and \( 0 \) respectively, while, Asian indices and European indices have strong correlation at a lag of \( 0 \) and \( 1 \). We conclude that the American indices have strong correlation with indices from Europe and Asia. Similarly, this phenomenon exists between Asian and European.

Based on the above results, we turn to consider two correlation structures between different continents and construct the correlation network. Fig. 1 shows that the influence strength and MST of indices from Asia and America at the same day. From this figure, we find that in Asia, KS11, HSI, STI, TA100 and BSESN have the strongest influence strength on American indices. Since the opening time of Asian indices is earlier than American indices, the changes of those indices above are more likely to influence the price changes of indices from America. Meanwhile, we find that in America, MXX, GSPTSE, MERV and BVSP have the strongest influence strength, however, indices from USA have the comparatively low influence strength, which indicates that the change of Asian indices has weaker influence on USA indices than on other American indices. In the MST analysis, we find that TA100 has 6 vertex connected, BVSP has 4 vertex connected and GSPTSE has 4. This demonstrates that TA100 is the closest with American indices, so as GSPTSE and BVSP in America.

Since the opening times of the American stock markets are late than Asia and Europe, simply calculating the correlation coefficient of two indices from different continents using the price change of the same day is difficult to accurately measure the real influence strength of each index. Fig. 2 displays that the influence strength and MST of indices from Asia and America on other indices from another continent with a delay of one day. It can be observed the influence strength of all indices is obviously stronger than those in the Fig. 1 except for TA100, BSESN and SHANG, while N225 from JAPAN and AORD from Australia have the strongest influence strength in Asia. The influence strengths of American indices are obviously stronger than those in Fig. 1, especially those from USA. In the MST analysis, MXX, DJI and GSPA from America have the most links, while AORD from Asia has the most links, connecting all other indices. It is noteworthy that China A-share has no link with other indices. This indicates that American indices have strong influence strength on Asian indices with a time delay of 1 day, while, most of indices from Asia except China have stronger influence strength compared with those at the same day.

Fig. 3 shows the bi-directed influence strengths between European and American indices. Fig. 4 displays the influence strengths with a delay of one day. Aforementioned results discovered that American and European indices have strong cross-correlations at lag 0 and 1. From Fig. 3, we can obtain that FCHI, FTSE, BFX and DAX have the strongest influence strength
Fig. 2. The values of influence strength and MST with weighted edges of indices from Asia and America with a lag of one day.

Fig. 3. The values of influence strength and MST with weighted edges of indices from Europe and America at the same day. The blue represents American indices, the yellow indicates European indices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 4. The values of influence strength and MST with weighted edges of indices from Europe and America with a lag of 1 day.

on American indices. The America indices have strong influence strengths on European indices. In the MST analysis we find that DAX from Europe and GSPC from America are the centers. In Fig. 4, we find that the influence strengths of the indices are weaker than those as shown in Fig. 3. We conclude that European and American indices have strong interdependence at the same day, while the interdependence is comparatively weak with time delay of one day. The results are different from that of Asia and America.

Fig. 5 shows the bi-directed influence strengths between Asia and Europe indices at the same day. In this figure, we can obtain that TA100 has the strongest influence on European indices, and STI, HSI and BSESN also have strong influence on European indices. While, FTSE, DAX, BFX and ATX have strong influence strength on Asian indices. For the MST analysis, we find that ATX from Europe links almost all Asian indices and TA100 from Asia links almost all indices from Europe. In Fig. 6,
we find that the European indices also have relatively strong influence on Asian indices with a time delay. AORD and N225 have stronger influence strength with one day delay than that in Fig. 5 with no delay. This figure also shows that AORD from Asia links all indices from Europe, while FTSE, BFX and DAX from Europe link more indices than other European indices. Note that, Fig. 6 displays that the influence strength of TA100 decreases to a very small value. Since TA100 has strong correlation with American indices as shown in Figs. 1 and 2, which indicates that, although Israel is an Asian country, TA100 is closer with European indices and American indices. Similarly, this phenomenon is existed in ATX from European, while, China A-share has little influence strength on European indices.

Coelho et al. [18] investigate 53 countries’ equity markets over the period 1997–2006 by using the MST approach and find that the markets of FRA and NED are centers in the network. Wang and Xie [25] investigated 20 countries’ indices in international real estate securities market over the period 2006–2012 by using MST and HT approach and find that NED and FRA are centers of Europe and have high correlation with American indices.

4.2. Dynamic interdependence analysis

We use time-varying correlation coefficient and construct the rolling windows to uncover the dynamic interdependence of the 27 indices. The time series is divided into 9 windows, in which each window contains all trading days of one year. Four measures, including the mean of correlation coefficients (MCC), standard deviation of correlation coefficients (STDCC), skewness of correlation coefficients (SCC) and kurtosis of correlation coefficients (KCC), are employed in this section, to help us understand the dynamic interdependence of these indices. The distance of MST (DMST) is also utilized to uncover the correlation structure of the interdependence network.

Fig. 7 shows the results of MCC, STDCC, SCC and KCC and DMST with a lag of one day and no lag between America and Europe indices from 2006 to 2015. The time in x-axis stands for the beginning date of the corresponding window. From this figure, we can obtain that the values of MCC between America and Europe have obvious changes with small slopes during the 2008 financial crisis. For the condition of no lag, the values of STDCC between America and Europe behave similarly. The values of SCC and KCC are smaller than zero. The mean of DMST changes oppositely compared with the time-varying
correlation coefficient, especially during the financial crisis. This demonstrates that the correlations between America and Europe indices have an obvious fluctuation during the 2008 financial crisis. For the condition of that with a delay of one day, there also exists an obvious fluctuation during the financial crisis corresponds to that of indices with no lag. However, different with that with no lag, MCC decreases with small slope to a stable level at the end of 2008 financial crisis, and the SCC and KCC increase to a high peak at the same time. While, the mean of DMST changes oppositely during the financial crisis. This indicates that the most important correlations among indices from different continents determine the overall trend of correlation of American and European Indices.

In Fig. 8, we show the results of MCC, STDCC, SCC and KCC and DMST with a lag of one day and no lag between indices from America and Asia. We find the MCC of indices between America and Asia with no lag has the same change with that between America and Europe during the 2008 financial crisis, however, the amplitude is smaller than that between America and Europe. The MCC with lag of one day also has the same change with that between America and Europe during the 2008 financial crisis, while there exists an obvious fluctuation during the US sub-prime crisis in 2007. The trends of the SCC and KCC with no lag all decrease to values smaller than zero during the crisis. As for the correlation with lag of 1 day, the STDCC increases to a high value with small slope during the crisis, the KCC and SCC all change close to zero during the crisis. From the above analysis we conclude that, firstly, during the 2008 financial crisis the MCC between America indices and the Asian indices all have an obvious change, the MCC with a lag of 1 day also has a peak during the US sub-prime crisis. Secondly, during the crisis, the SCC and KCC changes close to zero, it is to say that the influence strength with lag changes more synchronously during the crisis. Finally, same with the above analysis, the DMST changes almost synchronously with the time-varying correlation coefficient, especially during the financial crisis. Same with the correlation between American and European indices, the most important correlations determine the overall trend of correlation of indices from America and Asia.

Fig. 9 shows the time evolution graphs of four descriptive statistics (i.e., MCC, STDCC, SCC and KCC) and DMST of indices from Europe and Asia. The MCC with no lag has the same change with that between Asian and American indices during the 2008 crisis, the STDCC, SCC and KCC all have fluctuations during the crisis and the KCC and SCC decrease to values smaller than zero. Meanwhile, the MCC, STDCC, SCC and KCC with lag of 1 day also have fluctuations during the crisis, although the margin of the fluctuations is smaller than that with no lag.

From the influence strength analysis above we found that the China A-share has a relatively weak influence strength on indices from other two continents. It is known that China has surpassed Japan to become the world’s second largest economic entity since March 2011. However, we found that Chinese stock market show relatively weak influence strength on indices from other continents, meanwhile, hard to be influenced by other indices. In detail, we build the time-varying
Fig. 8. The mean, standard derivative, skewness and kurtosis of correlation coefficients and distance of MST of indices between America and Asia as functions of time. The blue curve represents the time-varying correlation coefficient and the red curve represents the changes of distance of MST. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 9. The mean, standard deviation, skewness and kurtosis of correlation coefficients and distance of MST of indices between Asia and Europe as functions of time. The blue curve represents the time-varying correlation coefficient and the red curve represents the changes of distance of MST. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
In Fig. 10, we show the time evolution graphs of four descriptive statistics (i.e., MCC, STDCC, SCC and KCC) between China A-share and other indices from Asia, America and Europe. Fig. 11 displays the price change of China A-share. From Fig. 10, we find that, compared with European and American indices, China A-share has a relatively strong correlation with Asian indices with no lag, the correlation between China A-share and European indices and American indices are very synchronous. The MCC between China A-share and Asian indices is stable at the most of the period of 2006–2015 except for 2015. Meanwhile, the MCC between China A-share and indices from America and Europe is stable except for 2007 and 2015. As the China A-share has a rapid increase in 2007, the MCC between China A-share and indices from America and Europe decreases rapidly to small values even smaller than zero while the MCC with Asian indices is stable. During the 2008 financial crisis, the MCC with indices from America and Europe increases to a stable level and the price of China A-share decreases rapidly. We can further obtain that as the China A-share begins to decrease in 2007, the MCC with indices from America and Europe with lag starts to increase to a stable level. Similarly, as the China A-share increased to a high level at 2015, the MCC with indices...
from America and Europe with lag decreases to a low level and the MCC increases as the China A-share decreases rapidly. Meanwhile, we find that as the China A-share has fluctuations during 2008, the MCC between China A-share and other Asian indices have relatively smaller changes compared with American and European, the STDCC between China A-share and other Asian indices has no obvious fluctuations in 2008. However, as China A-share has fluctuations in 2015, the MCC with Asian indices has an obvious fluctuation. From the above analysis, we find that China A-share has strong correlation with Asian indices, while relatively weak correlation with indices from America and Europe. When the China A-share has strong fluctuations, the correlation with indices from America and Europe decreases to small values, while the correlation with Asian indices decreases smaller. Then we conclude that China A-share has strong correlation with Asian indices and relatively weak correlation with indices from America and Europe, the fluctuation of China A-share has relatively strong influence on other Asian indices, during the global financial crisis, indices from America and Europe have relatively small influence on China A-share.

5. Concluding remarks

In this work, we investigated the correlation structure and dynamics of 27 international stock markets from 24 countries. Several significant results have been obtained. Firstly, we found that the price returns of indices from different continents have an obvious linear pattern at two time shifts: zero day and one day. Secondly, we obtained that the American indices have strong influence strength on other indices of different continents, while the previous literatures argued that the US indices have weaker influence strength. Thirdly, we found that except for Israel, the center indices of each continent have the most links connected with other indices. Fourthly, we obtained that those indices with close opening time have similar return changes. Further, we found that as the financial crisis comes, the interdependence of financial markets has obvious fluctuations, and the correlation with a time delay of one day can show some changes during the crisis which cannot be observed from the correlation with no lag. And the correlation between indices from America and Europe has the most obvious fluctuation during the crisis. Finally, we obtained that China A-share shows weak correlation with indices from America and Europe and the correlation changes during the fluctuations of China A-share.

Our findings can provide significant insights into understanding the country or region-specific financial vulnerabilities in times of global financial turbulence. The results from this work may also have implications for investors and policymakers related to the portfolio rebalancing and the construction of optimal portfolio diversification strategies at the country or regional levels. In our future work, we will mainly focus on integrating social media and other corresponding large-scale data with the trading time series data and further develop more reasonable and explainable measures to evaluate the dynamic interdependence of international financial markets. In addition to stock markets, more assets markets and the interdependences among these different types of markets should also be considered.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.physa.2016.12.062.

References