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Japanese and Chinese Stock Market Behaviour in Comparison – an analysis of dynamic networks

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ABSTRACT

Driven by the advancement of technology, emergence of financial institutional bodies superseding geographical constraints, as well as cross-regional liberalization paired with the removal of restrictions, global stock markets tend to become increasingly interconnected. On the one hand, it is believed that the globalization has made stock markets more efficient and alleviated the inherent risk thereof, resulting from greater access to financial assets, and thus the possibility to diversify therein. On the other hand, this may, however, lead to increased stock price volatility and trading instability, due to the major stock markets being increasingly correlated. Increasing interconnectedness between companies leads to the assumption that stock prices especially depend on the business sector and industry in which they operate. Thus, the interest in correlation network models is on the rise. However, despite the large number of literature providing network models, there is still uncertainty about their validity as well as true predictive power. Thus, this paper aims to identify stock return correlations between companies of selected industries. The quantitative analysis of historical daily stock returns is encompassing the correlation of the Japanese and Chinese corporate data from pharmaceutical, energy and banking sectors for the time period from 2009 until 2015 with relevant external events. The results show that the Japanese market reacts strongly to specific events during the observation and does not affect the Chinese market in any way, while events relating to the Chinese market have an immediate impact on the Japanese market behaviour.

1. Introduction

Acknowledging the fact that a stock market presents a set of opportunities for individuals and businesses to raise capital (Thakor, 2015), it is important for stock market participants to know or even predict, what drives stocks up or down. Depending on external events expectations on the future returns of the stocks can be changed (Beaudry & Portier, 2006). Especially macroeconomic events can trigger shocks that have the potential to impact the future development of stock prices and the market's volatility. These include supply and demand shifts (Phylaktis & Ravazzolo, 2005), as well as events like financial and sovereign debt crises (Grammatikos & Vermeulen, 2012; Schwert, 2011), but - beyond these - also natural disasters or other force majeure shocks. Furthermore, industry-specific developments supported by increased interconnectedness of businesses as well as some national or regional geopolitical decisions have the potential to influence stock exchanges (Onnela, Kaski, & Kertész, 2004; Tse, Liu, & Lau, 2010; Worthington & Valadkhani, 2004). Therefore, the interest in correlation networks as a tool to visualize and analyse associations between different financial entities as well as predict future developments, has been growing for decades (Eraker, 2004).

In order to understand the coherences of Japanese and Chinese stock prices and economic shifts, one must start with the share prices themselves as they provide a major implication as to whether these assumptions can be supported. Based on existing research it could be assumed, that the Japanese stock market is highly relevant in the global context as the Japanese stock market is seen as a benchmark, when it comes to cross-country comparison

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in Asia, which illustrates the importance of Japan as a location to invest in (Kassim, Abd Majid, & Hamid, 2011). With the reforms in the early 2000s, the Chinese stock market still remains separated from international equity markets, however stock prices have since been as informative about future profits as US markets and the market itself remains largely uncorrelated with other equity markets (Carpenter, Lu, & Whitelaw, 2015). The latter holds true for correlations, or the lack thereof, with most other equity markets, except for the Hong Kong Stock Exchange in terms of the banking industry.

2. Research problem

Despite a large number of existing literature, there is still uncertainty about the validity as well as the true predictive power of correlation networks. While macroeconomic events affect the economy as a whole, it is reasonable to assume that external events can have differing impacts on stock returns of companies, depending on the relevance of the event for a specific industry. Thus, the research particularly strives to identify, whether certain industries display stock return correlations and how external events affect these correlation networks. Albeit showing no direct correlation between companies of the two nations, the effects will give an insight whether the Japanese and Chinese market behaviour align due to the geographic closeness and economic ties. The analysis is encompassing Japanese and Chinese corporate data from pharmaceutical, energy and banking sectors for the observed time period from 2009 until 2015.

3. Literature review

The effect of external events on stock markets has been a point of interest in the past. Halme and Niskanen (2001) used event study methods to examine the effect of large scale environmental investment. They observed it having an immediate negative impact on the market, yet also observed rapid recovery shortly thereafter. Using the event parameter approach, Kalra, Henderson, and Raines (1993) concluded that the Chernobyl nuclear accident had a negative impact on US utility companies, however, this impact was small and short-lived. Similar results were published earlier by Fields and Janjigian (1989). According to their research, there was no significant change in “systematic risk, total risk, or market risk” due to the Chernobyl accident on the US utilities market. The study published by Kalra et al. (1993) confirmed these results for nuclear and non-nuclear utility companies as small and transitory, however found more profound effects on mixed utilities companies with a nuclear share of below 20%. According to the authors, this was due to extension of nuclear generating capacities (Kalra et al., 1993). A similarly fashioned study was conducted after the Fukushima Daiichi nuclear accident by Kawashima and Takeda (2012). They concluded that the accident had a negative impact on Japanese utility providers with nuclear power plants, however, investors were not bothered by risks concerning power plants that are similar to the one in Fukushima. Furthermore, they did observe an increase in systematic and total risk attributed to societal and regulatory changes. Other publications found a strong negative impact on stock markets and company stocks in the regards of the publication of pollution data by the United States Environmental Protection Agency (Hamilton, 1995), and accidents in the aviation industry (Kaplanski & Levy, 2010). The latter publication also implied a price reversal within two days. Additionally, it is found that such macroeconomic events like supply shift induced oil price changes generally have a positive correlation with stock prices, varying, of course, according to the dependency of the stocks’ underlying companies to oil supply (Gogineni, 2008). Other sources even claim the existence of a predictive power of oil prices regarding the future values of stocks (Driesprong, Jacobsen, & Maat, 2008). The effect of such events, however, have not been observed on a company level in different countries, and is therefore identified as a research gap.

Stock market behaviour is a topic that is of particular importance in the world of finance, as it tries to predict future returns of markets to properly diversify and secure investments (Fama, 1965). This idea was followed up by the idea, whether markets overreact to unexpected, extraordinary – force majeure - events, which was found to be correct and in contradiction to Bayes’ rule (Bondt & Thaler, 1985). A first approach to describe the Japanese market behaviour by Kato and Schallheim (1985), found the Tokyo Stock Exchange to be very similar to the US equivalent in terms of seasonal anomalous stock returns, and concluded that this may be a sign of international integration of these markets (Kato & Schallheim, 1985). This was followed up by an observation of the market’s ex-dividend-day behaviour and found that prices generally rise on the ex-day (Kato & Loewenstein, 1995). In an attempt to predict the returns of the Japanese stock market, Chan et al. found significant relationships between the expected returns and several observed fundamental variables, such as book to market ratio and cash flow yield (Chan, Hamao, & Lakonishok, 1991). In a recent development, Cajueiro and Tabak (2009) analysed the herding behaviour on the Japanese stock market and found evidence, that it is particularly strong during extreme market movements (Cajueiro & Tabak, 2009). In comparison to other global stock exchanges, the Chinese stock markets are a relatively new development, being founded in 1990 in Shanghai and 1991 in Shenzen. In an initial study of the Chinese stock markets, Su and Fleisher (1998) observed low stock returns and, in comparison to developed markets, high volatility, which were affected also by government interventions (Su & Fleisher, 1998). Similar to the Japanese market, recent studies focussed on the herding behaviour of the Chinese stock market (Chiang, Li, & Tan, 2010; Yao, Ma, & He, 2014). Analysis of stock market behaviour appears to be limited to single markets. A cross-country comparison between the Japanese and Chinese stock market is an identified research gap to be investigated in this paper.

In a following step the literature for correlation between stocks and stock markets has been reviewed. The research of geographical distance and its effect on stock market correlation concluded that within the US, there is no significant change in correlation, if the distance exceeds the 50 mile barrier (Eckel, Löffler, Maurer, & Schmidt, 2011). The correlation of multiple stock markets has been researched with a multitude of different methods. Nezu and Kurihara (2006) employed a vector error correction method and concluded, that neither interest rate, nor exchange rate, but the US stock prices affect the Japanese stock prices. Sarmas (2005) found positive pre- and post-crisis correlation between the US and certain Asian markets, using regression analyses. Similar results were published by Hwang (2012) using a GARCH correlation model. As volatility on global financial markets is synchronous, information similarities in returns on a more general level is prevented. A multivariate GARCH model can estimate both the variance and the mutual influences of the returns of the time series, thereby giving more accurate information about stocks with similar returns (Raddant & Kenett, 2016). There appears to be consensus in the literature, that the US stock market has a direct impact on Asian stock markets. The previous research takes the stock markets as a whole to determine similarities. Furthermore, while Asian stock markets are becoming more popular in research, an intra-Asian comparison of stock markets on a company level is a new approach and therefore identified as a research gap.

Although the reasons for interactions between companies are unknown, many theories assume a connection between the interconnectedness of companies and their stock returns (Onnela et al., 2004). Likewise, Tse et al. (2010) states that fluctuations of stock prices are highly dependent on the business sector and industry to which a firm belongs (Tse et al., 2010). This appears to hold true for the Chinese market, where sub sector correlation was observed (Chen, Mai, & Li, 2014). Analyses of the Chinese stock market using complex networks show that these networks have a power-law distribution and small-world-properties (Huang, Zhuang, & Yao, 2009; Liu, Sarkar, Kumar, & Jin, 2017). Similar results can be seen in the wake of catastrophes on the Japanese stock market. While the market overall is not significantly impacted, certain industries stocks strive under these circumstances, while others give negative returns (Yang, Wang, & Chen, 2008). Similarly, the Japanese stock market exhibits negative returns in the case of supply chain disruptions (Liu, Wang, & Wei, 2017). These effects however, have not been compared to other nations' markets and industries. The identified research gap is being explicitly addressed in this paper.

Correlation analysis can provide information about the benefits between diversification and market volatility (Tse et al., 2010). Thus, the interest in correlation networks, which can be applied to visualize the relationship between different financial entities as well as predict future correlations, has grown in recent years (Eraker, 2004). Network analysis for complex networks has been used as previously mentioned, while other scholars use social network analysis to observe the popularity of global stock markets over time (Cetorelli & Peristiani, 2013). A first approach on building a correlation network based on logarithmic returns of US American stocks was conducted by Mantegna in the late 1990s (Mantegna, 1999). This was followed up by a series of papers facilitating additional methods to analyse these networks. Kullmann, Kertész, & Mantegna, 2000 identified clusters of companies in stock indices on the Dow Jones industrial average and the Standard & Poor's 500 (Kullmann et al., 2000). Onnela et al. made use of minimal spanning trees to visualize a stock correlation network and additionally observed the shrinking of the minimal spanning trees during market crisis (Onnela, Chakraborti, Kaski, & Kertiész, 2002) specifically conducting research on the latter part in the following year with a paper concerned with the "Black Monday" and observing "*strong reconfiguration*" resulting from the event (Onnela, Chakraborti, Kaski, & Kertész, 2003). An analysis of a network of global indices that observed a timespan from 1996 to 2009 showed that the network showed fast dynamics, such a reacting to a local or regional events, and slow dynamics, showing the effects of globalisation. A network analysis facilitating GARCH correlation was conducted by Raddant and Kenett (2016) and found the US and German market to be at the core of global stock markets. Previous research using correlation based stock networks focussed mainly on a single market such as the top US indices or at a global network of national indices. Furthermore, the focus of analyses lies on predictions of future market behaviour. The use of correlation network analysis based on company stocks and the cross-country comparison to analyse past events' effect on stock markets is a research gap in existing studies.

Many scholars focus heavily on the subprime crisis of 2008 in their analyses of impact on global stock market. The post crisis timeframe is therefore a research gap. Similarly, the interconnectedness or correlation between stock markets is done on the market level and not down to a single company. This level of detail can be insightful. Lastly, the analyses focus on either global markets or a single market. A comparative analysis of the Japanese and Chinese market with a correlation network analysis can fill those gaps.

4. Methodology and data

4.1. Dynamic networks

The term 'network' will be framed, to understand the significance for the analysis conducted herein. Networks are system with interconnected elements, while the visualisation thereof, and is termed as 'network graphs' (Katenka & Kolaczyk, 2012; Kolaczyk, 2009). Dynamic networks and correlation patterns are the key indicator in this research paper, to detect communities among different sectors and companies therein, and the extent to which they are respectively interrelated. Visualisation of networks predominantly relates to nodes and edges. Nodes are symbolic of companies, whereby connecting edges reflect on the similarity between the various firms. The absence of edges between companies therefore implies no direct linkage (Kolaczyk, 2009). To distinguish dynamic networks from static ones, the characteristics need to be examined first. Statistic networks are rigid in nature. This means, the amount of nodes never changes and they remain static. The same can be said for the edges. They remain in place and do not change quantitatively. In dynamic networks, however, nodes and edges are either removed or added, or disappear or reoccur. In the case of this analysis, nodes will unlikely differ in quantity, yet certainly in terms of their respective location (Jia, Noubir, Rajaraman, & Sundaram, 2006).

4.2. Particularities of the observed time frame

Since this paper's analysis is focused on the time period between 2009 and 2015, some attention must be dedicated to the global economic framework conditions. First of all, the first two examined years still fall into the time of the financial crisis of 2007–2009 which was initiated in the US (Grammatikos & Vermeulen, 2012). When the crisis eventually spilled over to other regions with the collapse of Lehman Brothers in 2008, the market conditions in terms of recapitalization - especially for the peripheral countries - worsened significantly through a rapid increase of their government bond yields (Sinn, 2014) .

4.3. Data sample

To be included in the dataset for the statistical analysis, Japanese and Chinese companies had to fulfil several requirements. This paper focuses on three particular industries, namely the banking, energy, and pharmaceutical sector. Companies within these sectors were previously studied in terms of their volatility from external sources (Chiou & Lee, 2009; Crouzille, Lepetit, & Tarazi, 2004; Elyasiani & Mansur, 1998; Nandha & Faff, 2008). Furthermore, a critical mass of company data could be collected within the two observed markets, to facilitate the single market analysis. These industries are selected for analysis, as banks do not only facilitate the financial markets, but in combination with the pharmaceutical industry, are located at the centre of the market network of the USA (Onnela et al., 2002). The energy sector is an appropriate industry for this particular study due to the strong effect of the Fukushima incident, followed by a hypothesised strong reaction within the industry to be addressed in this paper. Companies considered to be in the energy sector are producers and distributors of fossil fuels, such as coal, oil, and gas, producers and distributors of renewable energy, such as wind, and solar power, producers and distributors of nuclear power, as well as service providers for said businesses.

All companies selected for analysis had to be continuously listed and traded on the Tokyo Stock Exchange, Shanghai Stock Exchange, or Shenzen Stock Exchange from January 1st, 2009 to December 31st, 2015. Additionally, firms that had the initial public offering, or were either unlisted or dissolved during that time period were not considered for the analysis. This leaves a total of 56 companies, of which 17 are in the banking sector, 11 in the pharmaceutical sector, and 28 in the energy sector, s. Appendix table 1. These companies were traded on 1,715 (Japan) and 1,807 (China) days during the mentioned time period. Daily close price data was collected with the help of the “quantmod” package in “R”, a language and environment for statistical computing and graphics, with the source set to “Yahoo Finance Japan” and “Yahoo Finance”. To ensure comparability with similar upcoming analyses of other regions, the close price data was converted to Euro. The exchange rate data was similarly collected with the help of the “quandmod” package of “R” with the source set to “Oanda”. In the case of missing data points, the most recent valid close price was used to fill the missing value. The data was adjusted for stock splits to remove sudden spikes in either upwards or downwards direction.

For the purpose of the analysis and to ensure comparability between the companies, the adjusted daily close price data was transformed into daily logarithmic returns with the following formula:

$$R = \ln\left(\frac{L_1}{L_2}\right)$$

whereas R is the logarithmic return, and L_1 and L_2 are the close prices of two consecutive days. The basis of the analysis is a statistical network, which is defined as a mathematical structure with a graph G which has a set of vertices or nodes V and edges or links E. The networks will be displayed as illustrations, in which the nodes correspond to a certain stock-listed company and the links between them represent whether or not a certain correlation threshold has been met. For that purpose, the previously calculated logarithmic returns will be put through the algorithm of Pearson in order to calculate the corresponding correlation coefficients to build a network based on the correlation matrix. The correlation coefficient is calculated as follows:

$$\rho X, Y = \frac{Cov(X, Y)}{\sqrt{Var(X)Var(Y)}}$$

whereas ρ is the correlation coefficient, and X and Y represent the matrix of two companies' logarithmic returns each. The size of the matrix corresponds to the length of the observed timeframe. As the correlation threshold is set to a specific value, only nodes with a value that is equal or higher than the correlation threshold will form a visible link to another node. This holds true for a negative value, and is corresponding to a negative correlation.

5. Analysis and interpretation of results

5.1. Japan

The year by year analysis, as well as the monthly analysis make use of a correlation threshold of 0.61 as an analysis of the graph characteristics show high levels of both clustering and assortativity around this threshold (s. Appendix illustration 1). The threshold was set to the same value for both the Japanese and the Chinese market to ensure comparability. Furthermore, it was based on the Japanese observation, as the Japanese market is the more mature stock market of the two. Starting off with the banking industry, one can observe in Illustration 1 that 2009 shows the least amount of cohesion in the financial industry, because four out of the eight banks were unconnected to the banking cluster. This number is reduced to only one in the year 2013, before rising to three in the consecutive year, and finally dropping to zero in the final year of the observation. Four banks are observed to be the most robust and consistent in ways of forming connection to the banking industry. “Mitsubishi UFJ Financial Group”, “Sumitomo Mitsui Trust Holdings”, “Sumitomo Mitsui Financial Group”, and “Mizuho Financial Group” consistently form links in between each other and the remaining banking industry throughout the seven years. “Nomura Holdings Inc” shares a connection to the banking cluster in five years, “Resona Holdings Inc” in four years, and only twice during the observation do the companies “Aozora Bank Ltd” and “Shinsei Bank Ltd” form such a connection. The latter two are also the two smallest banks of the group, as both companies employ the fewest people. On average, the banking cluster throughout the years consists of 5.8 banks. The surveyed Japanese pharmaceutical companies show very little to no linking behaviour throughout the observed timeframe. Only two years, 2011 and 2015, show significant clustering in the pharmaceutical industry. Moreover, it must be noted that 2011 especially features visibly more correlating behaviour throughout all industries than the remaining six years. The likely explanation for that behaviour is the natural catastrophe that resulted in the nuclear meltdown of a nuclear reactor in Fukushima in March of 2011. This event had most likely a strong negative impact on the entire Japanese economy and stock prices, so a strong correlating behaviour, since most stock prices dropped throughout the economy, is expected.

Due to the aforementioned natural catastrophe, the Japanese energy sector is particularly interesting to focus on, as it was directly affected by the event. As it is visible in the illustration, for the first two years, there is a prominent cluster of electricity and gas providers, however, the oil and gas producing industry is largely unconnected. After the event of 2011, the energy industry exhibits visibly less linking behaviour, which means that the returns differ greatly in the time after the nuclear meltdown, than to the ones before. Only in 2015, a similar cluster of electricity and gas providers is distinguishable, similar to the ones in 2009 and 2010.

The company responsible for operating the nuclear power plant in question, “Tokyo Electric Power Company Holding Inc” (“TEPCO”), loses all its links in 2011 and 2012, but already starting in 2013, aligns itself again with few energy companies. For the purpose of gaining insight for the research, the nuclear meltdown in Fukushima appears to be an apt circumstance, as it is potentially a significant, and long-term event for certain business, or at least the operating company for said nuclear power plant. For this purpose, Illustration 2 starts the observation one month prior to the event and ends four months after it. The operating company has been marked with a red circle. The impact of the event is clearly visible in Illustration 2 in March 2011. All companies in the observation start to cluster very heavily, with the exception of the operating company. This illustration shows, how collectively and to the same extent, the stock prices of all companies have dropped during that month. Since the correlation graph does not indicate whether the logarithmic returns went up or down, this is the most likely explanation in the context of this event. The absence of “TEPCO” from that cluster is likely the result of an even larger drop in logarithmic return for this company in that particular month. After the severe impact of the event in March 2011, the following months, while still showing more linking behaviour, exhibit more resemblance to the graph prior to the event. Surprisingly, shortly after the event, “TEPCO” has connections to other energy companies.

The most feasible explanation for that behaviour is that after the immense shock of March 2011, most companies still faced losses in logarithmic return and the losses of “TEPCO” realigned themselves with the competition more after the first month. Once the economy

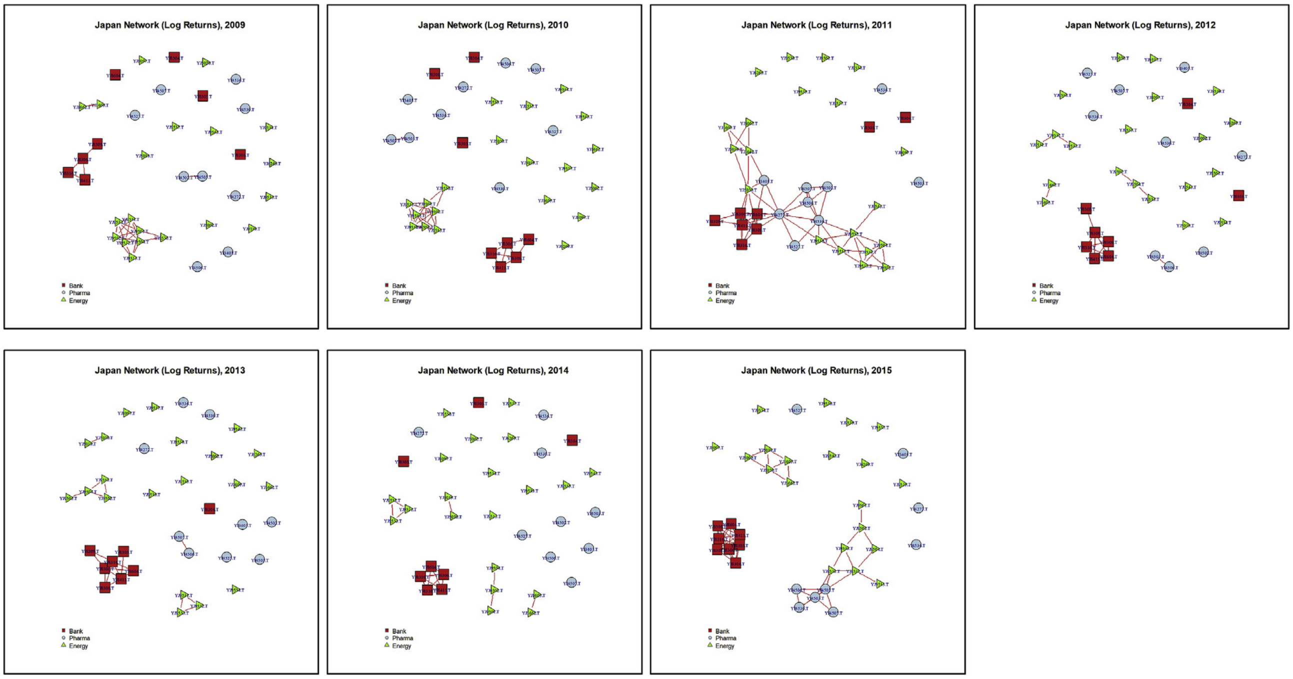


Illustration 1. Japan Network Graph - yearly: 2009 to 2015 (own illustration).

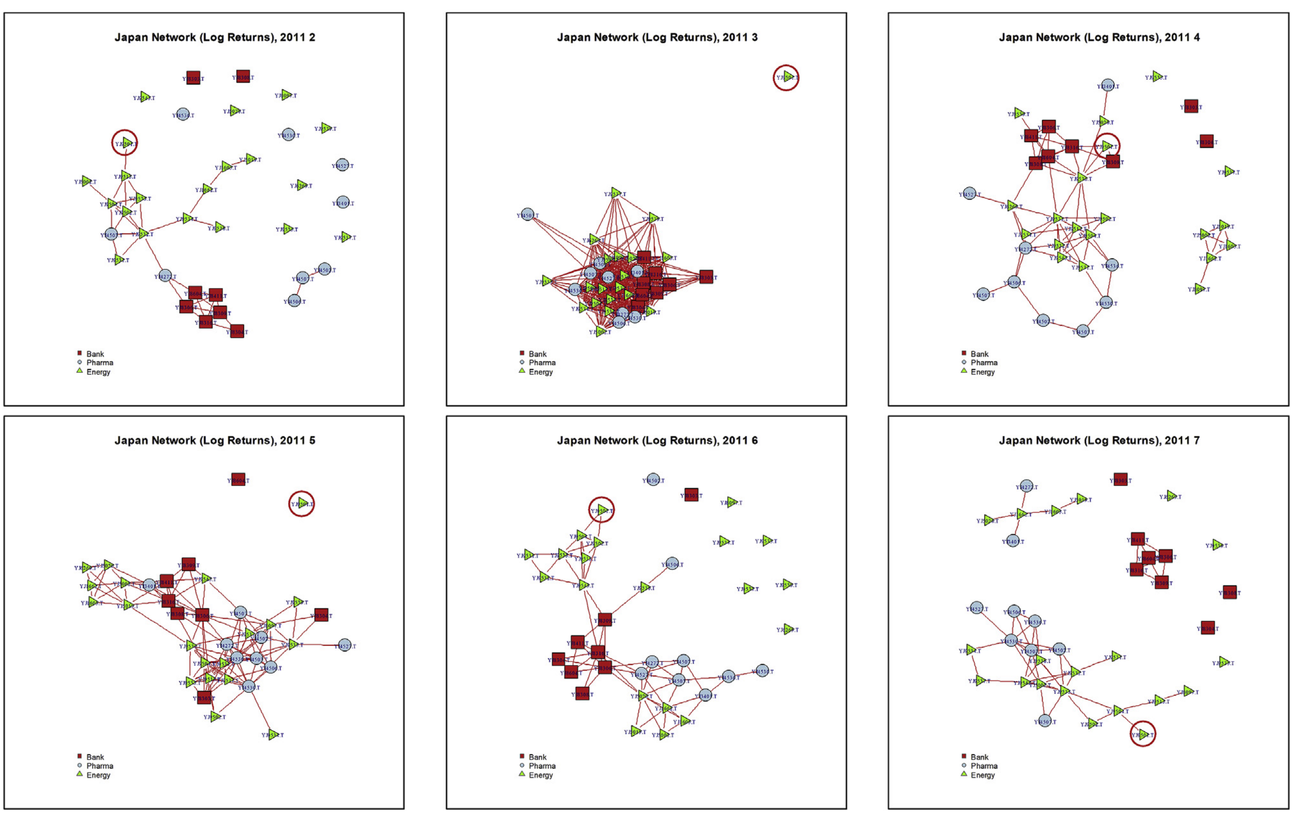


Illustration 2. Japan Network Graph - monthly: February to July 2011 (own illustration).

started recovering however, “TEPCO” fell out of the connections immediately, which is an indication for severe, long-term effects for this company. This can be observed in the month by month analysis starting in September 2011 as displayed in Appendix illustration 2.

“TEPCO” is indicated with a red circle. Even in the months thereafter, the operating company only sporadically forms connections to the other energy companies. According to the previous year by year analysis, it takes “TEPCO” until 2013 to recover from the event of 2011, indicated by the connection to the previously connected energy companies.

Upon closer review of the remaining months of the Japanese observation, on three other occasions a structure, similar to the one in March 2011, is visible. Once in January and February 2014 (Appendix illustration 3) and twice in 2015; two separate events in August and September (Illustration 3). The probable explanation for the structure to emerge in early 2014 is a particularly harsh winter, which brought much snow, injured thousands and was fatal to few. Overall, this event is neither as pronounced as the meltdown of Fukushima, nor is it as long lasting as the catastrophe of Fukushima. Already in March 2014, a network structure similar to December of 2013 is regained. The events of 2015 coincided around the same time. According to Reuters, the Japanese stock market suffered big losses due to “a stampede of selling as fears of a China-led global economic slowdown intensified”. Supposedly, it was the largest loss since June 2013. Potentially strengthening the negative impact on the Japanese stock market is yet another natural catastrophe in the form of heavy rain, which lead to severe floods in parts of Japan in September 2014. The impact of those two events combined appear to be more severe, as the cluster resembles the density of the cluster that formed in March 2011. Again, both events appear to have impacted only two months, because as soon as October 2015, the structure resembles pre-event conditions. These examples clearly demonstrate the sentiment of the research question, both in short-term and long-term effects.

5.2. China

The results from the year by year analysis of the Chinese market can be seen in Appendix illustration 4. While for the majority of the years the strong banking is present, during the years 2009 and 2010, both the “Agricultural Bank of China Limited” and the “China Everbright Bank Co., Ltd.” are completely separated from the large banking cluster and form a group of their own. This is due to the fact that both banks had their initial public offering in 2010, yet due to importance in the Chinese market, are not left out of the observation, resulting in a perfect correlation of these companies during the first 2 years as no real return is compared. The Chinese pharmaceutical industry remains largely unaffected by the year by year analysis. The observation of the Chinese energy industry differs in parts from the analysis of the whole timeframe. It was previously stated, that the Chinese energy industry should be separated into two groups due to the difference in products. In fact, a separation of energy companies is visible in the years 2011 and 2014. That said, in 2011, one cluster is in fact consistent of coal companies, the other cluster however, is a mix of a coke producer and an oil and gas producer and therefore contradictory to the expected result. The separated energy clusters in 2014 follow the sentiment and are consistent of only coal companies or oil companies.

Throughout the monthly analysis, the observed Chinese companies display a very robust and highly interconnected system. The high degree of connection between the especially large companies in the observation is unsurprising, as some are still partly owned by the state itself. Despite that fact, all companies are publicly listed and are therefore under the effect of open markets, one would expect more fluctuation overall. Results from the month by month analysis show, fluctuation is very little and changes in the structure of the industries are only short-lived. As both the year by year and the month by month analysis are conducted with the same correlation threshold, the results are very similar. As the year by year analysis showed previously, the overall structure of the network does not change drastically throughout the years. This holds true for all industries. Appendix illustration 5 shows an example of the ephemerality of changes in the banking industry from January 2013 to April 2013. A separation within the banking industry can be seen, that disappears in the next month. Furthermore, a loss of connection in the energy industry in March 2013 is equally reversed in the short time after.

5.3. Comparison

As stated earlier, the Chinese markets’ network structure hardly changes in the year by year analysis which is in contrast to the Japanese observation. In the latter a clear change in the network structure for the year is visible in 2011 and 2015 to account for the external events of “Fukushima” and the “Chinese market crash”. Neither are visible in the Chinese observation in the respective years. In the next step the month by month analyses are compared. As the Chinese observation does not feature any major disturbances in the analyses, the two Japanese, with the highest likelihood of affecting other markets will be looked at. Other than in the Japanese observation, there appears to be no structural change in the Chinese market in the early months of 2011 as visualised in Appendix illustration 6. That leads to the conclusion that the “Fukushima” incident had no effect on the Chinese market. Secondly, the “Chinese market crash” was identified to be a disruptive event for the Japanese stock market. While August 2015 visibly shows more interconnectivity on the Chinese market, it is, one the one hand, not resembling the densely connected clusters that can be seen in the Japanese observation, and, on the other hand, not robust and changes drastically in the next month. What is, however, notable, is the emergence of a similar network structure to disruptive events on the Japanese market in November and December of 2015 (Illustration 4). In the wake of the market crash,

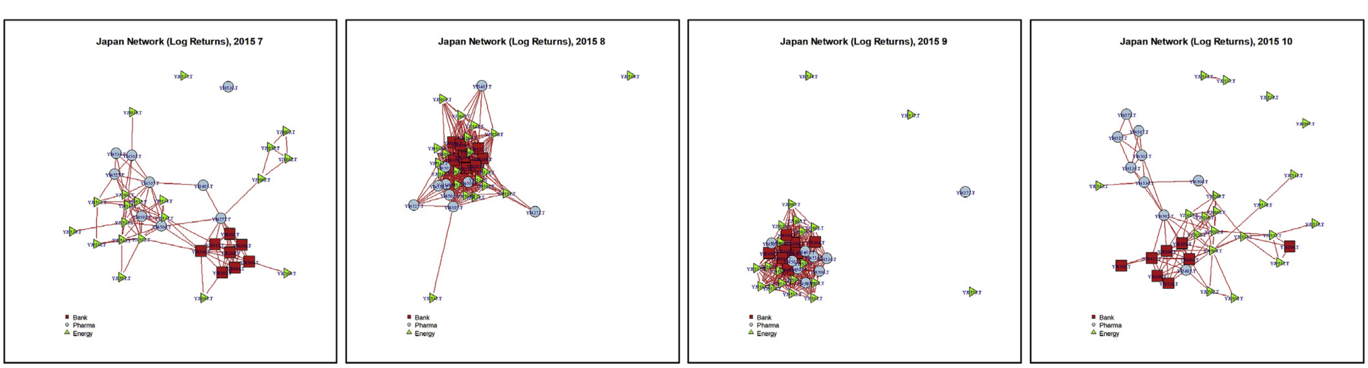


Illustration 3. Japan Network Graph - monthly: July to October 2015 (own illustration).

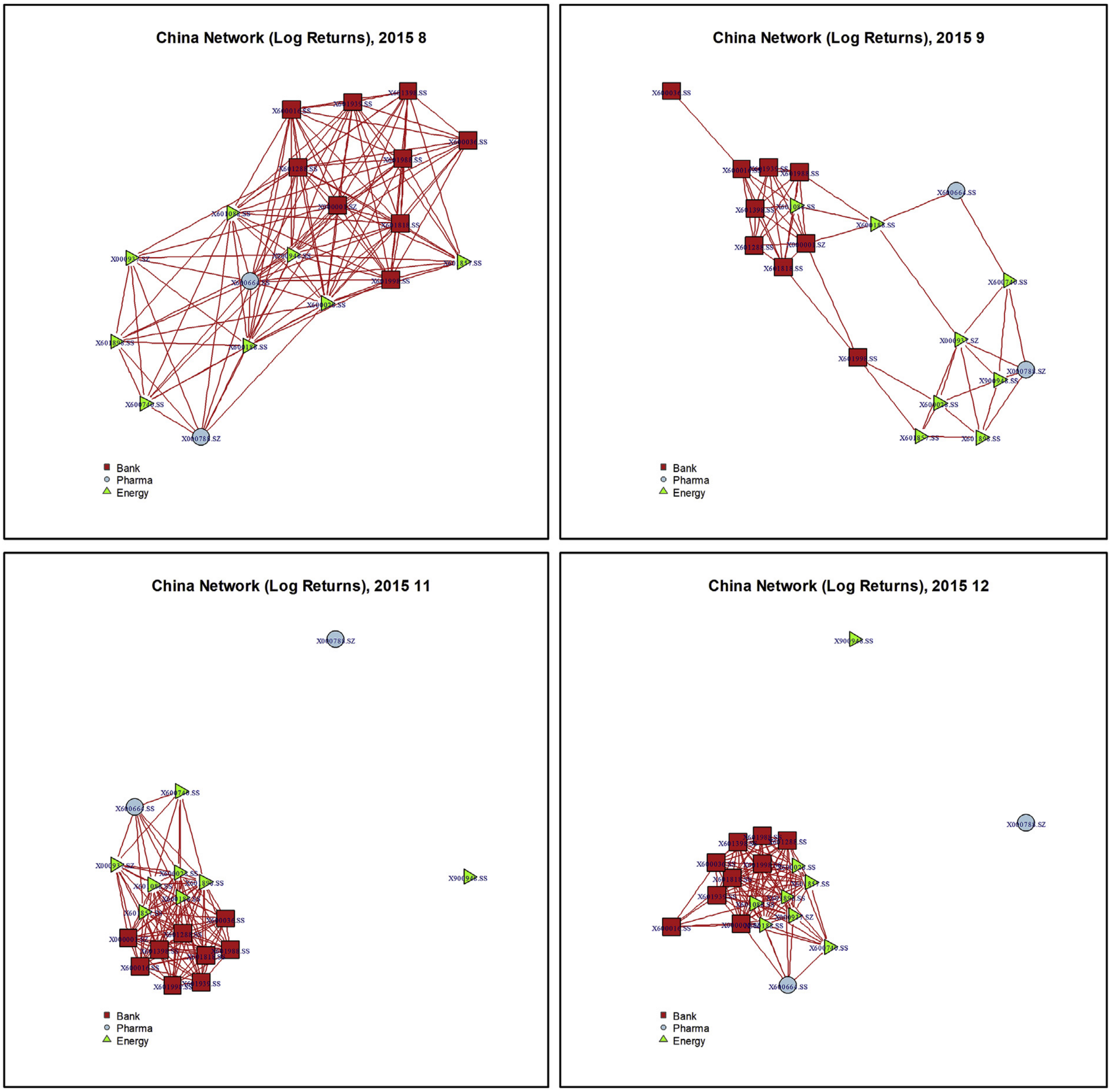


Illustration 4. China Network Graph – monthly: Aug. to Sep. & Nov. to Dec. 2015

the Chinese market behaviour appears to be relatively robust until that point. However, as the observation ends here, no clarity is given, as to how fast the market behaviour returned to normality.

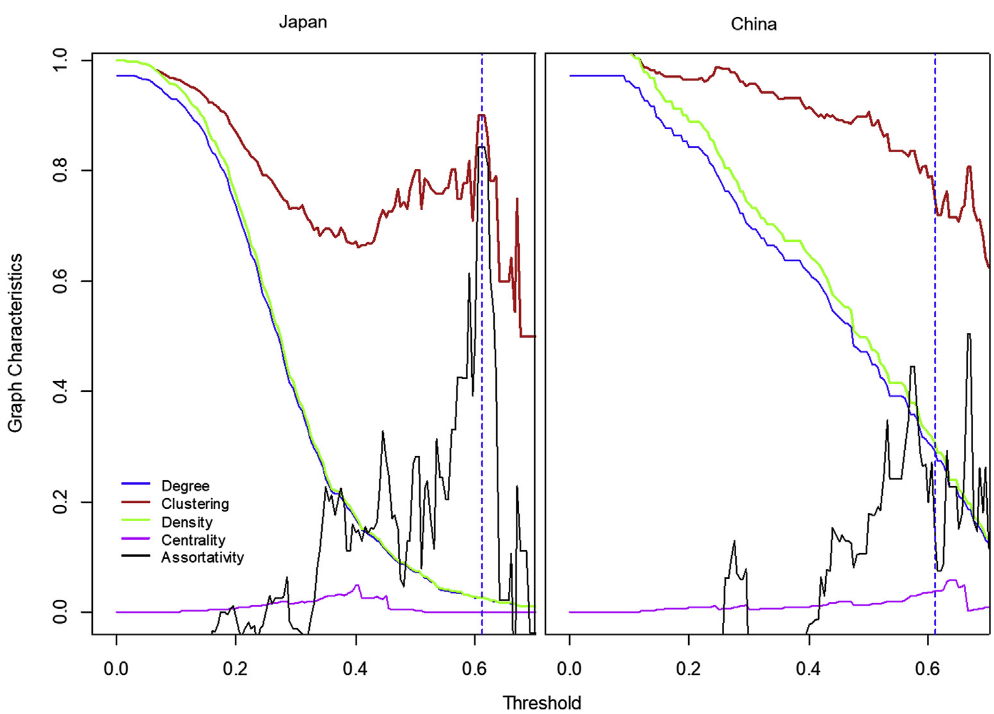
This result gives an interesting insight into the relationship between those two nations' stock markets and industries. Despite geographical and cultural closeness, the Chinese market is largely unaffected by an event like the Fukushima catastrophe, yet initiates a significant market reaction on Japanese soil with the fear of an economy that is slowing down. A potential explanation for this result might be that Japanese financial institutions, investors, and companies have a much higher stake in China than vice versa, and would be therefore directly more affected by shifts in the Chinese market. On the other hand, Chinese investors appear to have invested money elsewhere than Japan, explaining the mute reaction to an event, that triggered a global shift for nuclear power. Nevertheless, the reaction of the Japanese market towards shifts in the Chinese economy were only of short concern, as previously mentioned, and did not lead to a systematic shift in the correlation network structure.

6. Conclusion

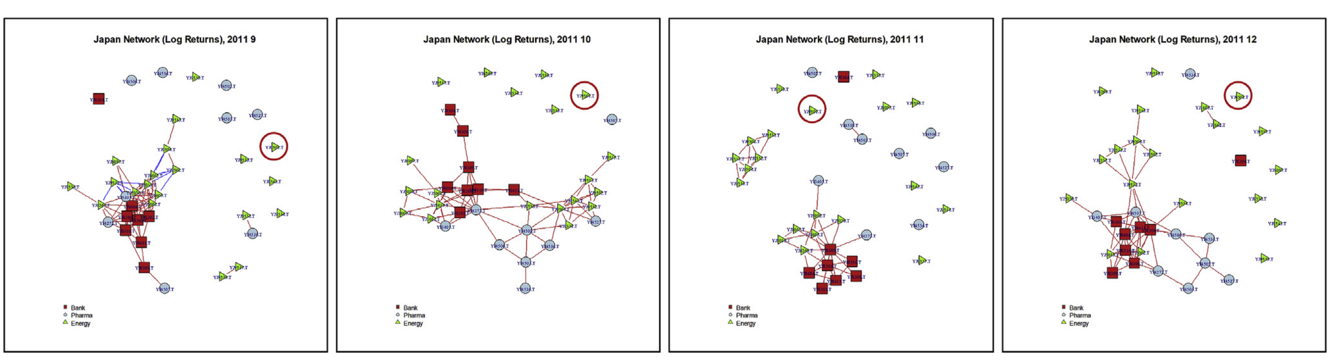
This paper posed the research question of whether and which industries display stock return correlations and how external events affect these correlation networks, focussed on the cases of Japan and China. For the purpose of this research, network correlation analysis is identified to be a suitable tool, as it can provide a visualisation of stock return correlations between different industries. Throughout all identified force majeure events, the Japanese market appeared to return to pre-event market behaviour within the short term, which means that market behaviour did not structurally change despite the external events. Among different types of events, the Fukushima Daiichi nuclear accident – classified as an force majeure event – had the most influential and longest lasting impact on stock returns. Yet still the Japanese stock market was normalized within the short term even under the consideration of this extraordinary event. Only the company "TEPCO" – being the operator of the nuclear plant in question – could be identified as an outlier. The loss of correlation to its market peers was reversed after a two year period (instead of a month, as can be seen in the analysis of peer behaviour), after which it returned to the pre-event conditions. The Chinese market appeared to be largely unaffected throughout the observation until the very end, when a similar disruption was visible. No further insight towards the research question was gathered by the Chinese observation. However, a strong impact of the Chinese economy on the Japanese market can be observed that is not mutual as the Chinese market appears to be unaffected by disruptive events on Japanese soil. Derived from the intra Japanese stock market behaviour analysis, the following conclusion can be made. External events – even those of extraordinary nature – have no long-lasting impact on stock market behaviour and do not lead to structural changes or redesign of network patterns.

The results furthermore confirm that these two major stock markets are still lacking co-integration (Cheng & Glascock, 2005), despite the ongoing, large scale regional integration efforts, such as the renegotiation of TPP and ASEAN.

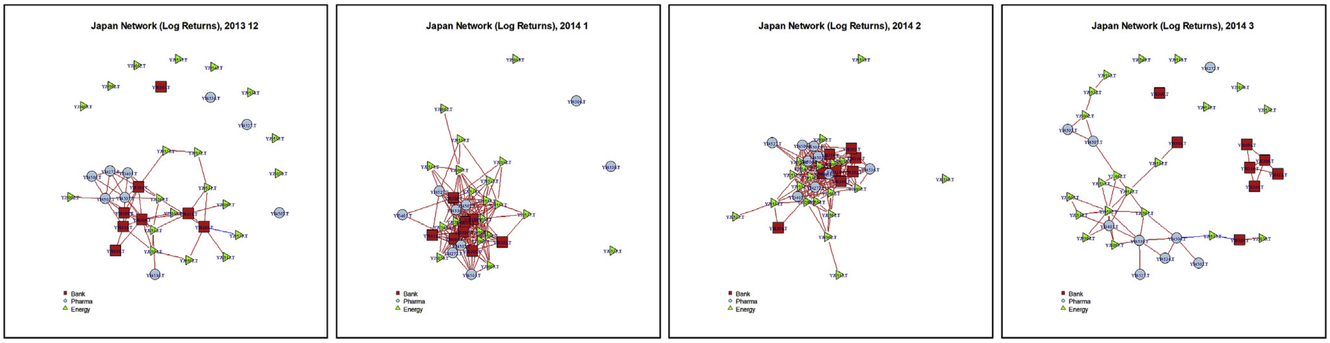
Appendix



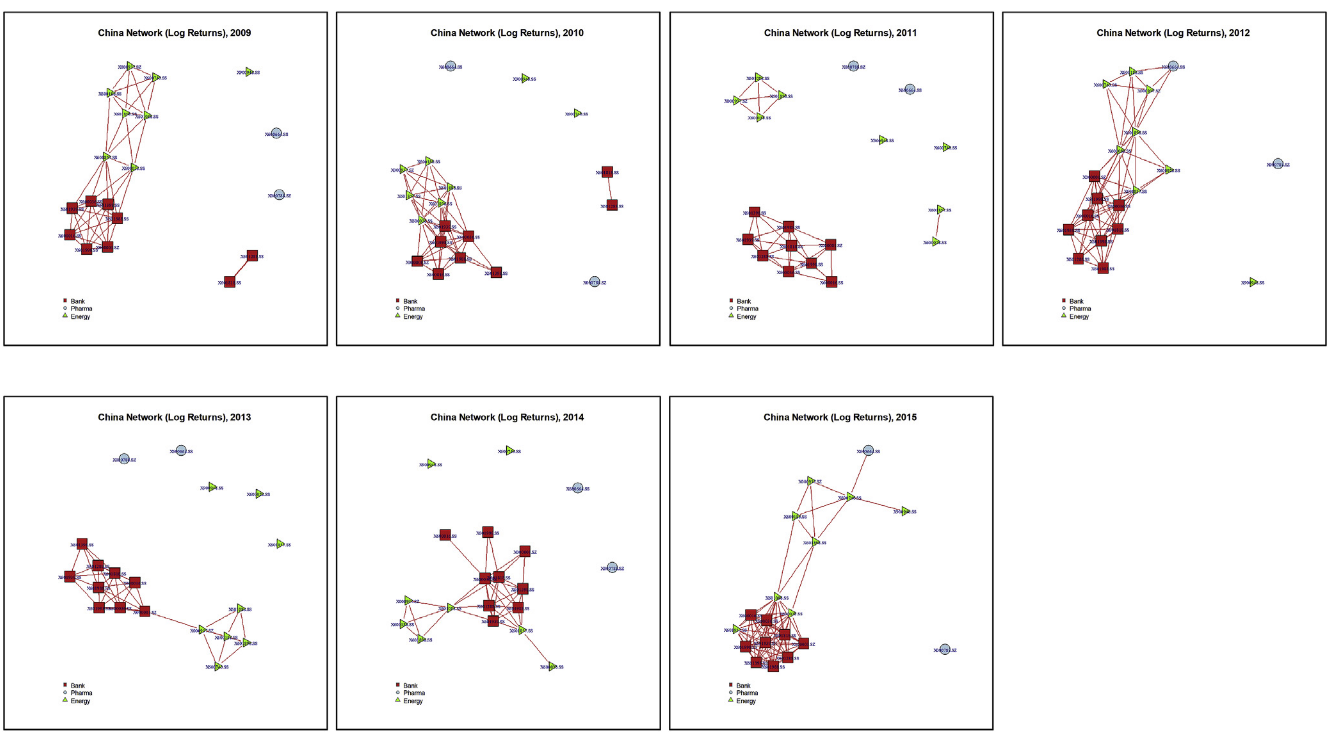
Appendix illustration 1. Network characteristics comparison (own illustration).



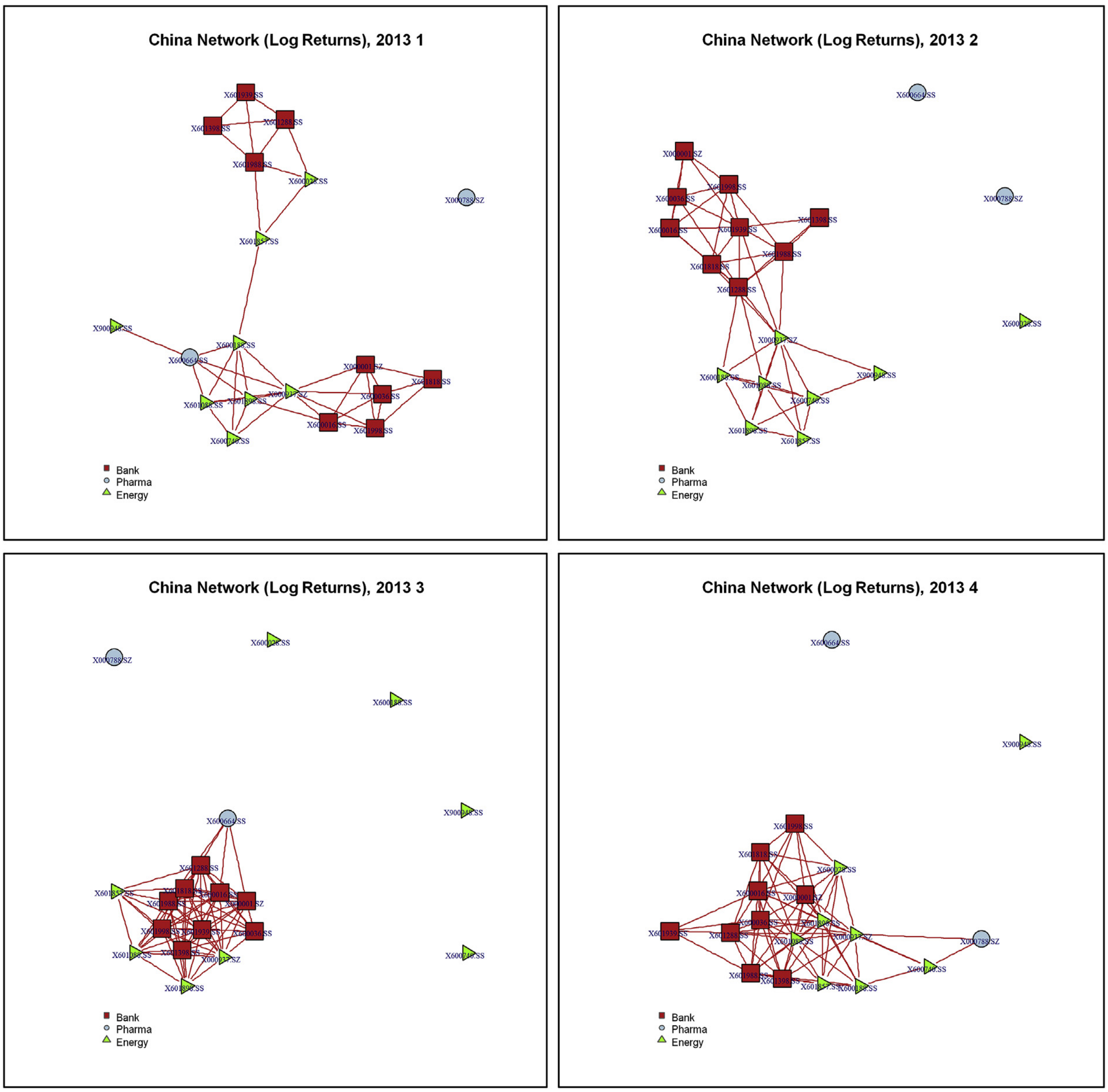
Appendix illustration 2. Japan Network Graph - monthly: September to December 2011 (own illustration).



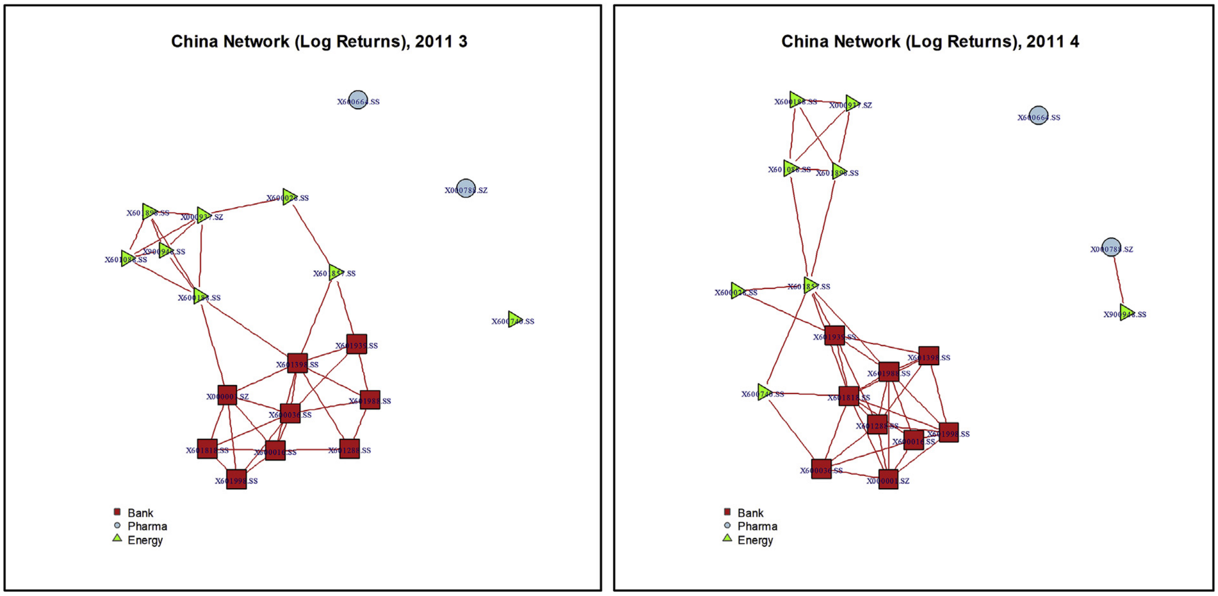
Appendix illustration 3. Japan Network Graph - monthly: December 2013 to March 2014 (own illustration).



Appendix illustration 4. China Network Graph - yearly: 2009 to 2015 (own illustration).



Appendix illustration 5. China Network Graph - monthly: January to April 2013 (own illustration).



Appendix illustration 6. China Network Graph – monthly: March to April 2011 (own illustration).

Appendix table 1
List of companies by country and sector.

Symbol	Name	Industry	Country
YJ8303.T	Shinsei Bank Ltd	Bank	Japan
YJ8304.T	Aozora Bank Ltd	Bank	Japan
YJ8306.T	Mitsubishi Ufj Finl Grp	Bank	Japan
YJ8308.T	Resona Holdings Inc.	Bank	Japan
YJ8309.T	Sumitomo Mitsui Tr.Hldgs	Bank	Japan
YJ8316.T	Sumitomo Mitsui Finl Grp	Bank	Japan
YJ8411.T	Mizuho Finl Group	Bank	Japan
YJ8604.T	Nomura Holdings Inc	Bank	Japan
YJ1605.T	Inpex Corp	Energy	Japan
YJ1662.T	Japan Petroleum Exploration Co Ltd	Energy	Japan
YJ5002.T	Showa Shell Sekiyu Kk	Energy	Japan
YJ5019.T	Idemitsu Kosan Co Ltd	Energy	Japan
YJ5020.T	Jx Holdings Inc	Energy	Japan
YJ6269.T	Modec Inc	Energy	Japan
YJ8097.T	San-Ai Oil Co Ltd	Energy	Japan
YJ9501.T	Tokyo Electric Power Company Holding Inc	Energy	Japan
YJ9502.T	Chubu Electric Power Co Inc	Energy	Japan
YJ9504.T	Chugoku Electric Power Co Inc	Energy	Japan
YJ9513.T	Electric Power Development Co Ltd	Energy	Japan
YJ9531.T	Tokyo Gas Co Ltd	Energy	Japan
YJ9532.T	Osaka Gas Co Ltd	Energy	Japan
YJ9533.T	Toho Gas Co Ltd	Energy	Japan
YJ9534.T	Hokkaido Gas Co Ltd	Energy	Japan
YJ9535.T	Hiroshima Gas Co Ltd	Energy	Japan
YJ9536.T	Saibu Gas Co Ltd	Energy	Japan
YJ9537.T	Hokuriku Gas Co Ltd	Energy	Japan
YJ9539.T	Keiyo Gas Co Ltd	Energy	Japan
YJ9543.T	Shizuoka Gas Co Ltd	Energy	Japan
YJ3401.T	Teijin Ltd	Pharma	Japan
YJ4272.T	Nippon Kayaku Co Ltd	Pharma	Japan
YJ4502.T	Takeda Pharmaceutical Co Ltd	Pharma	Japan
YJ4503.T	Astellas Pharma Inc	Pharma	Japan
YJ4506.T	Sumitomo Dainippon Pharma Co Ltd	Pharma	Japan
YJ4507.T	Shionogi & Co Ltd	Pharma	Japan
YJ4527.T	Rohto Pharmaceutical Co Ltd	Pharma	Japan
YJ4530.T	Hisamitsu Pharmaceutical Co Inc	Pharma	Japan
YJ4536.T	Santen Pharmaceutical Co Ltd	Pharma	Japan
X000001.SZ	Ping An Bank Ltd	Bank	China
X600016.SS	China Minsheng Banking Corp	Bank	China
X600036.SS	China Merchants Bank Co	Bank	China
X601288.SS	Agricultural Bank Of China Ltd	Bank	China
X601398.SS	Industrial & Commercial Bank of China Ltd	Bank	China
X601818.SS	China Everbright Bank Co Ltd	Bank	China
X601939.SS	China Construction Bank Corp	Bank	China
X601988.SS	Bank of China Ltd	Bank	China
X601998.SS	China Citic Bank Corp Ltd	Bank	China
X000937.SZ	Jizhong Energy Resources Co Ltd	Energy	China
X600028.SS	China Petroleum & Chemical Corp	Energy	China
X600188.SS	Yanzhou Coal Mining Co	Energy	China
X600740.SS	Shan Xi Coking Co	Energy	China
X601088.SS	China Shenhua Energy Co Ltd	Energy	China
X601857.SS	Petrochina Co Ltd	Energy	China
X601898.SS	China Coal Energy Co Ltd	Energy	China
X900948.SS	Inner Mongolia Yitai Coal Co Ltd	Energy	China
X000788.SZ	Pku Healthcare Corp Ltd	Pharma	China
X600664.SS	Harbin Pharmaceutical Group Co	Pharma	China

References

Beaudry, P., & Portier, F. (2006). Stock prices, news, and economic fluctuations. *The American Economic Review, 96*(4), 1293–1307.

Bondt, W. F. M. D., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance, 40*(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x.

Cajueiro, D. O., & Tabak, B. M. (2009). Multifractality and herding behavior in the Japanese stock market. *Chaos, Solitons & Fractals, 40*(1), 497–504. https://doi.org/10.1016/j.chaos.2007.07.091.

Carpenter, J. N., Lu, F., & Whitelaw, R. F. (2015). *The real value of China's stock market (working paper No. 20957)*. National Bureau of Economic Research.

Cetorelli, N., & Peristiani, S. (2013). Prestigious stock exchanges: A network analysis of international financial centers. *Journal of Banking & Finance, 37*(5), 1543–1551. https://doi.org/10.1016/j.jbankfin.2012.06.011.

Cheng, H., & Glascock, J. L. (2005). Dynamic linkages between the greater China economic area stock markets—Mainland China, Hong Kong, and Taiwan. *Review of Quantitative Finance and Accounting, 24*, 343–357. https://doi.org/10.1007/s11156-005-7017-7.

Chan, L. K. C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *The Journal of Finance, 46*(5), 1739–1764. https://doi.org/10.1111/j.1540-6261.1991.tb04642.x.

Chen, H., Mai, Y., & Li, S.-P. (2014). Analysis of network clustering behavior of the Chinese stock market. *Physica A: Statistical Mechanics and Its Applications, 414*, 360–367. https://doi.org/10.1016/j.physa.2014.07.039.

Chiang, T. C., Li, J., & Tan, L. (2010). Empirical investigation of herding behavior in Chinese stock markets: Evidence from quantile regression analysis. *Global Finance Journal, 21*(1), 111–124. https://doi.org/10.1016/j.gfj.2010.03.005.

Chiou, J.-S., & Lee, Y.-H. (2009). Jump dynamics and volatility: Oil and the stock

markets. *Energy, 34*(6), 788–796. https://doi.org/10.1016/j.energy.2009.02.011.
Crouzille, C., Lepetit, L., & Tarazi, A. (2004). Bank stock volatility, news and asymmetric information in banking: An empirical investigation. *Journal of Multinational Financial Management, Elements of Global Financial Stability, 14*(4–5), 443–461. https://doi.org/10.1016/j.mulfin.2004.03.004.
Driesprong, G., Jacobsen, B., & Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics, 89*(2), 307–327. https://doi.org/10.1016/j.jfineco.2007.07.008.
Eckel, S., Löffler, G., Maurer, A., & Schmidt, V. (2011). Measuring the effects of geographical distance on stock market correlation. *Journal of Empirical Finance, 18*(2), 237–247. https://doi.org/10.1016/j.jempfin.2010.12.001.
Elyasiani, E., & Mansur, I. (1998). Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M model. *Journal of Banking & Finance, 22*(5), 535–563. https://doi.org/10.1016/S0378-4266(98)00003-X.
Eraker, B. (2004). Do Stock Prices and Volatility Jump? Reconciling Evidence from Spot and Option Prices. *The Journal of Finance, 59*(3), 1367–1403. https://doi.org/10.1111/j.1540-6261.2004.00666.x.
Fama, E. F. (1965). The behavior of stock-market prices. *Journal of Business, 38*(1), 34–105.
Fields, M. A., & Janjigian, V. (1989). The effect of Chernobyl on electric-utility stock prices. *Journal of Business Research, 18*(1), 81–87. https://doi.org/10.1016/0148-2963(89)90053-2.
Gogineni, S. (2008). *The stock market reaction to oil price changes* (p. 23). Norman: Division of Finance, Michael F. Price College of Business, University of Oklahoma.
Grammatikos, T., & Vermeulen, R. (2012). Transmission of the financial and sovereign debt crises to the EMU: Stock prices, CDS spreads and exchange rates. *Journal of International Money and Finance, Financial Stress in the Eurozone, 31*(3), 517–533. https://doi.org/10.1016/j.jimonfin.2011.10.004.
Halme, M., & Niskanen, J. (2001). Does corporate environmental protection increase or decrease shareholder value? The case of environmental investments. *Business Strategy and the Environment, 10*(4), 200–214. https://doi.org/10.1002/bse.290.
Hamilton, J. T. (1995). Pollution as news: Media and stock market reactions to the toxics release inventory data. *Journal of Environmental Economics and Management, 28*(1), 98–113. https://doi.org/10.1006/jeem.1995.1007.
Huang, W.-Q., Zhuang, X.-T., & Yao, S. (2009). A network analysis of the Chinese stock market. *Physica A: Statistical Mechanics and Its Applications, 388*(14), 2956–2964. https://doi.org/10.1016/j.physa.2009.03.028.
Hwang, J.-K. (2012). Dynamic correlation analysis of Asian stock markets. *International Advances in Economic Research, 18*(2), 227–237. https://doi.org/10.1007/s11294-012-9343-6.
Jia, L., Noubir, G., Rajaraman, R., Sundaram, R., et al. (2006). GIST: Group-Independent Spanning Tree for Data Aggregation in Dense Sensor Networks. In P. B. Gibbons, T. Abdelzaher, J. Aspnes, & R. Rao (Eds.), *Distributed Computing in Sensor Systems*. Springer, Berlin, Heidelberg.
Kalra, R., Henderson, G. V., & Raines, G. A. (1993). Effects of the Chernobyl nuclear accident on utility share prices. *Quarterly Journal of Business & Economics, 32*, 52–77.
Kaplanski, G., & Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics, 95*(2), 174–201. https://doi.org/10.1016/j.jfineco.2009.10.002.
Kassim, S., Abd Majid, M. S., & Hamid, Z. (2011). The 2007 global financial crisis and the Malaysian stock market: A sectoral analysis. *Afro-Asian Journal of Finance and Accounting, 2*(3), 185–209.
Katenka, N., & Kolaczyk, E. D. (2012). Inference and characterization of multi-attribute networks with application to computational biology. *Annals of Applied Statistics, 6*(3), 1068–1094. https://doi.org/10.1214/12-AOAS550.
Kato, K., & Loewenstein, U. (1995). The ex-dividend-day behavior of stock prices: The case of Japan. *Review of Financial Studies, 8*(3), 817–847. https://doi.org/10.1093/rfs/8.3.817.
Kato, K., & Schallheim, J. S. (1985). Seasonal and size anomalies in the Japanese stock market. *Journal of Financial and Quantitative Analysis, 20*(2), 243–260. https://doi.org/10.2307/2330958.
Kawashima, S., & Takeda, F. (2012). The effect of the Fukushima nuclear accident on stock prices of electric power utilities in Japan. *Energy Economics, 34*(6), 2029–2038. https://doi.org/10.1016/j.eneco.2012.08.005.
Kolaczyk, E. D. (2009). Statistical analysis of network data: Methods and models. In *Springer series in statistics*. New York:NY: Springer-Verlag.
Kullmann, L., Kertész, J., & Mantegna, R. N. (2000). Identification of clusters of companies in stock indices via Potts super-paramagnetic transitions. *Physica A: Statistical Mechanics and Its Applications, 287*(3–4), 412–419. https://doi.org/10.1016/S0378-4371(00)00380-0.
Liu, F., Wang, N., & Wei, D. (2017b). Analysis of Chinese stock market by using the method of visibility graph. *The Open Cybernetics & Systemics Journal, 11*(1). https://doi.org/10.2174/1874110X01711010036.
Liu, J., Sarkar, S., Kumar, S., & Jin, Z. (2017a). An analysis of stock market impact from supply chain disruptions in Japan. *International Journal of Productivity and Performance Management, 67*(1), 192–206. https://doi.org/10.1108/IJPPM-06-2016-0104.
Mantegna, R. N. (1999). Hierarchical structure in financial markets. *European Physical Journal B, 11*(1), 193–197. https://doi.org/10.1007/s100510050929.
Nandha, M., & Faff, R. (2008). Does oil move equity prices? A global view. *Energy Economics, 30*(3), 986–997. https://doi.org/10.1016/j.eneco.2007.09.003.
Nezu, E., & Kurihara, Y. (2006). Recent stock price relationships between Japanese and US stock markets. *Studies in Economics and Finance, 23*(3), 211–226. https://doi.org/10.1108/10867370610711057.
Onnela, J.-P., Chakraborti, A., Kaski, K., & Kertész, J. (2003). Dynamic asset trees and black Monday. *Physica A Statistical Mechanics and its Applications, 324*(1–2), 247–252. https://doi.org/10.1016/S0378-4371(02)01882-4.
Onnela, J.-P., Chakraborti, A., Kaski, K., & Kertiész, J. (2002). Dynamic asset trees and portfolio analysis. *European Physical Journal B, 30*(3), 285–288. https://doi.org/10.1140/epjb/e2002-00380-9.
Onnela, J.-P., Kaski, K., & Kertész, J. (2004). Clustering and information in correlation based financial networks. *The European Physical Journal B, 38*(2), 353–362. https://doi.org/10.1140/epjb/e2004-00128-7.
Phylaktis, K., & Ravazzolo, F. (2005). Stock prices and exchange rate dynamics. *Journal of International Money and Finance, 24*(7), 1031–1053. https://doi.org/10.1016/j.jimonfin.2005.08.001.
Raddant, M., & Kenett, D. Y. (2016). *Interconnectedness in the global financial market (SSRN scholarly paper No. ID 2848348)*. Rochester, NY: Social Science Research Network.
Sarmas, P. (2005). *Correlation among stock markets under different exchange rate systems, Research in Finance* (pp. 155–173). Emerald Group Publishing Limited.
Schwert, G. W. (2011). Stock volatility during the recent financial crisis. *European Financial Management, 17*(5), 789–805. https://doi.org/10.1111/j.1468-036X.2011.00620.x.
Sinn, H.-W. (2014). *The Euro Trap: On Bursting Bubbles, Budgets, and Beliefs*. OUP Oxford.
Su, D., & Fleisher, B. M. (1998). Risk, return and regulation in Chinese stock markets. *Journal of Economics and Business, 50*(3), 239–256. https://doi.org/10.1016/S0148-6195(98)00002-2.
Thakor, A. (2015). *International financial markets – a diverse system is the key to commerce, 64P.* US Chamber of Commerce.
Tse, C. K., Liu, J., & Lau, F. C. M. (2010). A network perspective of the stock market. *Journal of Empirical Finance, 17*(4), 659–667. https://doi.org/10.1016/j.jempfin.2010.04.008.
Worthington, A., & Valadkhani, A. (2004). Measuring the impact of natural disasters on capital markets: An empirical application using intervention analysis. *Applied Economics, 36*(19), 2177–2186. https://doi.org/10.1080/0003684042000282489.
Yang, C. C., Wang, M., & Chen, X. (2008). Catastrophe effects on stock markets and catastrophe risk securitization. *The Journal of Risk Finance, 9*, 232–243. https://doi.org/10.1108/15265940810875568.
Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics & Finance, 29*, 12–29. https://doi.org/10.1016/j.iref.2013.03.002.