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Cointegration analysis and influence rank—A network approach to global stock markets

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HIGHLIGHTS

- We investigate the cointegration relationships among global stock markets over different periods from a network perspective.
- Ranking the influence of each stock market index based on our constructed cointegration network.
- The crises cause variations of cointegration relationships among market indices.
- The influence rank of each stock market is entirely distinguished over different periods.

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ABSTRACT

In this paper, cointegration relationships among 26 global stock market indices over the periods of sub-prime and European debt crisis and their influence rank are investigated by constructing and analyzing directed and weighted cointegration networks. The obtained results are shown as follows: the crises have changed cointegration relationships among stock market indices, their cointegration relationship increased after the Lehman Brothers collapse, while the degree of cointegration gradually decreased from the sub-prime to European debt crisis. The influence of US, Japan and China market indices are entirely distinguished over different periods. Before European debt crisis US stock market is a 'global factor' which leads the developed and emerging markets, while the influence of US stock market decreased evidently during the European debt crisis. Before sub-prime crisis, there is no significant evidence to show that other stock markets co-move with China stock market, while it becomes more integrated with other markets during the sub-prime and European debt crisis. Among developed and emerging stock markets, the developed stock markets lead the world stock markets before European debt crisis, while due to the shock of sub-prime and European debt crisis, their influences decreased and emerging stock markets replaced them to lead global stock markets.

1. Introduction

In the context of financial integration and globalization, the interdependence and mutual restraint among different economics have reached a higher level, which has garnered a lot of attention of academics and investors on the co-movements among stock markets around the world. Specially, under impacts of global crises, what is going on for their co-movements is currently a hot issue. Hence lots of people adopted a range of different methodologies like wavelet analysis, multivariate

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GARCH model, VARFIMA model and correlation analysis [1–3] and so on to investigate the co-movement between stock markets. Generally, the correlation coefficient is always used to measure the degree of co-movement between stock markets. It is well known that the correlation describes a kind of degree of the association between any two stock markets, and is completely symmetrical. So it cannot describe this sort of situation from the quantity: when one market index changes a little, what is the variation of another market. Besides when the above variable and dependent variable exchange position, their relationship will be varied undoubtedly. Similarly such variation cannot still be revealed by the symmetrical correlation coefficient. Hence we need another method to investigate the co-movement between stock markets. Due to the cointegration theory allows capturing the amount changes between stock markets, and then we adopted it. Since it was first introduced by Granger in 1981 [4,5], it has been applied to study different questions like whether there exists a long-run equilibrium relationship between stock markets; whether the cointegration relationships among stock markets increase or decrease due to financial crises, and so on. Depending on the choice of stock markets, sample periods and the frequency of observations (daily, weekly, monthly), many scholars have made a great contribution to solving above problems. For instance, Jang and Sul [6] investigated the co-movement of seven Asian stock markets (i.e. Korea, Japan, Hong Kong, Taiwan, Thailand, Indonesia, Singapore). They found no significant linkages among such markets before Asian financial crisis, however, the co-movement of Asian stock markets increased during and even after the crisis. Up to now, the cointegration theory has still been widely used to study the long-run relationship of Asian market [7–9], European market [10,11], American market [12,13], Africa market [14,15], or the cross-market [16–18], *etc*. As mentioned above, such results seem to be very perfect. But we all know, obtaining such results depends on selecting the sample data. Besides they only provide relationship between some limited markets. That is to say, how to break through the limitation of chosen sample data or chosen stock markets to completely investigate the relationships among global stock markets is still a problem that needs to be solved.

In recent years, complex network is widely used in the research of complex system [19–24]. Especially, it provides an effective tool to investigate the complex financial and economic system [25–31], *etc*. So far, various networks have been constructed to investigate the integration between stock markets or stocks [32–37], *etc*. Note that in the above works, correlation of a pair of stock markets or stocks is used to construct networks. As discussed above the correlation is not an effective method, so we combine the cointegration theory and the complex network to study the long-term relationships among global stock markets, which not only plays the merits of cointegration, also overcomes the restrictions of chosen sample data or chosen stock markets. Based on the cointegration analysis, we have constructed the cointegration networks through cointegration coefficients matrix. Then differentiating our analysis from finding influential stock market using centrality measure [38] or k-shell method [39,40], we combine the PageRank algorithm [41–46] and the cointegration network to identify the most influential stock market index and rank the influence of each index. The interesting thing is that we just get a lot of valuable results.

The paper is organized as follows. Section 2 provides the data. Section 3 presents methodologies applied to examine the cointegration relationship between stock market indices, to derive the cointegration network and to identify the influence of each stock market index. Section 4 reports our empirical results. Finally, concluding remarks are stated in Section 5.

2. Data

We use the natural log of daily stock market indices of 26 different countries and regions around the world, which cover the period from January 2, 2002 to April 20, 2012. The 26 countries and regions are as follows: Netherlands (AEX), Austria (ATX), France (FCHI), German (GDAXI), UK (FTSE), Norway (OSEAX), Sweden (OMXSPI), Switzerland (SSMI), Russia (RTS), Australia (AORD), India (BSESN), Hong Kong (HIS), VietNam (VN), Malaysia (KLSE), Korea (KS11), Japan (N225), China (SSEC), Singapore (STI), Taiwan (TWII), Israel (TA_100), Brazil (BVSP), Mexico (MXX), Argentina (MERV), Canada (GSPTSE), US (GSPC) and South African (JALSH). In order to investigate what is going on for the co-movements among different markets under impacts of global crises, we divide the sample period into the following sub-periods [47–49]:

Period I: before sub-prime crisis (January 2, 2002 to December 30, 2005).

Period II: early stage of the sub-prime crisis and the recession of US (January 3, 2006 to September 12, 2008).

Period III: after the collapse of Lehman Brothers (September 15, 2008 to December 31, 2009).

Period IV: European debts crisis (January 4, 2010 to April 20, 2012).

3. Methodology

3.1. Unit root test

Most of the economic and financial time series have a non-stationary behavior [50]. If two time series are non-stationary, a regression of one on the other could have a high R^2 even if they are totally unrelated. This phenomenon is called spurious regression [51]. Therefore, before the regression analysis, we must verify each time series whether to be stationary, or to contain a unit root (non-stationary). Generally, the commonly used method is Augment Dickey–Fuller (ADF) test [52], which could eliminate the residuals autocorrelation by adding lagged differences of dependent variables. We consider time series x_t is an pth-order autoregressive process $AR(p)$:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \varepsilon_t, \tag{1}$$