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On the predictive power of network statistics for financial risk indicators

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ABSTRACT

An understanding of the financial instability during financial crises is an important topic in risk management. Market participants actively use risk indicators, such as the VIX in the US, the VHSI in Hong Kong and the V2TX in Europe, which are derived from derivative products, to measure market anxiety and fear and thus to estimate systemic risk in the market. In this paper, we present the findings of a study on the lead–lag relationship between financial connectedness and risk indicators. Specifically, we examine the predictive power of time-varying network statistics, compiled from more than 1300 stocks from international stock markets, on the risk indicators. Our empirical findings show strong evidence in favor of using network statistics to predict risk indicators. The findings reveal the importance of network connectedness in measuring systemic risk.

1. Introduction

How financial institutions assess systemic risk, which is the risk of a possible financial crisis or major financial incident causing a substantial breakdown of financial systems, has long been debated, even though substantial financial instability may not be avoidable during crisis periods. The 1987 worldwide market crisis, the 2008 financial tsunami, and the recent financial market turbulence due to the Covid-19 pandemic each strengthened investors' intentions to engage in risk management and their awareness of the need for good systemic risk measures for risk management. One primary source of systemic risk is attributed to financial contagion (Allen and Gale, 2000), wherein financial risk can be transmitted from one institution to another, thus causing widespread problems (Pericoli and Sbracia, 2003). A natural approach to quantifying and modeling financial contagion and systemic risk is the network analysis, which has been applied to various other domains, such as co-authorship (Newman, 2004), social networks (Scott, 1988) and epidemiology (El-Sayed et al., 2012). The use of network analysis to discuss financial contagion also appears as a viable approach in the literature (Kali and Reyes, 2010; Minoiu and Reyes, 2013; Glasserman and Young, 2015). To objectively assess of the impact of financial contagion and systemic risk in financial markets, an useful technique is to measure financial network connectedness.

Financial connectedness (Brunetti et al., 2019; So et al., 2021) is closely related to the financial contagion and is considered to be one of the most useful indicators for quantifying systemic risk in financial markets. During a crisis, the interconnectedness among financial institutions, along with the global financial integration, causes risk from the crisis to spill over onto different markets throughout the world (Committee et al., 2011; Brunetti et al., 2011; Acemoglu et al., 2015a). Such disasters not only expose the whole financial system to the threat of a potential risk spillover effect, but they also reveal the theoretical relationships among risk, financial stability, and system connectivity.

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However, financial connectedness feels a bit abstract when we cannot observe the patterns or quantify the connectedness. Thus, network analysis has been widely used in financial research (Scott, 1988; Brandes, 2005; Billio et al., 2012; Diebold and Yılmaz, 2014). A network, containing individual nodes and edges connecting different nodes, can best describe how a system forms and how the information transmits within the system (Scott, 1988; Brandes, 2005). The characteristics of financial networks can reflect financial connectedness and systemic risk.

It is common to use volatility indices to trace market risk and market anxiety. Volatility, which has potential to transmit systemic risk and reinforces the crisis in financial markets (Mieg, 2020), closely correlates to the systemic risk and somehow can be an indicator to reflect the systemic risk (Stolbov and Shchepeleva, 2018). The Chicago Board Options Exchange's CBOE Volatility Index, known as the VIX index (Russon and Vakil, 2017) is derived from S&P 500 options for the 30 days following the measurement date. As a widely-used indicator of market fears, VIX has been used as an important indicator to measure the systemic risk and always serves as a common determinant of systemic risk in the market (Bianconi et al., 2015). In Asia, the VHSI index from Hong Kong also adopts the VIX methodology and measures the 30-day expected volatility of the Hang Seng Index, as implied from Hang Seng Index options (Chen and Lai, 2013). Similarly, the V2TX (VSTOXX) index is a volatility index derived from Euro STOXX 50 options (Hilpisch, 2016). In a crisis period, rather than absorbing shocks as normal, the financial connectedness may cause shocks to increase and propagate in the system, thereby increasing systemic risk in financial systems. In other words, a causal relationship may exist between financial connectedness and common risk indicators such as the VIX, VHSI, and V2TX, and that connectedness may result in a predictive power of the connectedness to predict systemic risk.

To examine the relationship between financial market connectedness and benchmark risk indicators, we used the Granger causality test to detect any significant lead–lag relationships among the returns of more than 1300 stocks from different international stock markets. The lead–lag relationship was used to construct dynamic financial networks. The empirical analysis of this paper consists of three parts. Firstly, we studied the time-series properties of the financial networks from 2013 to April 2020. We constructed the financial networks using the Granger causality test and explored how the networks evolved over time, especially in times of financial crises. Secondly, we conducted a within-region analysis to test whether any causal relationship existed between the risk indicators VIX, VHSI, and VT2X, and their financial market connectedness (measured by network statistics) in the US, Asia, and Europe, respectively. That within-region analysis yielded ideas on whether risk indicators were predictable by using network statistics. Finally, we conducted a cross-regional analysis to test whether there was any causal relationship between the VIX, VHSI, and VT2X, and the financial market connectedness of other regions. In those within-region and cross-regional analyses, we found strong evidence of the predictive power for the risk indicators, based on network statistics in crisis periods.

The rest of the paper is as follows. Section 2 provides a review of the literature, especially on financial networks and systemic risk measures. In Section 3, we present the study's methodology, including the network construction and exploration of causal relationships. Sections 4 and 5 present visual analyses of network statistics and empirical causal analysis results, including those from the within-regional and cross-regional Granger causality tests. Section 6 discusses the conclusions we drew from the study's results.

2. Literature review

Two risk-related bodies of literature focus on market interconnectedness based on network analysis, highlighting the methodology and framework for measuring and quantifying market interconnectedness. Many of the studies include banking contexts. Billio et al. (2012) used principal components analysis and a Granger-causality test to propose correlation-based network measures of interconnectedness, in an effort to capture the systemic risk among the returns of hedge funds, banks, brokers, and insurance companies. Demirer et al. (2018) used LASSO to shrink, select, and estimate the high-dimensional network linking the publicly-traded subset of the world's top 150 banks and then study the evolution of the network dynamically. Brunetti et al. (2019) used network analysis to construct a correlation network based on publicly traded bank returns and a physical network based on interbank lending transactions in order to forecast the liquidity problems, and forecast the financial crises in the banking system.

Apart from the literature focusing largely on the banking industry, empirical research using various measurement methods has been conducted on the global stock market's connectedness. Lucey et al. (2006) used a Minimum Spanning Tree to study the process of market integration for a large group of national stock market indices, and they showed how the asset tree evolved over time and described the dynamics of its normalized length. Diebold and Yılmaz (2014) proposed several connectedness measurements built from pieces of variance decompositions, and they illustrated insights on connectedness by tracking the time-varying connectedness of major U.S. financial institutions' stock return volatilities during the financial crisis of 2007–2008. Similarly, normalizing the returns by estimated volatility via a GARCH model, Raddant and Kenett (2016) used a robust regression process to estimate pairwise statistical relationships between stocks from different markets. León et al. (2017) focused on the method of agglomerative clustering to explore the financial hierarchical structure in stock indices' daily returns, and their results showed a strong geographical clustering effect.

Another burgeoning collection of literature highlights the measures of systemic risk. Huang et al. (2009) measured systemic risk by the price of insurance against financial distress, which was based on data on credit default swaps (CDSs) of financial institutions and equity return correlations. Zhou (2009) used a multivariate Extreme Value Theory framework to purpose the systemic impact index and the vulnerability index as two measurements of systemic risk, assessing the risk that an institution contributes to the system and that the system imposes on the institution. Adrian and Brunnermeier (2011) introduced Conditional Value-at-Risk (CoVaR) as a new risk measure, aiming to go beyond idiosyncratic risk and to capture possible risk spillover among financial institutions. Dhaene et al. (2011) introduced the Herd Behavior Index as a new indicator to measure the systemic risk, based on the VIX methodology.

Their results showed that, similar to volatility indices and correlation indices, the herd behavior indices exhibited a tendency to increase when the stock prices were decreasing. Civitarese (2016) tested some systemic risk measures based on correlation matrices using Granger-causation of the S&P 500 and the VIX indices. The indicators were shown to Granger-cause the S&P 500 in all windows observed, but they did not necessarily Granger-cause the VIX. To measure the systemic risk contribution of a financial firm, Brownlees and Engle (2017) introduced SRISK, defined as the expected capital shortfall of a financial entity, conditional on a prolonged market decline. Their results showed that the SRISK was excellent for predicting worsening macroeconomic conditions (e.g., industrial production declines and unemployment rate increases). Borovkova et al. (2017) introduced a sentiment-based systemic risk indicator-'SenSR'. Using the VIX/SRISK as a baseline indicator to measure systemic risk, they carried out the Granger causality test to find out the lead–lag relationship between SenSR and VIX/SRISK and found that the SenSR could anticipate other systemic risk measurements such as SRISK or VIX in signaling stressed times. Similarly, Yu et al. (2019) introduced a new measurement for systemic risk — FRM and checked the Granger causality relationship between FRM and VIX/SRISK/Google Trends. They found that mutual Granger causality existed between the FRM and these measurements, indicating the validity of the FRM as a systemic risk measurement.

Several researchers have studied the mechanism of risk transmission, which gives us a clearer way of thinking how the financial connectedness connected is associated with systemic risk. Allen and Gale (2000) showed that a small liquidity preference shock in one region can spread by contagion throughout the economy, where the network structure may exacerbate or attenuate the effects of that contagion. Cabrales et al. (2014) modeled contagion after the transmission of a pathologic disease, linking firms as they exchanged assets to meet capital requirements and noting a trade-off between risk sharing and contagion resulting from an increased exposure to risk. Acemoglu et al. (2015b) provided a framework for studying the relationship between a financial network's architecture and the likelihood of systemic failures due to a contagion of counterparty risk. They showed that financial contagion exhibits a form of phase transition as interbank connections increase: As long as the magnitude and the number of negative shocks affecting financial institutions are sufficiently small, more complete interbank claims enhance the stability of the system. Based on an assessment of market interconnectedness, Kravchuk (2017) was able to define a possible risk contagion level in capital markets that was the result of shocks in main international stock and bond market.

Obviously, most studies have focused more on one of the two objectives: measuring connectedness, or measuring systemic risk. Most of the papers focusing on measuring connectedness paid more attention to how to measure the connectedness and to how insightful the connectedness indicators were (for forecasting the crisis and economy), with few of them quantifying the systemic risk (they just observed the evolution of the networks). Likewise, of the papers highlighting the measurements of systemic risk, few cared about the connectedness. Thus, in this paper, we advanced the understanding of both the interconnectedness within the financial system and the systemic risk in the global stock market. On the interconnectedness side, we measured the connectedness using correlation networks, wherein edges were based on asset return correlations (as in Billio et al. (2012)). On the systemic risk side, we used the volatility indices in different markets to measure the systemic risk in the stock market globally, especially during crisis periods. We used the Granger-causality test to identify the relationship between interconnectedness and systemic risk in the financial system, and that in turn helped us better understand how the connectedness reflects the systemic risk in times of crisis.

3. Methodology

3.1. Network construction

In this section, we discuss the methodology we developed to construct dynamic financial networks, to obtain time series of network statistics, and to study the causal relationship between financial network connectedness and common risk indicators. We began by constructing a financial network at time t using N stocks. Each stock in the network was taken as a node. In the financial network at time t, if there was a directed edge from node i to node j, we set $A_{tij} = 1$, where A_{tij} was the (i, j)th element of an adjacency matrix A_t of the financial network at time t that defined the network structure at time t.

In this study, we adopted a rolling-window approach that enabled us to observe the dynamic patterns of the financial networks. Like the approaches in Diebold and Yılmaz (2014) and Balcilar and Ozdemir (2013), who used bootstrap rolling-window estimations to evaluate the estimation power of stock returns and economic indicators, ours used recent observations before and at time t to define A_{tij}. We named w as the window width, which we set at 30 days in this study. We built the financial network at time t using financial information from time $t - w + 1$ to time t. Further details of the network construction are described below.

To define the directed edges between network nodes/stocks at time t, we adopted the Granger causality test (Granger, 1969). With the help of the Granger causality test, we measured the connections, as well as the direction of such connections within the stock network. That served as an ideal method for detecting how the transmitted information was concealed by time series data, such as stock returns. As discussed in Castiglionesi et al. (2009), Danielsson et al. (2011), and Battiston et al. (2012), the degree of a Granger causality test result from asset returns can demonstrate how the risk-spillover affects the market. As in other network models that describe the relationship between nodes (Jackson, 2010; Diebold and Yılmaz, 2014; Brunetti et al., 2019), in our financial networks, each stock represented a node in the network and their relationships were defined by the Granger causality test, which can determine whether two time series Granger-cause each other. Specifically, two nodes (stocks) are connected when one can Granger-cause the other, and that test result also tells the direction of such a connection, as shown in Billio et al. (2012). We denoted by x^i_s the return time series of stock i at time s. Using the return information from $s = t + w - 1$ to $s = t$, we set up the following regression for these two series

$$x^j_s = \sum_{l=1}^{q} \alpha_l x^i_{s-l} + \sum_{k=1}^{q} \beta_k x^j_{s-k} + u_{1s}, \tag{1}$$

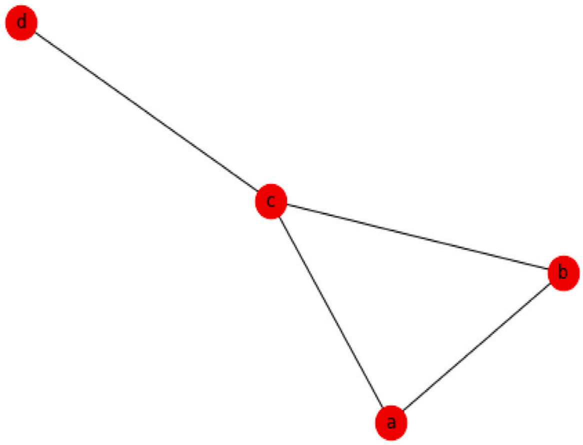


Fig. 1. A network example.

$$x_s^i = \sum_{l=1}^{q} \lambda_l x_{s-l}^i + \sum_{k=1}^{q} \delta_k x_{s-k}^j + u_{2s}. \tag{2}$$

Testing the null hypothesis $H_0^{i\to j}$: $\alpha_1 = \alpha_2 = \cdots = \alpha_q = 0$ based on Eq. (1), we could determine whether there was an edge from node i to node j. Similarly, we could determine whether there was an edge from node j to node i by testing $H_0^{j\to i}$: $\delta_1 = \delta_2 = \cdots = \delta_q = 0$ based on Eq. (2). To check whether the null hypothesis could be rejected, the above regression problem can be regarded as a constrained linear regression problem. The above Granger-causality tests were performed using a standard F-test (Judge and Takayama, 1966). To summarize, we list the below four possible situations from our Granger-causality tests.

Situation 1 Neither hypothesis was significant: $A_{tij} = A_{tji} = 0$.

Situation 2 Only the test of $H_0^{i\to j}$ was significant: $A_{tij} = 1$ and $A_{tji} = 0$.

Situation 3 Only the test of $H_0^{j\to i}$ was significant: $A_{tij} = 0$ and $A_{tji} = 1$.

Situation 4 Both hypotheses were significant: $A_{tij} = A_{tji} = 1$.

3.2. Network statistics

Using the dynamic financial networks, A_{tij} constructed, we obtained network statistics that helped us measure important features of the financial networks over time. By examining the time series of network statistics, we summarized causality information of the financial returns and were able to describe financial network connectedness. Our aim was to investigate how the integration of stocks with respect to Granger causality affected the time evolution of risk indicators. Through the impact of network statistics on the common risk indicators that are adopted by financial analysts, the above analysis through the time series of network statistics can shed light on the understanding of any lead–lag relationship between financial network connectedness and systemic risk. In this study, we considered three specific network statistics – the degree, the closeness, and the clustering coefficient – to assess dynamic network connectedness (Brunetti et al., 2019). Here are the three network statistics.

Degree estimates the risk of a systemic event and reflects the level of liquidity, which shows how densely the network is connected. It is defined as

$$Deg_t = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j\neq i} A_{tij}. \tag{3}$$

Degree is defined as the proportion of links in the network, which is the average number of edges of each node divided by $N-1$. To explain this concept, we can image that there is a network with N nodes, each node has at most $N-1$ edges with other nodes. Actually, if we calculate the average number of connected edges of each node, we can find out that its maximum value is $N-1$ (when every node has a link to every other one). Normalized into a range of [0,1], the average is divided by $N-1$ to get the formula of the degree in Eq. (3). For instance, in Fig. 1, there are 4 nodes in the network, so its degree equals to

$$\frac{Link_a + Link_b + Link_c + Link_d}{number\ of\ nodes * the\ maximum\ number\ of\ possible\ links\ of\ a\ node} = \frac{2+2+2+1}{4*3} = \frac{7}{12}$$

where $Link_i$ is the number of edges connecting node $i (i \in \{a,b,c,d\})$. Degree represents the proportion of links in the financial network at time t, which is an important measure for describing financial networks because a larger degree indicates tighter connectedness in the network and a greater tendency for stock returns to move together.

Closeness estimates how many steps there are between stocks, on average. In the network perspective, the edges between nodes/stocks can link the stocks together through paths formed by joining the edges connecting the stocks. We let C_{tij} denote the shortest path length from stock i to stock j, based on the financial network at time t, which was represented by A_{tij}. If there was no path from i to j, C_{tij} would be $N-1$, where N is the total number of stocks in the network. The shortest path length of two nodes is defined as the shortest length among all paths between two nodes in a network, which can be obtained using the *networkx* package in Python. The closeness thus reflects the distance between stocks on the network and thus measures how fast the information can transmit within the network. It is defined as follows and is normalized to [0,1]:

$$Clo_t = \frac{1}{N(N-1)(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} C_{tij}. \tag{4}$$

The closeness is defined as average distance of each shortest path divided by $N-1$. To explain this concept, we also assume that there is a network with N nodes. For each node i, we can calculate the average shortest path length of it to every other node, obtaining $N-1$ shortest path lengths. Repeating this calculation for every node in the whole network system, we can get $N(N-1)$ shortest path lengths in total. Because the maximum length of one shortest path is $N-1$, we finally get the formula of the closeness by normalization: the average number of each shortest path length divided by $N-1$. Take the network in Fig. 1 as an example. There are two paths from node d to node a: one is $d \to c \to a$ and the other is $d \to c \to b \to a$. Obviously, the shortest path from node d to node a is $d \to c \to a$, whose length is equal to 2. And the closeness of this network equals to

$$\frac{\sum_{i,j \in \{a,b,c,d\}, i \neq j} SPL_{ij}}{number\ of\ shortest\ paths\ *(N-1)} = \frac{1+1+2+1+1+2+1+1+1+2+2+1}{12*3} = \frac{2}{9}$$

where the SPL_{ij} is the shortest path length from node i to node j. A larger closeness means slower transmission speed and consequently less connectedness.

Clustering Coefficient (**CC**) measures how often triangular connections occur, or the probability that neighbors of a stock are themselves connected. It too has been rescaled to [0,1] because it measures the probability. A triangular connection means that if nodes i and j are connected and nodes i and k are connected, then j and k are also connected. The clustering coefficient is given by

$$CC_t = \frac{number\ of\ connected\ triples}{number\ of\ possible\ connected\ triples}. \tag{5}$$

Clustering Coefficient is defined as the proportion of connected triples. For a network with N nodes, the number of possible connected triples is C_3^N. For each possible connected triple, we check whether this triple is triangularly connected and then calculate the number of triangles and divide it by C_3^N. We can then get the formula of CC in Eq. (5). For the CC of the network in Fig. 1, we can determine the number of possible triples to be 4 and the number of triangles to be 1 (with the triple abc). Therefore, CC is equal to 1/4. Larger values of the clustering coefficient indicates greater tendency to see more connectedness in financial markets.

3.3. Causality between network statistics and risk indices

One main objective of this study was to investigate the causal relationship between financial market connectedness and market risk indices. After constructing the dynamic networks, A_{tij}, and the three time series of network statistics, a research question arose as to whether changes in the network statistics "lead" changes in the risk indices. We defined $RDeg_t = \log Deg_t - \log Deg_{t-i}$, $RClo_t = \log Clo_t - \log Clo_{t-i}$ and $RCC_t = \log CC_t - \log CC_{t-i}$ as the changes of the network statistics. We then performed Granger causality tests to determine whether $RDeg_t$, $RClo_t$, and RCC_t were significant leading indicators of changes in the three selected risk indices in the US, Asian, and European regions.

4. Financial data properties

4.1. Summary statistics

Our data were the daily returns of global stocks from 15 stock markets during the period from January 2013 through April 2020, obtained from the Yahoo finance terminal[1] and the Wind financial terminal.[2] All of the stocks were components of stock indices. In total, there were more than 1300 stocks from three regions: the US stock markets, the European stock markets, and the Asian stock markets. We used the stock returns to build four networks: three regional networks and one international network. Because not all markets open for trading on the same date, it was possible that some days had missing values. To clean the data, we first removed the days with less than 50% of stocks opening. Because stocks may stop trading for their own reasons or in response to regulatory requirements, stocks were also removed if their returns data were not available for more than 20 consecutive days. Eventually, 1042 stocks (459 stocks from the US market, 399 stocks from the Asian market, and 184 stocks from the European market) and 2141 trading days remained.

1 Resource: Yahoo.
2 Resource: Wind.

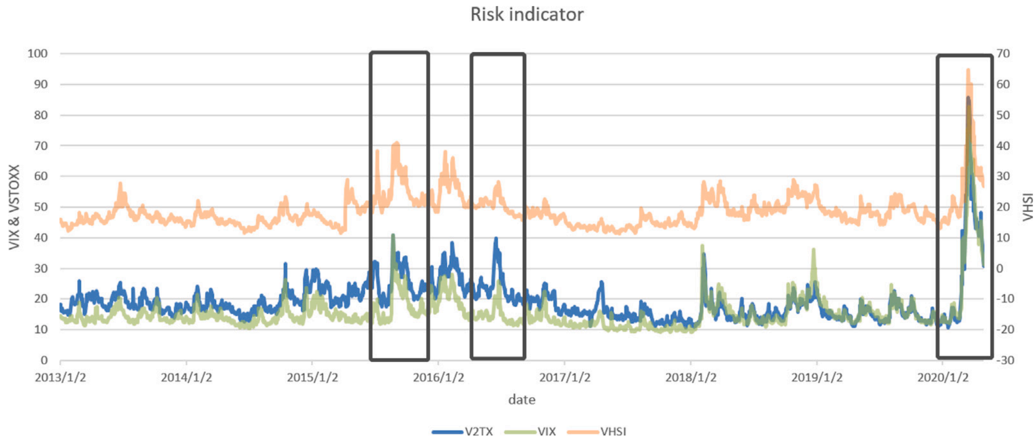


Fig. 2. Time series plots of the VIX, VHSI, and V2TX from 2 January 2013 through 6 April 2020. For convenient observation, VHSI is described by secondary axis (on the right). The black frames indicate the time around the three subperiods: (1) the first crisis period from 24 August to 21 September in 2015; (2) the second crisis period from 13 June to 30 June in 2016; and (3) the third crisis period after 24 February in 2020.

To relate the network statistics and market risk, we also collected risk indices such as the VIX (Bekaert and Hoerova, 2014), VHSI (Chen and Lai, 2013) and V2TX (Äijö, 2008) to serve as proper representatives. One of the most popular risk indices is the VIX, the CBOE's volatility index,[3] which is calculated from S&P 500 option prices. It is regarded as an indicator of US market fluctuations and is thought to be reflecting investors' anxiety about current market situations. The HSI Volatility Index (VHSI) is the volatility benchmark for Hong Kong's stock market.[4] Its calculation is similar to that of the VIX, and it is used to express views from investors on volatility through selected derivatives tradings. The third risk index is the V2TX, the EURO STOXX 50 volatility index,[5] which is the implied volatility index based on EURO STOXX 50 options prices. By design, all three indices are well-utilized by market participants to reflect the market volatility and market risk. Therefore, a focus in this study was to investigate any causal relationships between the time series of network statistics and the risk indices.

In order to study the relationship between risk indicators and network statistics, we examined the daily returns during three subperiods: (1) an initial crisis period, from 24 August to 21 September in 2015, that can be attributed to global stock market instability caused by unexpected depreciation of the Chinese yuan; (2) a second crisis period, from 13 June to 30 June in 2016, that was the market panic caused by increased uncertainty in the European market due to the upcoming referendum for the UK leaving the EU; (3) a third crisis period, the circuit breaker crisis from 24 February in 2020 until late March (20 March 2020). Of the three, subperiod 1 and subperiod 3 experienced a global market shock and panic, and subperiod 2 had a great influence on the European market.

In Fig. 2, we present the time series from the three risk indices. We found that in subperiod 1, the three risk indices reached their peaks at the same time, thus indicating that the unexpected devaluation of the Chinese yuan may have a great impact on European, Asian, and American markets. In subperiod 2, the V2TX reached its peak (the second highest in history), while the VHSI and VIX also reached a short-term peak. Subperiod 3 is a well-known circuit breaker crisis that has caused a long-term and large-scale impact on the world financial market. In Table 1, we list the average sample means and sample standard deviations of stock returns and risk index returns for the whole period from 2 January 2013 to 24 April 2020, and for each of the three subperiods. Regarding the volatility of stock returns in the US, European, and Asian regions, the average standard deviation was the highest in subperiod 2 or subperiod 3. The average standard deviation in the US in subperiod 3 is much higher than that during the whole period and in subperiods 1 and 2. The circuit breaker crisis in 2020 had a global impact on stock returns in the three regions, with an effect that was greater than those in 2015 and in the local financial turmoil caused by Brexit in 2016. Not surprisingly, the VIX, VHSI, and V2TX profiles were more volatile in the three subperiods than during the overall period. All risk index returns had the highest means and standard deviations in subperiod 3, which is consistent with what we observe in Fig. 2: The risk indices jumped up to a local peak in a very short period of time.

4.2. Network visualization

To present visual examples of financial networks, we took the network of the US market at two points in time for comparison. Fig. 3(a) is a graph of the US market network for 21 June 2012 (with a degree of 0.0426, a closeness of 0.5482, and a clustering coefficient of 0.0506), and Fig. 3(b) is a graph of the US market network for 24 August 2015 (at the beginning of subperiod 1, with

[3] Resource: Chicago Board Options Exchange(CBOE).
[4] Resource: HKE.
[5] Resource: EURO.

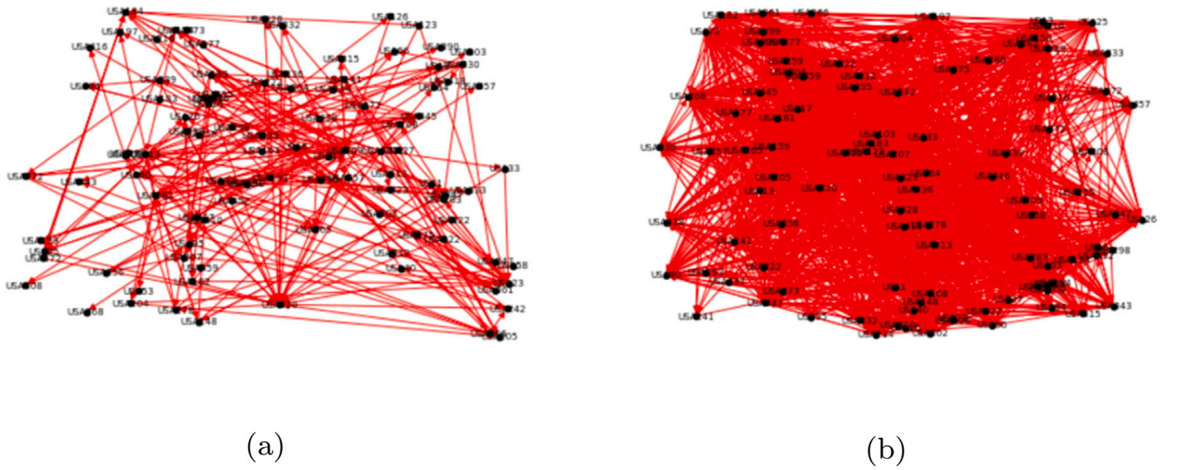


Fig. 3. Two example networks showing different pattern of network statistics.

a degree of 0.2818, a closeness of 0.0611, and a clustering coefficient of 0.225). Obviously, the density of the edges in Fig. 3(b) is much greater than that in Fig. 3(a). In accordance with the observed density in the two network graphs, the degree and the clustering coefficient of Fig. 3(b) were several times higher than that of the network in Fig. 3(a). On the other hand, the closeness is larger in Fig. 3(a). In short, we would expect to observe higher network connectedness during volatile periods, as is seen in Fig. 3(b) for subperiod 1.

5. Empirical results

5.1. Results of network statistics

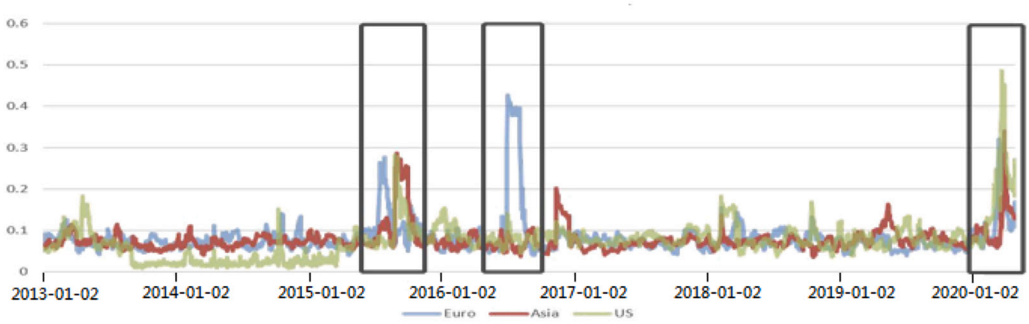
As we discussed in Section 3, we performed a rolling-window network analysis to describe financial network properties over time. We presented time series for the degree, closeness, and clustering coefficient to analyze the evolution of the dynamic financial networks represented by the adjacency matrices, A_{tij}. To better observe the trend of each network statistic, we separated Deg_t, CC_t, and Clo_t as described in Section 3.2, into three graphs in Fig. 4. There is a strong similarity between the time series of the degrees and of the clustering coefficients in the three regions. Specifically, in subperiod 1 and subperiod 3, the degrees of three region reached local peaks, whereas in subperiod 2, a big jump in the time series of degree was observed only in the European region. It is difficult to see any particular pattern in the closeness plots except in subperiod 3, where the closeness was particular low, indicating that the shortest path lengths in subperiod 3 were relatively small compared with the other periods. All the three network statistics revealed high connectedness in the financial networks in subperiod 3. In subperiods 1 and 2, the high connectedness was mainly reflected in the high values of the degree and clustering coefficient. Compared with subperiods 1 and 2, much higher connectedness is recorded in subperiod 3 due to higher values of the degree and clustering coefficient, indicating that the Covid-19 may have more severe impact than the crises happened in subperiod 1 and subperiod 2.

The financial network connectedness and the risk indices both reflected a certain level of systemic risk in the stock markets. Thus it was interesting to explore whether the network statistics followed patterns similar to those of the risk indices especially during crisis periods such as the three subperiods in this paper. Fig. 5 displays the time series of the degree and the respective risk index for each of the three regions. From the figure, we can observe that spikes in the risk indices and the degree occurred coherently, suggesting co-movement between risk indices and network statistics. In fact, both the degree and the risk index increased during the crisis periods, and when the crisis news was digested by the market, they returned to a normal level synchronously. From among the three regions, the degree of the US market appeared to have had the strongest relationship with its corresponding risk index, the VIX. Risk indices are commonly used to track market volatility or even systemic risk, making it interesting to explore causal relationships between network statistics and risk indices, and especially to investigate whether network statistics 'lead' risk indices.

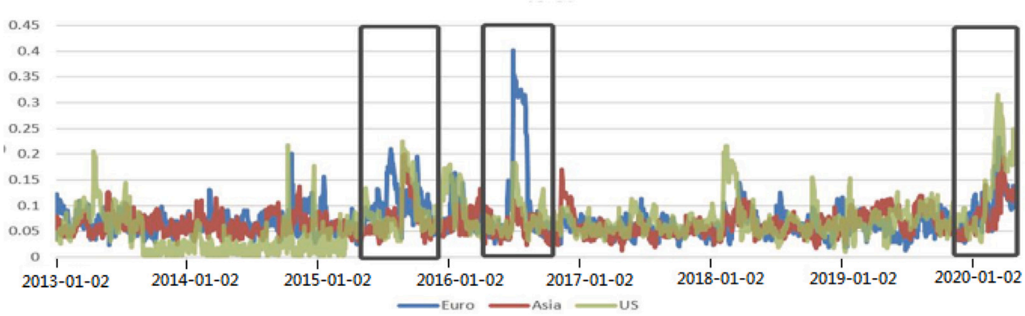
5.2. Within-region Granger causality

To study the causal relationship between network statistics and risk indices, we first focused on the relationship between the network statistics and the risk indices within the same region, for the US, Asia, and Europe. We considered the following autoregressive model to conduct Granger causality tests:

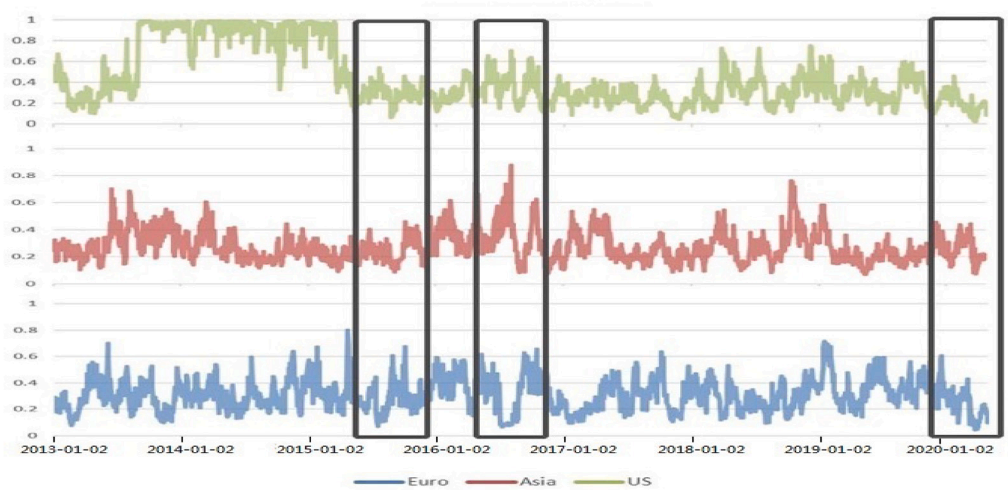
$$Risk_t = \sum_{i=1}^{q} \alpha_i Risk_{t-i} + \sum_{i=1}^{q} \beta_i RDeg_{t-i} + \sum_{i=1}^{q} \gamma_i RClo_{t-i} + \sum_{i=1}^{q} \delta_i RCC_{t-i} + u_t, \tag{6}$$



(a) degree time series plot



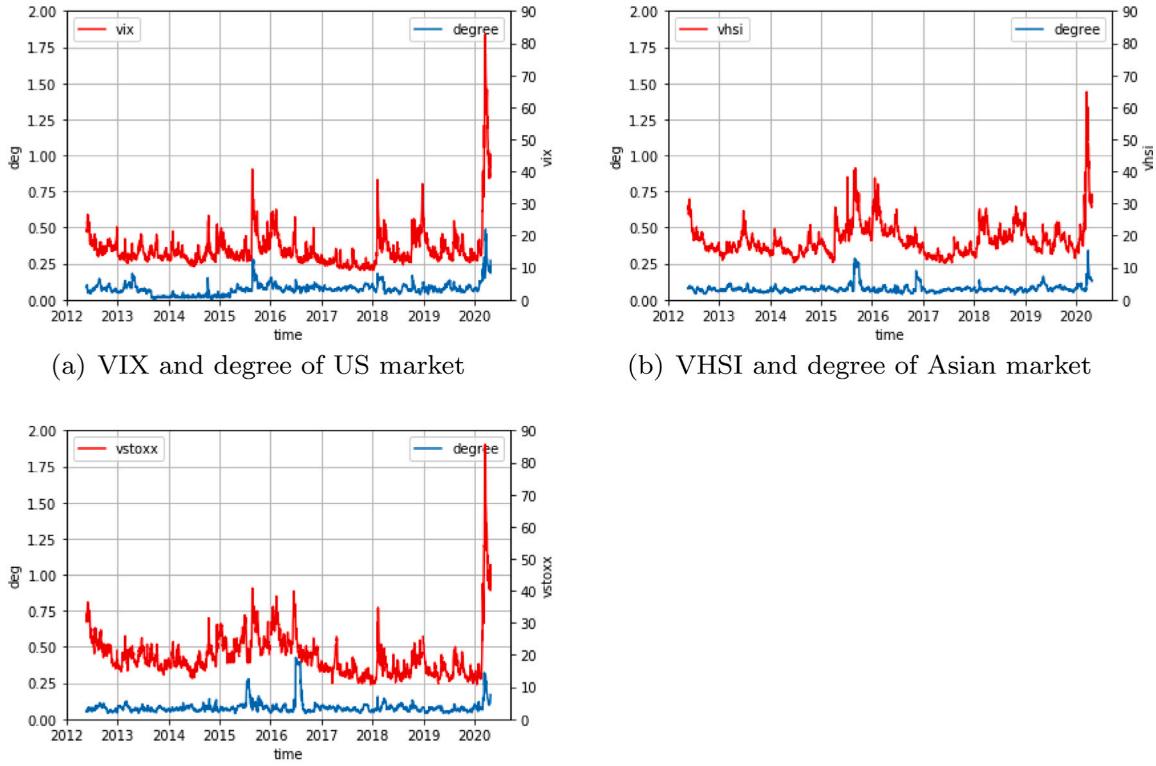
(b) clustering coefficient time series plot



(c) closeness time series plot

Fig. 4. Time series plots of the degree, closeness, and clustering coefficients for the study's three regional markets (US, Europe, and Asia) from Jan 2, 2013 through April 6, 2020. The black frames indicate the times around the three subperiods that we studied.

where the $Risk_t$ is the change of a risk index in a region on day t, and $RDeg_t$, $RClo_t$, RCC_t are the changes of regional network statistics of the degree, closeness, and the clustering coefficient, respectively. For example, in the US region, $Risk_t$ was defined as $\log\text{VIX}_t - \log\text{VIX}_{t-1}$, where VIX_t was the VIX at time t, and $RDeg_t, RClo_t, RCC_t$ were calculated based on the financial networks constructed using the stocks in the US region only. To examine daily relationships between the network statistics and the risk indices,



(a) VIX and degree of US market

(b) VHSI and degree of Asian market

(c) V2TX and degree of European market

Fig. 5. Comparison of the time series of the degree and the respective risk index from each of the three regional markets: the US and the VIX, Asia and the VHSI, and Europe and the V2TX.

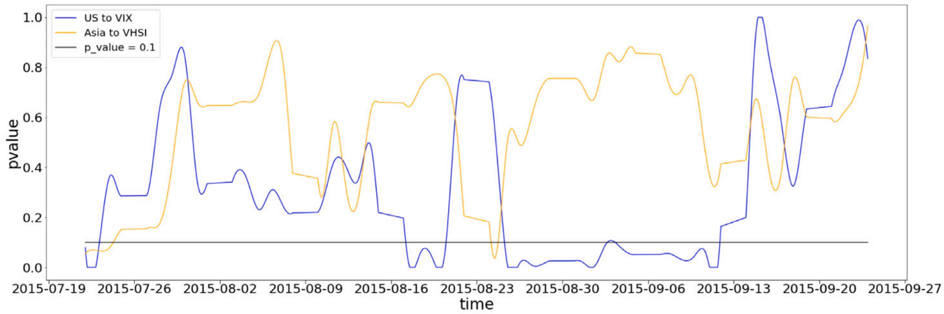
we used the rolling-window Granger causality test.[6] In that exercise, we set the length of the rolling window at 15 trading days, as discussed in Section 3.1. The null hypothesis for Eq. (6) is $\beta_i = \gamma_i = \delta_i = 0$, $i = 1, \ldots, q$, whose rejection represented sufficient evidence to claim that changes in the network statistics Granger-caused changes in the risk indices.

To study the relationship between network statistics and risk indicators during crisis periods, we focused on the three subperiods discussed earlier. As Fig. 4 shows, the network statistics for both the US and Asian appeared to change dramatically in subperiod 1. Therefore, it was meaningful to study the causal patterns between the network statistics in the two regions and the corresponding risk indices, in subperiod 1. We plotted the p-values of the Granger causality test of $\beta_i = \gamma_i = \delta_i = 0$, for the US market and the Asian market during subperiod 1, in Fig. 6(a), where the reference horizontal line is 0.1. The test statistics were computed on the basis of Granger causality test between the returns of the network statistics and the returns of the corresponding risk indices. We can see that at the beginning of that crisis (24 August 2015), the p-values for the US market declined to a point below 0.1 and then remained a very small value, close to 0, during most of the time that subperiod(24 August 2015 to 21 September 2015). The p-value for the Asian markets, reacting faster but more dramatically than those of US market, dropped sharply after the crisis broke out and rebounded immediately. Those findings show that the network statistics of the US market and the Asian market could have Granger-caused the profiles of the corresponding risk indices(the VIX and the VHSI).

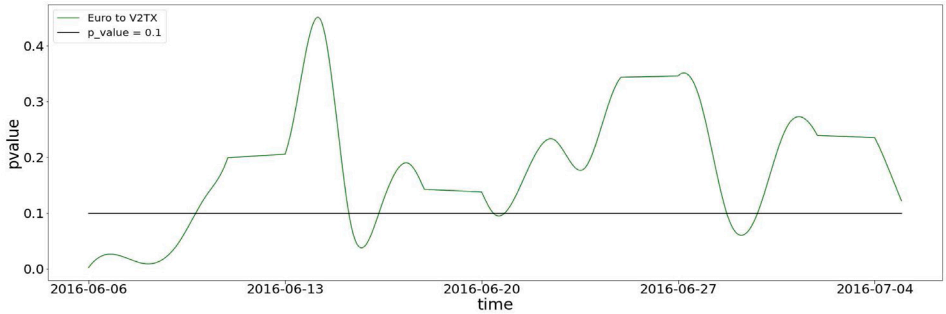
In subperiod 2 (13 June 2016 to 30 June 2016), the impact of Brexit was much greater on the European stock market than it was on the Asian and US markets. Therefore, we present the p-values of the Granger test between the European network statistics and the V2TX in Fig. 6(b). We found that the p-value curve were below 0.1 on the first few days of June 2016, which was well before the beginning of the crisis period, 13 June 2016, showing that the European network statistics appeared to lead a change in the V2TX values in response to the financial instability in subperiod 2.

In subperiod 3 (24 February 2020 to 21 March 2020), we found that on the initial day of the crisis (Feb 24 2020), the p-values of US market dropped sharply and reached the values below 0.1 while the p-values for Asian and European market were below 0.1

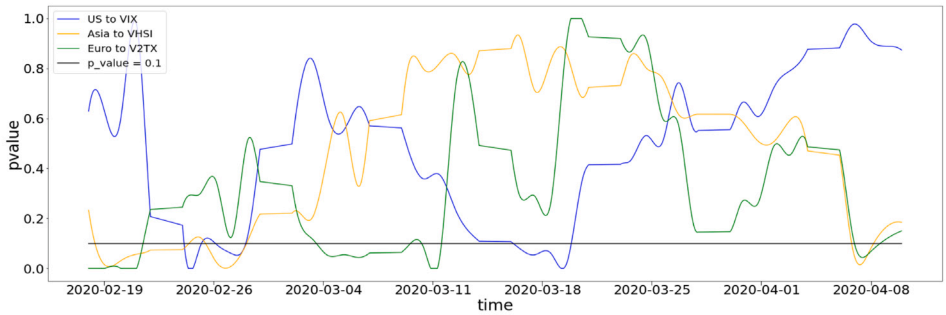
[6] The ADF stationarity test and JJ (Johansen) cointegration test were used to check whether Granger causality test can be used. The results are quite robust to the number of lags included.



(a) P-values of the Granger causality test for the US and Asian markets in subperiod 1



(b) P-values of the Granger causality test for the European market in subperiod 2



(c) P-values of the Granger causality test for the US, Asian and European markets in subperiod 3

Fig. 6. Time series plots of the *p*-values of the within-region Granger causality tests. To test whether a network statistic Granger-caused the corresponding risk index profile, we used a threshold *p*-value of 0.1 as a reference.

as early as mid-Feb 2020, which was well before the crisis(Feb 24 2020). This shows that network statistics could have been the Granger-cause of the corresponding risk indices in the early stage of the Covid-19 pandemic. Different regions appeared to have different time periods during which the network statistics had a significant leading effect on the corresponding risk indices. For example, Asian market's *p*-values remained below 0.1 until 2 March 2020, whereas the *p*-values in the European market began to increase on 23 Feb 2020. The US market's *p*-values rebounded just four day after the initial day of the crisis, on 28 Feb 2020, thus signifying the fact that the network statistics only led the US indices for four day. It is easy to find that in subperiod 3, compared with subperiod 1 and subperiod 2, the *p*-values of the three markets are significantly lower than 0.1, and the significance of the Granger causality lasted longer, indicating the global impact caused by the COVID-19 pandemic.

From the results of the within-regional Granger causality tests, we found that when a large financial market turbulence occurred, network statistics often appeared to be Granger-cause of risk index responses. To strengthen our conclusion, we checked whether there is a two-way Granger causality between network statistics and risk indicators. Consider the following model:

$$\begin{aligned}
\begin{pmatrix} VIX_t \\ Net_t^{US} \end{pmatrix} &= \sum_{i=1}^{q} \begin{pmatrix} \alpha_{11,i}, & \alpha'_{12,i} \\ \alpha_{21,i}, & \alpha'_{22,i} \end{pmatrix} \begin{pmatrix} VIX_{t-i} \\ Net_{t-i}^{US} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \\
\begin{pmatrix} VHSI_t \\ Net_t^{AS} \end{pmatrix} &= \sum_{i=1}^{q} \begin{pmatrix} \alpha_{11,i}, & \alpha'_{12,i} \\ \alpha_{21,i}, & \alpha'_{22,i} \end{pmatrix} \begin{pmatrix} VHSI_{t-i} \\ Net_{t-i}^{AS} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \\
\begin{pmatrix} V2TX_t \\ Net_t^{EU} \end{pmatrix} &= \sum_{i=1}^{q} \begin{pmatrix} \alpha_{11,i}, & \alpha'_{12,i} \\ \alpha_{21,i}, & \alpha'_{22,i} \end{pmatrix} \begin{pmatrix} V2TX_{t-i} \\ Net_{t-i}^{EU} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}
\end{aligned} \tag{7}$$

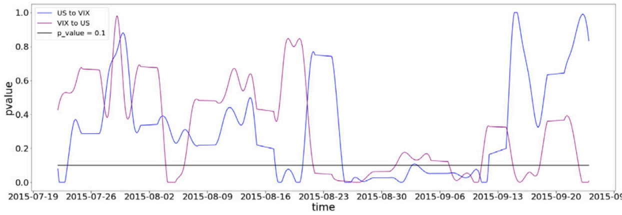
where Net_t^{US}, Net_t^{AS}, Net_t^{EU} are vectors of network statistics such as, $\left(Deg_t^{US}, Clo_t^{US}, CC_t^{US}\right)'$, $\left(Deg_t^{AS}, Clo_t^{AS}, CC_t^{AS}\right)'$ and $\left(Deg_t^{EU}, Clo_t^{EU}, CC_t^{EU}\right)'$, $\alpha_{11,i}$ and $\alpha_{21,i}$ are (1×1) dimensional vectors and $\alpha_{12,i}$ and $\alpha_{22,i}$ are (3×1) dimensional vectors. The acronym "AS" stands for Asia in the above vectors. The null hypothesis that the risk indicators $(VIX_t, VHSI_t, V2TX_t)$ do not Granger cause the network statistics $(Net_t^{US}, Net_t^{AS}, Net_t^{EU})$ is defined as $\alpha_{21,i} = 0$, and that the network statistics $(Net_t^{US}, Net_t^{AS}, Net_t^{EU})$ do not Granger cause the risk indicators $(VIX_t, VHSI_t, V2TX_t)$ is defined as $\alpha_{12,i} = 0$. To compare the lead–lag relationship between network statistics and risk indicators, Fig. 7 plots the p-value of the Granger test of $\alpha_{21,i} = 0$ and $\alpha_{12,i} = 0$.

For subperiod 1, as shown in Fig. 7(a), the network statistics of US market appeared to serve as leading indicators for the VIX as early as mid-Aug 2015, which was one week before the VIX Granger-caused the network statistics of US market, showing that the US network statistics may have predictive power for the VIX before the crisis broke out in subperiod 1. At the same time, the VHSI seems to Granger-cause network statistics in Asian market earlier (Fig. 7(b)). The two-way Granger causality test results showed that the leading effect for network statistics to risk indicators can be more obvious in the US market than in the Asian market. In Fig. 7(c), the leading impact that the network statistics of the European market had on the European index, the V2TX, appeared earlier than the impact of the V2TX did on European network statistics. For example, the p-value of "European to V2TX" curve was below 0.1 at the beginning of June 2016, which was earlier than when the V2TX Granger-caused network statistics in European market. For subperiod 3, the two-way Granger test results are shown in Figs. 7(d)–7(f). We find that the European network statistics can be used as a Granger-cause of the V2TX on 18 Feb 2020, which was one day earlier than the day when the V2TX Granger-caused the European network statistics, whereas the p-value "rebounded" earlier than that of the curve for "V2TX to European" network statistics. In contrast, the Asian network statistics remained to be Granger-cause of the VHSI until 2 March 2020, whereas the VHSI did not seem to Granger-cause the Asian network statistics in late February 2020 (Fig. 7(e)). For the US market, the US network statistics can serve as leading indicators when the crisis broke out on 24 February 2020, reacting faster than that of the curve "VIX to US".

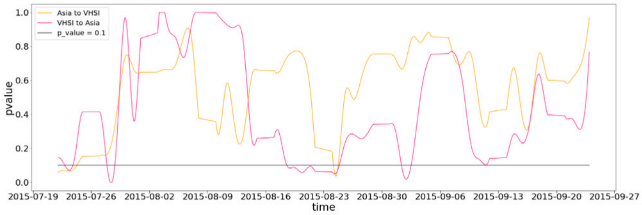
The results show that during the crisis periods, there was two-way Granger causality relationship between network statistics and risk indicators and that the time when network statistics Granger-caused the risk indicators can be earlier than the time when risk indicators Granger-caused the network statistics, indicating that before the crises broke out, the market had reacted in advance, and the correlation of trading behaviors between stocks had been strengthened (reflected in the increasing network statistics), eventually elevating the market volatility. Therefore, the network statistics can have leading-effect in the lead–lag relationship with risk indicators and have predictability for the financial market risk indicators. Hence, we posit that the p-values obtained from within-region Granger causality tests can be used as an early warning signal of substantial changes in market volatility and can be helpful for monitoring systemic risk in financial markets.

5.3. Cross-regional Granger causality

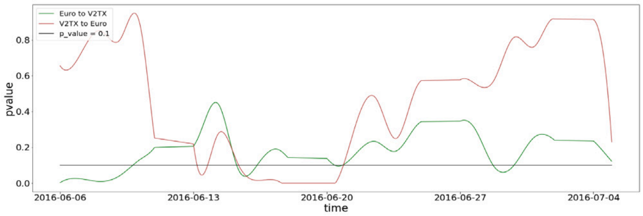
To determine whether the network statistics of a region can be used as the Granger-cause of other regional risk indices, we adopted cross-regional rolling-window Granger causality tests, which took as their independent variables the network statistics of other regions as well as the within-region networks statistics. The dependent variables were still changes in the risk indices, denoted by VIX_t, $V2TX_t$, and $VHSI_t$. We employed the following model in the three subperiods, and we used superscripts (US, AS, EU)



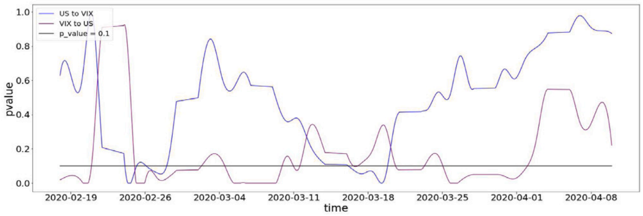
(a) P-values of the Granger causality test for the US market in subperiod 1



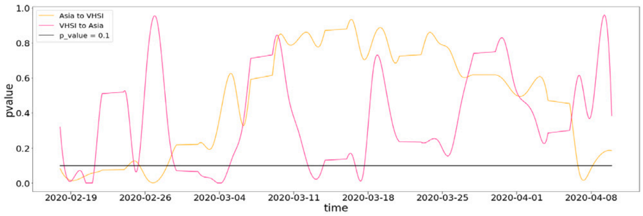
(b) P-values of the Granger causality test for the Asian market in subperiod 1



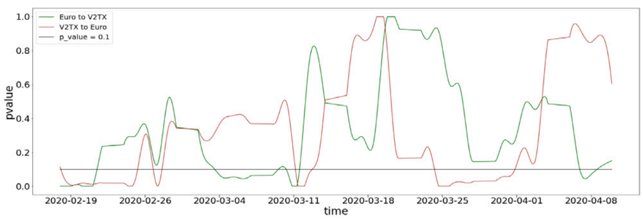
(c) P-values of the Granger causality test for the European market in subperiod 2



(d) P-values of the Granger causality test for the US market in subperiod 3



(e) P-values of the Granger causality test for the Asian market in subperiod 3



(f) P-values of the Granger causality test for the European market in subperiod 3

Fig. 7. Time series plots of *p*-value of the two-way Granger causality test.

to indicate which region in (US, Asia and European market) the network statistics are represented:

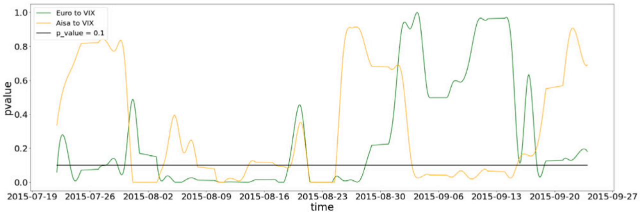
$$
\begin{aligned}
VIX_t &= \sum_1^q \alpha_i VIX_{t-i} + \sum_0^q \beta_i RDeg_{t-i}^{AS} + \sum_0^q \gamma_i RClo_{t-i}^{AS} + \sum_0^q \delta_i RCC_{t-i}^{AS} + \\
&\quad \sum_1^q \theta_i RDeg_{t-i}^{US} + \sum_1^q \phi_i RClo_{t-i}^{US} + \sum_0^q \omega_i RCC_{t-i}^{US} + u_{1t}, \\
VIX_t &= \sum_1^q \alpha_i VIX_{t-i} + \sum_0^q \beta_i RDeg_{t-i}^{EU} + \sum_0^q \gamma_i RClo_{t-i}^{EU} + \sum_0^q \delta_i RCC_{t-i}^{EU} + \\
&\quad \sum_1^q \theta_i RDeg_{t-i}^{US} + \sum_1^q \phi_i RClo_{t-i}^{US} + \sum_0^q \omega_i RCC_{t-i}^{US} + u_{2t}, \\
V2TX_t &= \sum_1^q \alpha_i V2TX_{t-i} + \sum_0^q \beta_i RDeg_{t-i}^{AS} + \sum_0^q \gamma_i RClo_{t-i}^{AS} + \sum_0^q \delta_i RCC_{t-i}^{AS} + \\
&\quad \sum_1^q \theta_i RDeg_{t-i}^{EU} + \sum_1^q \phi_i RClo_{t-i}^{EU} + \sum_0^q \omega_i RCC_{t-i}^{EU} + u_{3t}, \\
V2TX_t &= \sum_1^q \alpha_i V2TX_{t-i} + \sum_1^q \beta_i RDeg_{t-i}^{US} + \sum_1^q \gamma_i RClo_{t-i}^{US} + \sum_1^q \delta_i RCC_{t-i}^{US} + \\
&\quad \sum_1^q \theta_i RDeg_{t-i}^{EU} + \sum_1^q \phi_i RClo_{t-i}^{EU} + \sum_0^q \omega_i RCC_{t-i}^{EU} + u_{4t}, \\
VHSI_t &= \sum_1^q \alpha_i VHSI_{t-i} + \sum_1^q \beta_i RDeg_{t-i}^{US} + \sum_1^q \gamma_i RClo_{t-i}^{US} + \sum_1^q \delta_i RCC_{t-i}^{US} + \\
&\quad \sum_1^q \theta_i RDeg_{t-i}^{AS} + \sum_1^q \phi_i RClo_{t-i}^{AS} + \sum_0^q \omega_i RCC_{t-i}^{AS} + u_{5t}, \\
VHSI_t &= \sum_1^q \alpha_i VHSI_{t-i} + \sum_1^q \beta_i RDeg_{t-i}^{EU} + \sum_1^q \gamma_i RClo_{t-i}^{EU} + \sum_1^q \delta_i RCC_{t-i}^{EU} + \\
&\quad \sum_1^q \theta_i RDeg_{t-i}^{AS} + \sum_1^q \phi_i RClo_{t-i}^{AS} + \sum_0^q \omega_i RCC_{t-i}^{AS} + u_{6t},
\end{aligned} \tag{8}
$$

If the data for the network statistics appeared prior to the risk index response, we added the network statistics and risk indicators for the same day into the model (the independent variable of the traditional Granger causality tests must be a lag term). Therefore, in the first three equations of (8), because of the time zone difference, we included the network statistics at time t for the Granger causality test with VIX_t and $V2TX_t$. The null hypothesis for Eq. (8) is $\beta_i = \gamma_i = \delta_i = 0, \quad where \quad i = 0, \ldots, q$, whose rejection represented sufficient evidence to claim that changes in cross-regional network statistics Granger-caused changes in the risk indices.

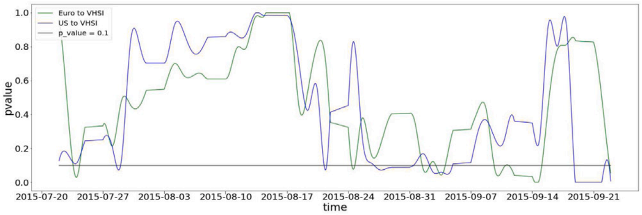
Figs. 8(a) and 8(b) show the time series plots of the p-values from the cross-regional Granger causality tests for subperiod 1. The network statistics of both European and Asian markets appeared to serve as leading indicators for the US's VIX index before the crisis period. For example, the p-values of the European market were below 0.1 from the beginning of August 2015, which was well before the beginning of the crisis period on 24 August 2015, showing that the European network statistics appeared to lead a change in the VIX values in response to the financial instability in subperiod 1 (Fig. 8(a)). On the contrary, in Fig. 8(b), the network statistics for both the US and European markets did not seem to Granger cause the Asian VHSI profile.

In Fig. 8(c), the impact that the network statistics of the Asian market had on the European index, the V2TX, was more obvious than the impact of US network statistics was, with the test for the hypothesis of "the European network statistics Granger-cause the V2TX response" being significant at the 10% level during many days of subperiod 2. For subperiod 3, the cross-regional test results are shown in Figs. 8(d), 8(e), and 8(f). Before the outbreak of the Covid-19 pandemic, the Asian network statistics can be used as the Granger-cause of the US's VIX response, whereas the p-values rebounded in the latter part of the subperiod. In contrast, the European network statistics remained to be the Granger-cause of a VIX response after the outbreak of the crisis (Fig. 8(d)). At the same time, the network statistics for both the US and European markets did not seem to work well as a Granger reason for the Asian VHSI profile (Fig. 8(e)). In Fig. 8(f), the results of the cross-regional Granger tests seem to indicate that the US network statistics are the Granger reason for the V2TX in subperiod 3.

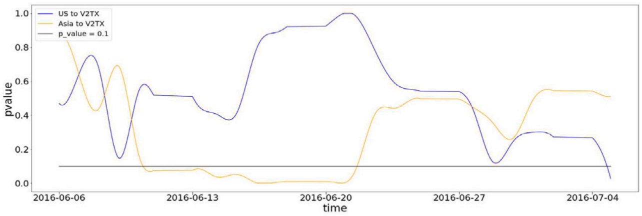
Unlike the results in the within-regional Granger causality tests where the causal effects from the network statistics had a time lag of one day, the cross-regional Granger causality tests can provide more flexible and complementary information, meaning that we can use network statistics from other regions on the same day because of the time differences among the US, Asian, and European regions. As shown in Figs. 6(a) and 8(a), the Asian and European network statistics at time t appeared to be more influential on US's VIX than the US's network statistics were at time $t-1$. When the US stock market is closed and followed by the occurrence of unfavorable news on a particular day, the news can be digested during the opening of the European and the Hong Kong stock markets and is reflected in the Asian and European network statistics. This may explain why the network statistics of the Asian and European markets can Granger-cause the VIX. From the risk management perspective, combining the within-regional and cross-regional network statistics can be more effective in tracking changes in risk indices and more helpful in monitoring systemic risk than simply using the within-region network statistics is.



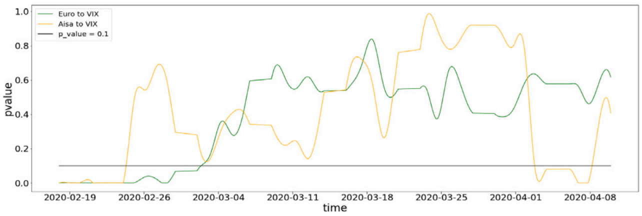
(a) P-values of the Granger causality test for the US market in subperiod 1



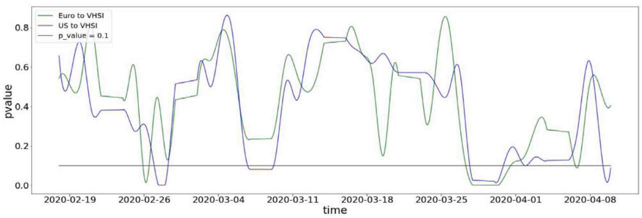
(b) P-values of the Granger causality test for the Asian market in subperiod 1



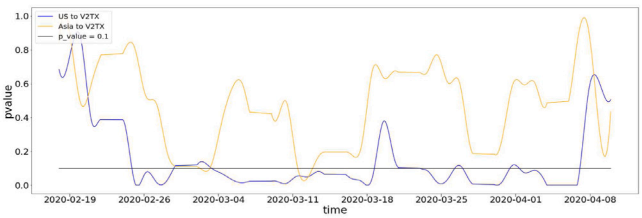
(c) P-values of the Granger causality test for the European market in subperiod 2



(d) P-values of the Granger causality test for the US market in subperiod 3



(e) P-values of the Granger causality test for the Asian market in subperiod 3



(f) P-values of the Granger causality test for the European market in subperiod 3

Fig. 8. Time series plots of the *p*-values of the cross-regional Granger causality tests in the three subperiods.

6. Conclusions

The network connectedness in financial markets plays an important role in quantifying systemic risk caused by contagion effects. In this study, we analyzed financial returns in three regional stock markets: the US, Europe, and Asia, along with their representative risk indices: the US's VIX, Europe's V2TX, and Asia's VHSI, to better understand how the financial network connectedness impacts the global market. We constructed stock networks over time in which network links were determined by the statistical results of tests to ascertain whether one stock return was Granger-caused by influence from another stock. We also calculated the network statistics, such as each network's degree, closeness, and clustering coefficient, to describe network properties of the financial networks and the connectedness characteristics of markets, over time. Finally, making use of the network statistics and risk indices, we adopted within-region and cross-regional Granger causality tests to better interpret such connectedness effects on stock markets. We focused particularly on three subperiods in the past decade, when three separate financial events which caused great panic in stock markets.

This paper contributes to our understanding of risk and risk management in international financial markets by using Granger causality tests to explore the relationship between changes in risk indices and changes in financial network statistics. For the first subperiod we studied, which was partly characterized by the depreciation of the Chinese yuan, the within-region network statistics of the US markets and the Asian markets appeared to have been the Granger cause of their region's corresponding risk index changes, in the US the VIX and in Asia the VHSI. For our study's subperiod 2, the network statistics for Europe appeared to have been the Granger cause of a V2TX response, when there was extra financial instability due to Brexit, the referendum for the United Kingdom leaving the European Union. For our study's subperiod 3, early in the Covid-19 pandemic, we again came to a similar conclusion — that each region's network statistics appeared to have been the Granger cause of changes in that region's corresponding risk index.

We also investigated whether the same causality effects could be found using cross-regional network statistics. Considering the time zone differences between different regions, we examined additional relationships and found that, in the first subperiod, the US market network statistics were a significant Granger cause of an Asian VHSI index response, and still maintained such a relationship after the outbreak of the crisis. However, the network statistics of European markets did not seem to have the same effect on the VHSI. In the second subperiod, the network statistics of the US market seemed to be the Granger cause of changes in Europe's V2TX index, and the Asian network statistics not only reacted quickly when the crisis broke out, but also possibly could have been used as an early warning signal for the crisis. In the third subperiod, Asian and European network statistics could be taken as the Granger cause of changes in the US's VIX, and the European network statistics continues to be the Granger cause of the VIX response after the outbreak of the Covid-19 pandemic.

In this paper, therefore, using more than 1300 stocks from the US, Asian and European financial markets, we have provided strong evidence that dynamic network statistics on financial market connectedness can be a leading indicator of common risk indices, such as the VIX, V2TX, and VHSI. Further research is warranted and should include financial connectedness in quantifying systemic risk in financial markets.

CRediT authorship contribution statement

Jianhua Song: Methodology, Data curation, Formal analysis, Interpreted the results, Writing – original draft. **Zhepei Zhang:** Methodology, Data curation, Formal analysis, Interpreted the results, Writing – original draft. **Mike K.P. So:** Conceptualization, Methodology, Interpreted the results, Finalized the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Stock list

See table below.

Table 1
Descriptive statistics of stock and risk index returns.

	US	Asia	Europe	VIX	VHSI	V2TX
The entire period from 2-Jan-13 to 24-Apr-20						
Mean	0.0453	0.0738	0.0575	0.3572	0.1683	0.2556
St.Dev.	1.8575	3.8037	3.0293	8.6146	5.8275	7.2297
Sub-period 1, 24-Aug-15 to 21-Sep-15						
Mean	−0.0079	−0.1654	−0.0293	−0.838	1.0887	0.0205
St.Dev.	2.0982	3.0846	2.2045	13.777	11.3168	11.1922
Sub-period 2, 13-Jun-16 to 30-Jun-16						
Mean	0.0248	0.0899	0.0646	0.7164	0.6903	−0.6951
St.Dev.	2.0636	3.9417	4.1499	18.0682	8.4652	8.7576
Sub-period 3, 24-Feb-20 to 20-Mar-20						
Mean	−2.1226	−1.4676	−2.0116	7.2	6.6244	9.1244
St.Dev.	6.7023	3.2658	5.0874	19.889	18.7105	18.9465

* In the US, Asian, and European markets, we calculated the averages of the sample means of stock returns in the three regions, and also the averages of the sample standard deviations of the stock returns during the overall period and each of the three subperiods.
** For the VIX, VHSI, and V2TX, we calculated the sample means and sample standard deviations of their returns during the corresponding periods.

Security code	Security name	Security code	Security name
002311.SZ	HAID GROUP	6305.T	HITACHI CONSTRUCTION MACHINERY
002304.SZ	YANGHE	6302.T	SUMITOMO HEAVY INDUSTRIES
002271.SZ	ORIENTAL YUHONG	6301.T	KOMATSU
002241.SZ	GOERTEK	6113.T	AMADA
002236.SZ	DAHUA INC	6103.T	OKUMA
002202.SZ	GOLDWIND	5901.T	TOYO SEIKAN GROUP HOLDINGS
002142.SZ	BANK OF NINGBO	5803.T	FUJIKURA
002032.SZ	SUPOR	5802.T	SUMITOMO ELECTRIC INDUSTRIES
600048.SH	PRE	5801.T	FURUKAWA ELECTRIC
002024.SZ	SUNING COMMERCE	5714.T	DOWA HOLDINGS
002007.SZ	HUALAN BIO.	1925.T	DAIWA HOUSE INDUSTRY
002001.SZ	NHU	5713.T	SUMITOMO METAL MINING
000895.SZ	SHUANGHUI	5711.T	MITSUBISHI MATERIALS
600036.SH	CMB	5707.T	TOHO ZINC
000783.SZ	CJZQ	5706.T	MITSUI MINING AND SMELTING
000776.SZ	GF SECURITIES	5631.T	JAPAN STEEL WORKS
000725.SZ	BOE	5541.T	PACIFIC METALS
600031.SH	SANY	5411.T	JFE HOLDINGS
000596.SZ	GUJING DISTILLERY	5406.T	KOBE STEEL
000338.SZ	WEICHAI POWER	5401.T	NIPPON STEEL
000157.SZ	ZOOMLION	5333.T	NGK INSULATORS
000001.SZ	PAB	1812.T	KAJIMA
601988.SH	BANK OF CHINA	5332.T	TOTO
601939.SH	CCB	5301.T	TOKAI CARBON
600028.SH	SINOPEC CORP.	5233.T	TAIHEIYO CEMENT
601857.SH	PETROCHINA	5232.T	SUMITOMO OSAKA CEMENT
601688.SH	HTSC	5214.T	NIPPON ELECTRIC GLASS
601668.SH	CSCEC	5202.T	NIPPON SHEET GLASS
601628.SH	CHINA LIFE	5201.T	AGC
601601.SH	CPIC	5108.T	BRIDGESTONE
601398.SH	ICBC	5101.T	THE YOKOHAMA RUBBER
600016.SH	CMBC	5020.T	ENEOS

(*Continued on next page*)

Security code	Security name	Security code	Security name
601328.SH	BANKCOMM	1808.T	HASEKO
601318.SH	PING AN OF CHINA	5019.T	IDEMITSU KOSAN
601288.SH	AGRICULTURAL BANK OF CHINA	4911.T	SHISEIDO
601186.SH	CRCC	4902.T	KONICA MINOLTA
601166.SH	INDUSTRIAL BANK	4901.T	FUJIFILM
600837.SH	HAITONG SECURITIES	4755.T	RAKUTEN GROUP
600009.SH	SIA	4751.T	CYBERAGENT
600585.SH	ACC	4704.T	TREND MICRO
600519.SH	KWEICHOW MOUTAI	4689.T	Z
600340.SH	CFLD	4631.T	DIC
600276.SH	HR	4578.T	OTSUKA
300015.SZ	AIER EYE HOSPITAL	1803.T	SHIMIZU
002594.SZ	BYD	4568.T	DAIICHI SANKYO
002493.SZ	RSPC	4543.T	TERUMO
0011.HK	HANG SENG BANK	4523.T	EISAI
0010.HK	HANG LUNG GROUP	4519.T	CHUGAI PHARMACEUTICAL
0008.HK	PCCW	4507.T	SHIONOGI
0006.HK	POWER ASSETS	4506.T	SUMITOMO DAINIPPON PHARMA
0005.HK	HSBC HOLDINGS	4503.T	ASTELLAS PHARMA
3988.HK	BANK OF CHINA	4502.T	TAKEDA PHARMACEUTICAL
3968.HK	CM BANK	4452.T	KAO
3328.HK	BANKCOMM	4324.T	DENTSU GROUP
2628.HK	CHINA LIFE	1802.T	OBAYASHI
2600.HK	CHALCO	4272.T	NIPPON KAYAKU
2388.HK	BOC HONG KONG	4208.T	UBE INDUSTRIES
2318.HK	PING AN	4188.T	MITSUBISHI CHEMICAL
1898.HK	CHINA COAL	4183.T	MITSUI CHEMICALS
1800.HK	CHINA COMM CONS	4151.T	KYOWA KIRIN
0004.HK	WHARF HOLDINGS	4063.T	SHIN-ETSU CHEMICAL
1398.HK	ICBC	4061.T	DENKA
1088.HK	CHINA SHENHUA	4043.T	TOKUYAMA
0941.HK	CHINA MOBILE	4042.T	TOSOH
0939.HK	CCB	4021.T	NISSAN CHEMICAL
0883.HK	CNOOC	1801.T	TAISEI
0857.HK	PETROCHINA	4005.T	SUMITOMO CHEMICAL
0836.HK	CHINA RES POWER	4004.T	SHOWA DENKO
0762.HK	CHINA UNICOM	3861.T	OJI HOLDINGS
0728.HK	CHINA TELECOM	3436.T	SUMCO
0700.HK	TENCENT	3407.T	ASAHI KASEI
0003.HK	HK & CHINA GAS	3405.T	KURARAY
0688.HK	CHINA OVERSEAS	3402.T	TORAY INDUSTRIES
0683.HK	KERRY PPT	3401.T	TEIJIN
0494.HK	LI & FUNG	3382.T	SEVEN & I
0390.HK	CHINA RAILWAY	3105.T	NISSHINBO
0388.HK	HKEX	1721.T	COMSYS
0386.HK	SINOPEC CORP	3103.T	UNITIKA
0330.HK	ESPRIT HOLDINGS	3101.T	TOYOBO
0293.HK	CATHAY PAC AIR	3099.T	ISETAN MITSUKOSHI
0151.HK	WANT WANT CHINA	3086.T	J.FRONT RETAILING
0144.HK	CHINA MER PORT	2914.T	JAPAN TOBACCO
0002.HK	CLP HOLDINGS	2871.T	NICHIREI
0101.HK	HANG LUNG PPT	2802.T	AJINOMOTO
0087.HK	SWIRE PACIFIC B	2801.T	KIKKOMAN
0083.HK	SINO LAND	9984.T	SOFTBANK GROUP
0069.HK	SHANGRI-LA ASIA	9983.T	FAST RETAIL-DRS
0066.HK	MTR CORPORATION	9766.T	KONAMI HOLDINGS

(*Continued on next page*)

Security code	Security name	Security code	Security name
0023.HK	BANK OF E ASIA	9735.T	SECOM
0019.HK	SWIRE PACIFIC A	9613.T	NTT DATA
0017.HK	NEW WORLD DEV	9602.T	TOHO
0016.HK	SHK PPT	9532.T	OSAKA GAS
0012.HK	HENDERSON LAND	9531.T	TOKYO GAS
0001.HK	CKH HOLDINGS	9503.T	KANSAI ELECTRIC POWER
002380.KS	KCC	2768.T	SOJITZ
086900.KS	MEDYTOX	9502.T	CHUBU ELECTRIC POWER
086790.KS	HANA FINANCIAL GR	9501.T	TOKYO ELECTRIC POWER
086280.KS	HYUNDAI GLOVIS	9437.T	NTT DOCOMO
078930.KS	GS HOLDINGS	9433.T	KDDI
071050.KS	KIH	9432.T	NIPPON TELEGRAPH & TELEPHONE
069960.KS	HYUNDAI DEPARTMENT	9412.T	SKY PERFECT JSAT HOLDINGS
066570.KS	LG ELECTRONICS INC.	9301.T	MITSUBISHI LOGISTICS
000720.KS	HYUNDAI ENG & CONST	9202.T	ANA
051910.KS	LG CHEM	9107.T	KAWASAKI KISEN KAISHA
051900.KS	LG H&H	9104.T	MITSUI O.S.K.LINES
051600.KS	KEPCO KPS	2531.T	TAKARA
048260.KS	OSSTEMIMPLANT	1605.T	INPEX
047810.KS	KOREA AEROSPACE	9101.T	NIPPON YUSEN KABUSHIKI KAISHA
036570.KS	NCSOFT CORPORATION	9064.T	YAMATO
035420.KS	NAVER	9062.T	NIPPON EXPRESS
035250.KS	KANGWON LAND, INC.	9022.T	CENTRAL JAPAN RAILWAY
034730.KS	SK	9021.T	WEST JAPAN RAILWAY
000660.KS	SK HYNIX	9020.T	EAST JAPAN RAILWAY
034220.KS	LG DISPLAY	9009.T	KEISEI ELECTRIC RAILWAY
033780.KS	KT&G	9008.T	KEIO
032830.KS	SAMSUNG LIFE	9007.T	ODAKYU ELECTRIC RAILWAY
030200.KS	KT	9005.T	TOKYU
030000.KS	CHEIL WORLDWIDE	2503.T	KIRIN
029780.KS	SAMSUNG CARD	9001.T	TOBU RAILWAY
024110.KS	IBK	8830.T	SUMITOMO REALTY & DEVELOPMENT
021240.KS	COWAY	8804.T	TOKYO TATEMONO
018880.KS	HANON SYSTEMS	8802.T	MITSUBISHI ESTATE
000270.KS	KIA MTR	8801.T	MITSUI FUDOSAN
017670.KS	SK TELECOM	8795.T	T&D
016360.KS	SAMSUNG SECU	8766.T	TOKIO MARINE HOLDINGS
015760.KS	KEPCO	8750.T	DAI-ICHI LIFE HOLDINGS
012750.KS	S-1	8729.T	SONY FINANCIAL
011780.KS	KUMHO PETRO CHEM	8725.T	MS&AD INSURANCE
011170.KS	LOTTE CHEMICAL CORP	2502.T	ASAHI
011070.KS	LG INNOTEK	8630.T	SOMPO
010950.KS	S-OIL	8628.T	MATSUI SECURITIES
010130.KS	KOR ZINC	8604.T	NOMURA HOLDINGS
000210.KS	DAELIM IND	8601.T	DAIWA SECURITIES
010060.KS	OCI	8411.T	MIZUHO FINANCIAL GROUP
009830.KS	HANWHA SOLUTIONS	8355.T	SHIZUOKA BANK
009540.KS	KSOE	8354.T	FUKUOKA FINANCIAL
009240.KS	HANSSEM	8331.T	CHIBA BANK
009150.KS	SAMSUNG ELEC MECH	8316.T	SUMITOMO MITSUI FINANCIAL GROUP
007070.KS	GS RETAIL	8309.T	SUMITOMO MITSUI TRUST
006800.KS	MIRAE ASSET DAEWOO	2501.T	SAPPORO
006400.KS	SAMSUNG SDI	8308.T	RESONA

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Security code	Security name	Security code	Security name
005930.KS	SAMSUNG ELEC	8306.T	MITSUBISHI UFJ FINANCIAL GROUP
000120.KS	CJ LOGISTICS	8304.T	AOZORA BANK
005830.KS	DB INSURANCE	8303.T	SHINSEI BANK
005490.KS	POSCO	8267.T	AEON
005380.KS	HYUNDAI MTR	8253.T	CREDIT SAISON
004990.KS	LOTTE	8252.T	MARUI GROUP
004800.KS	HYOSUNG	8233.T	TAKASHIMAYA
004370.KS	NONGSHIM	8058.T	MITSUBISHI
004170.KS	SHINSEGAE	8053.T	SUMITOMO
002790.KS	AMORE GROUP	2432.T	DENA
000100.KS	YUHAN	8035.T	TOKYO ELECTRON
C61U.SG	CapitaComm	8031.T	MITSUI
C52.SG	COMFORTDELGRO	8028.T	FAMILYMART
C38U.SG	CapitaMall	8015.T	TOYOTA TSUSHO
C31.SG	CAPITALAND LIMITED	8002.T	MARUBENI
C09.SG	CITYDEV	8001.T	ITOCHU
C07.SG	JARDINE C&C	7951.T	YAMAHA
Z74.SG	SINGTEL	7912.T	DAI NIPPON PRINTING
BS6.SG	YANGZIJIANG SHIPBLDG HLDGS LTD	7911.T	TOPPAN PRINTING
Y92.SG	THBEV	7832.T	BANDAI NAMCO HOLDINGS
V03.SG	VENTURE	2413.T	M3
U96.SG	Sembcorp Industries	7762.T	CITIZEN WATCH
U14.SG	UOL	7752.T	RICOH
U11.SG	UOB	7751.T	CANON
T39.SG	SPH	7735.T	SCREEN HOLDINGS
S68.SG	SINGAPORE EXCHANGE	7733.T	OLYMPUS
S63.SG	ST ENGG	7731.T	NIKON
S58.SG	SATS	7272.T	YAMAHA MOTOR
O39.SG	OCBC BK	7270.T	SUBARU
BN4.SG	KEP CORP	7269.T	SUZUKI MOTOR
N2IU.SG	MapletreeCom	7267.T	HONDA MOTOR
M44U.SG	MapletreeLog	2282.T	NH FOODS
J37.SG	JSH 500US$	7261.T	MAZDA MOTOR
J36.SG	JMH 400US$	7211.T	MITSUBISHI MOTORS
H78.SG	HONGKONG LAND HOLDINGS LIMITED	7205.T	HINO MOTORS
F34.SG	WILMAR	7203.T	TOYOTA MOTOR
D05.SG	DBS	7202.T	ISUZU MOTORS
D01.SG	DAIRYFARM 900 US$	7201.T	NISSAN MOTOR
C6L.SG	SIA	7013.T	IHI
A17U.SG	Ascendasreit	7012.T	KAWASAKI HEAVY INDUSTRIES
COF.N	CAPITAL ONE FINANCIAL	7011.T	MITSUBISHI HEAVY INDUSTRIES
CNP.N	CENTERPOINT	7004.T	HITACHI ZOSEN
CNC.N	CENTENE	2269.T	MEIJI
CMS.N	CMS ENERGY	7003.T	MITSUI E&S
CMI.N	CUMMINS	6988.T	NITTO DENKO
CMG.N	CHIPOTLE MEXICAN GRILL	6976.T	TAIYO YUDEN
CME.O	CME	6971.T	KYOCERA
CMCSA.O	COMCAST A	6954.T	FANUC
CMA.N	COMERICA	6952.T	CASIO COMPUTER
CLX.N	CLOROX	6902.T	DENSO
ADI.O	ANALOG DEVICES	6857.T	ADVANTEST
CL.N	COLGATE PALMOLIVE	6841.T	YOKOGAWA ELECTRIC

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Security code	Security name	Security code	Security name
CINF.O	CINCINNATI FINANCIAL	6770.T	ALPS ALPINE
CI.N	CIGNA	2002.T	NISSHIN SEIFUN
CHTR.O	CHARTER COMMUNICATIONS	6762.T	TDK
CHRW.O	CH ROBINSON WORLDWIDE	6758.T	SONY
CHD.N	CHURCH & DWIGHT	6752.T	PANASONIC
CF.N	CF INDUSTRIES	6724.T	SEIKO EPSON
CERN.O	CERNER	6703.T	OKI ELECTRIC INDUSTRY
CE.N	CELANESE	6702.T	FUJITSU
CDNS.O	CADENCE	6701.T	NEC
ADBE.O	ADOBE	6674.T	GS YUASA
CCL.N	CARNIVAL	6645.T	OMRON
CCI.N	CROWN CASTLE INT	6506.T	YASKAWA ELECTRIC
CBRE.N	CBRE	1963.T	JGC HOLDINGS
CBOE.BAT	CBOE GLOBAL MARKETS	6504.T	FUJI ELECTRIC
CB.N	CHUBB LTD	6503.T	MITSUBISHI ELECTRIC
CAT.N	CATERPILLAR	6501.T	HITACHI
CAH.N	CARDINAL HEALTH	6479.T	MINEBEA MITSUMI
CAG.N	CONAGRA BRANDS	6473.T	JTEKT
C.N	CITIGROUP	6472.T	NTN
BXP.N	BOSTON PROPERTIE	6471.T	NSK
ACN.N	ACCENTURE-A	6367.T	DAIKIN INDUSTRIES
BWA.N	BORGWARNER	6361.T	EBARA
BSX.N	BOSTON SCIENTIFIC	6326.T	KUBOTA
BRK_B.N	BERKSHIRE HATHAWAY-B	1928.T	SEKISUI HOUSE
BR.N	BROADRIDGE FINANCIAL SOLUTIONS	1332.T	NIPPON SUISAN KAISHA
BMY.N	BRISTOL-MYERS SQUIBB	NFLX.O	NETFLIX
BLL.N	BALL	NEM.N	NEWMONT
BLK.N	BLACKROCK	NEE.N	NEXTERA ENERGY
BKNG.O	BOOKING	NDAQ.O	NASDAQ
BK.N	BANK OF NEW YORK MELLON	NBL.O	NOBLE ENERGY
BIIB.O	BIOGEN	AMD.O	ADVANCED MICRO DEVICES
ABT.N	ABBOTT LABORATORIES	AAPL.O	APPLE
BF_B.N	BROWN-FORMAN-B	MYL.O	MYLAN
BEN.N	FRANKLIN RESOURCES	MXIM.O	MAXIM INTEGRATED PRODUCTS
BDX.N	BECTON DICKINSON	MU.O	MICRON TECHNOLOGY
BBY.N	BEST BUY	MTD.N	METTLER-TOLEDO
BAX.N	BAXTER INTERNATIONAL	MTB.N	M&T BANK
BAC.N	BANK OF AMERICA	MSI.N	MOTOROLA SOLUTIONS
BA.N	BOEING	MSFT.O	MICROSOFT
AZO.N	AUTOZONE	MSCI.N	MSCI
AXP.N	AMERICAN EXPRESS	MS.N	MORGAN STANLEY
AWK.N	AMERICAN WATER WORKS	MRO.N	MARATHON OIL
ABMD.O	ABIOMED	AMAT.O	APPLIED MATERIAL
AVY.N	AVERY DENNISON	MRK.N	MERCK
AVGO.O	BROADCOM	MPC.N	MARATHON PETROLEUM
AVB.N	AVALONBAY COMMUNITIES	MOS.N	MOSAIC
ATVI.O	ACTIVISION BLIZZARD	MO.N	ALTRIA
ZION.O	ZIONS BANCORPORATION	MNST.O	MONSTER BEVERAGE
ZBRA.O	ZEBRA	MMM.N	3M
ZBH.N	ZIMMER BIOMET	MMC.N	MARSH & MCLENNAN
YUM.N	YUM BRANDS	MLM.N	MARTIN MARIETTA
XYL.N	XYLEM	MKTX.O	MARKETAXESS
XRX.N	XEROX	MKC.N	MCCORMICK & CO-NON VTG SHRS
XRAY.O	DENTSPLY SIRONA	ALXN.O	ALEXION PHARM

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Security code	Security name	Security code	Security name
XOM.N	EXXON MOBIL	MHK.N	MOHAWK INDUSTRIES
XLNX.O	XILINX	MGM.N	MGM RESORTS INTERNATIONAL
XEL.O	XCEL ENERGY	MET.N	METLIFE
ATO.N	ATMOS ENERGY	MDT.N	MEDTRONIC
WYNN.O	WYNN RESORTS	MDLZ.O	MONDELEZ INTERNATIONAL
WY.N	WEYERHAEUSER	MCO.N	MOODYS
WU.N	WESTERN UNION	MCK.N	MCKESSON
WRB.N	BERKLEY W R	MCHP.O	MICROCHIP TECHNOLOGY
WMT.N	WALMART	MCD.N	MCDONALDS
WMB.N	WILLIAMS	MAS.N	MASCO
WM.N	WASTE MANAGEMENT	ALL.N	ALLSTATE
WLTW.O	WILLIS TOWERS WATSON	MAR.O	MARRIOTT INTERNATIONAL
WHR.N	WHIRLPOOL	MAA.N	MID AMERICA APARTMENT COMMUNITIES
WFC.N	WELLS FARGO	MA.N	MASTERCARD CLASS A
ARE.N	ALEXANDRIA REAL ESTATE EQUITIES	LYV.N	LIVE NATION ENTERTAINMENT
WELL.N	WELLTOWER	LYB.N	LYONDELLBASELL INDUSTRIES
WEC.N	WEC ENERGY	LVS.N	LAS VEGAS SANDS
WDC.O	WESTERN DIGITAL	LUV.N	SOUTHWEST AIRLINES
WBA.O	WALGREENS BOOTS ALLIANCE	LRCX.O	LAM RESEARCH
WAT.N	WATERS	LOW.N	LOWES
WAB.N	WESTINGHOUSE AIR BRAKE TECHNOLOGIES	LNT.O	ALLIANT ENERGY
VZ.N	VERIZON COMMUNICATIONS	ALK.N	ALASKA AIR
VTR.N	VENTAS	LNC.N	LINCOLN NATIONAL
VRTX.O	VERTEX PHARMACEUTICALS	LMT.N	LOCKHEED MARTIN
VRSN.O	VERISIGN	LLY.N	ELI LILLY
APTV.N	APTIV	LKQ.O	LKQ
VRSK.O	VERISK ANALYTICS	LHX.N	L3HARRIS TECHNOLOGIES
VNO.N	VORNADO REALTY	LH.N	LABORATORY OF AMERICA
VMC.N	VULCAN MATERIALS	LEN.N	LENNAR
VLO.N	VALERO ENERGY	LEG.N	LEGGETT & PLATT
VIAC.O	VIACOMCBS	LDOS.N	LEIDOS
VFC.N	VF	LB.N	L BRANDS
VAR.N	VARIAN MEDICAL SYSTEMS	ALGN.O	ALIGN TECHNOLOGY
V.N	VISA	L.N	LOEWS
USB.N	US BANCORP	KSU.N	KANSAS CITY SOUTHERN
URI.N	UNITED RENTALS	KSS.N	KOHLS
APH.N	AMPHENOL	KR.N	KROGER
UPS.N	UNITED PARCEL SERVICE	KO.N	COCA COLA
UNP.N	UNION PACIFIC	KMX.N	CARMAX
UNM.N	UNUM	KMI.N	KINDER MORGAN
UNH.N	UNITEDHEALTH	KMB.N	KIMBERLY CLARK
ULTA.O	ULTA BEAUTY	KLAC.O	KLA
UHS.N	UNIVERSAL HEALTH SERVICES	KIM.N	KIMCO REALTY
UDR.N	UDR	ALB.N	ALBEMARLE
UAL.O	UNITED AIRLINES	KEY.N	KEYCORP NEW
UAA.N	UNDER ARMOUR-A	K.N	KELLOGG
TXT.N	TEXTRON	JWN.N	NORDSTROM
APD.N	AIR PRODUCTS & CHEMICALS	JPM.N	JPMORGAN CHASE
TXN.O	TEXAS INSTRUMENTS	JNPR.N	JUNIPER NETWORKS

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Security code	Security name	Security code	Security name
TTWO.O	TAKE TWO INTERACTIVE SOFTWARE	JNJ.N	JOHNSON & JOHNSON
TT.N	TRANE TECHNOLOGIES	JKHY.O	JACK HENRY & ASSOCIATES
TSN.N	TYSON FOODS	JCI.N	JOHNSON CONTROLS INTERNATIONAL
TSCO.O	TRACTOR SUPPLY	JBHT.O	JB HUNT TRANSPORT SERVICES
TRV.N	TRAVELERS	J.N	JACOBS ENGINEERING
TROW.O	PRICE T ROWE	AKAM.O	AKAMAI
TPR.N	TAPESTRY	IVZ.N	INVESCO
TMUS.O	T-MOBILE US	ITW.N	ILLINOIS TOOL WORKS
TMO.N	THERMO FISHER SCIENTIFIC	IT.N	GARTNER
APA.N	APA	ISRG.O	INTUITIVE SURGICAL
ABC.N	AMERISOURCEBERGEN	IRM.N	IRON MOUNTAIN
TJX.N	TJX	IPGP.O	IPG PHOTONICS
TIF.N	TIFFANY	IPG.N	INTERPUBLIC
TGT.N	TARGET	IP.N	INTERNATIONAL PAPER
TFX.N	TELEFLEX	INTU.O	INTUIT
TFC.N	TRUIST FINANCIAL	INTC.O	INTEL
TEL.N	TE CONNECTIVITY	AJG.N	ARTHUR J. GALLAGHER
TDG.N	TRANSDIGM	INCY.O	INCYTE
TAP.N	MOLSON COORS BEVERAGE	ILMN.O	ILLUMINA
T.N	AT&T	IFF.N	INTL FLAVORS & FRAGRANCES
SYY.N	SYSCO	IEX.N	IDEX
AOS.N	AO SMITH	IDXX.O	IDEXX LABORATORIES
SYK.N	STRYKER	ICE.N	INTERCONTINENTALEX-CHANGE
SWKS.O	SKYWORKS SOLUTIONS	IBM.N	IBM
SWK.N	STANLEY BLACK & DECKER	HUM.N	HUMANA
STZ.N	CONSTELLATION BRANDS-A	HSY.N	HERSHEY
STX.O	SEAGATE TECHNOLOGY	HST.N	HOST HOTELS & RESORTS
STT.N	STATE STREET	AIZ.N	ASSURANT
STE.N	STERIS	HSIC.O	HENRY SCHEIN
SRE.N	SEMPRA ENERGY	HRL.N	HORMEL FOODS
SPGI.N	S&P GLOBAL	HRB.N	H&R BLOCK
SPG.N	SIMON PROPERTY	HPQ.N	HP
AON.N	AON	HP.N	HELMERICH & PAYN
SO.N	SOUTHERN	HON.O	HONEYWELL INTERNATIONAL
SNPS.O	SYNOPSYS	HOLX.O	HOLOGIC
SNA.N	SNAP-ON	HOG.N	HARLEY-DAVIDSON
SLG.N	SL GREEN REALTY	HII.N	HUNTINGTON INGALLS INDUSTRIES
SLB.N	SCHLUMBERGER	HIG.N	HARTFORD FINANCIAL SERVICES
SJM.N	THE J.M. SMUCKER	AIV.N	APARTMENT INVESTMENT & MANAGEMENT
SIVB.O	SVB FINANCIAL	AAP.N	ADVANCE AUTO PAR
SHW.N	SHERWIN-WILLIAMS	HFC.N	HOLLYFRONTIER
SEE.N	SEALED AIR	HES.N	HESS
SCHW.N	SCHWAB CHARLES	HD.N	HOME DEPOT
ANTM.N	ANTHEM	HCA.N	HCA HEALTHCARE
SBUX.O	STARBUCKS	HBI.N	HANESBRANDS
SBAC.O	SBA COMMUNICATIONS	HBAN.O	HUNTINGTON BANCSHARES
RTX.N	RAYTHEON TECHNOLOGIES	HAS.O	HASBRO
RSG.N	REPUBLIC SERVICES	HAL.N	HALLIBURTON
ROST.O	ROSS STORES	GWW.N	W.W. GRAINGER
ROP.N	ROPER TECHNOLOGIES	GS.N	GOLDMAN SACHS

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Security code	Security name	Security code	Security name
ROL.N	ROLLINS	AIG.N	AMERICAN INTERNATIONAL
ROK.N	ROCKWELL AUTOMATION	GRMN.O	GARMIN
RMD.N	RESMED	GPS.N	THE GAP
RL.N	RALPH LAUREN	GPN.N	GLOBAL PAYMENTS
ANSS.O	ANSYS	GPC.N	GENUINE PARTS
RJF.N	RAYMOND JAMES FINANCIAL	GOOGL.O	ALPHABET-CL-A
RHI.N	ROBERT HALF INTERNATIONAL	GM.N	GENERAL MOTORS
RF.N	REGIONS FINANCIAL	GLW.N	CORNING
REGN.O	REGENERON PHARMACEUTICALS	GL.N	GLOBE LIFE
REG.O	REGENCY CENTERS	GIS.N	GENERAL MILLS
RE.N	EVEREST RE	GILD.O	GILEAD SCIENCES
RCL.N	ROYAL CARIBBEAN	AGN.N	ALLERGAN
QCOM.O	QUALCOMM	GE.N	GENERAL ELECTRIC
PXD.N	PIONEER NATURAL RESOURCES	GD.N	GENERAL DYNAMICS
PWR.N	QUANTA SERVICES	FTNT.O	FORTINET
AMZN.O	AMAZON	FTI.N	TECHNIPFMC
PVH.N	PVH	FRT.N	FEDERAL REALTY INVESTMENT TRUST
PSA.N	PUBLIC STORAGE	FRC.N	FIRST REPUBLIC BANK
PRU.N	PRUDENTIAL FINANCIAL	FMC.N	FMC
PRGO.N	PERRIGO	FLT.N	FLEETCOR TECHNOLOGIES
PPL.N	PPL	FLS.N	FLOWSERVE
PPG.N	PPG INDUSTRIES	FLIR.O	FLIR SYSTEMS
PNW.N	PINNACLE WEST CAPITAL	AFL.N	AFLAC
PNR.N	PENTAIR	FITB.O	FIFTH THIRD BANCORP
PNC.N	PNC FINANCIAL SERVICES	FISV.O	FISERV
PM.N	PHILIP MORRIS INTERNATIONAL	FIS.N	FIDELITY NATIONAL INFO
AMT.N	AMERICAN TOWER	FFIV.O	F5 NETWORKS
PLD.N	PROLOGIS	FE.N	FIRSTENERGY
PKI.N	PERKINELMER	FDX.N	FEDEX
PKG.N	PACKAGING CORP OF AMERICA	FCX.N	FREEPORT MCMORAN
PHM.N	PULTE	FBHS.N	FORTUNE BRANDS HOME & SECURITY
PH.N	PARKER HANNIFIN	FAST.O	FASTENAL
PGR.N	THE PROGRESSIVE	F.N	FORD MOTOR
PG.N	PROCTER & GAMBLE	AES.N	AES
PFG.O	PRINCIPAL FINANCIAL	EXR.N	EXTRA SPACE STORAGE
PFE.N	PFIZER	EXPE.O	EXPEDIA
PEP.O	PEPSICO	EXPD.O	EXPEDITORS INTL WASH
AMP.N	AMERIPRISE	EXC.O	EXELON
PEG.N	PUBLIC SERVICE ENTERPRISE	EW.N	EDWARDS LIFE
PEAK.N	HEALTHPEAK PROPERTIES	ETR.N	ENTERGY
PCAR.O	PACCAR	ETN.N	EATON
PBCT.O	PEOPLE’S UNITED FINANCIAL	ETFC.O	E TRADE FINANCIAL
PAYX.O	PAYCHEX	ESS.N	ESSEX PROPERTY
OXY.N	OCCIDENTAL PETROLEUM	ES.N	EVERSOURCE ENERGY
ORLY.O	O REILLY AUTOMOTIVE	AEP.O	AMERICAN ELECTRIC POWER
ORCL.N	ORACLE	EQR.N	EQUITY RESIDENTIAL
OMC.N	OMNICOM	EQIX.O	EQUINIX
OKE.N	ONEOK	EOG.N	EOG RESOURCES
AMGN.O	AMGEN	EMR.N	EMERSON ELECTRIC
ODFL.O	OLD DOMINION FREIGHT LINE	EMN.N	EASTMAN CHEMICAL

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Security code	Security name	Security code	Security name
O.N	REALTY INCOME	EL.N	ESTEE LAUDER-CL A
NWL.O	NEWELL BRANDS	EIX.N	EDISON INTERNATIONAL
NVR.N	NVR	EFX.N	EQUIFAX
NVDA.O	NVIDIA	ED.N	CONSOLIDATED EDISON
NUE.N	NUCOR	ECL.N	ECOLAB
NTAP.O	NETAPP	AEE.N	AMEREN
NSC.N	NORFOLK SOUTHERN	EBAY.O	EBAY
NRG.N	NRG ENERGY	EA.O	ELECTRONIC ARTS
NOV.N	NOV	DVN.N	DEVON ENERGY
AME.N	AMETEK	DVA.N	DAVITA
NOC.N	NORTHROP GRUMMAN	DUK.N	DUKE ENERGY
NLSN.N	NIELSEN	DTE.N	DTE ENERGY
NLOK.O	NORTONLIFELOCK	DRI.N	DARDEN RESTAURANTS
NKE.N	NIKE	DRE.N	DUKE REALTY
NI.N	NISOURCE	DOV.N	DOVER
CTXS.O	CITRIX SYSTEMS	DLTR.O	DOLLAR TREE
CTSH.O	COGNIZANT TECHNOLOGY SOLUTIONS	ADSK.O	AUTODESK
CTL.N	CENTURYLINK	DLR.N	DIGITAL REALTY TRUST
CTAS.O	CINTAS	DISH.O	DISH NETWORK
ADP.O	AUTOMATIC DATA PROCESSING	DISCK.O	DISCOVERY-C
CSX.O	CSX	DISCA.O	DISCOVERY-A
CSCO.O	CISCO SYSTEMS	DIS.N	WALT DISNEY
CRM.N	SALESFORCE	DHR.N	DANAHER
CPRT.O	COPART	DHI.N	HORTON D R
CPRI.N	CAPRI	DGX.N	QUEST DIAGNOSTICS
CPB.N	CAMPBELL SOUP	DG.N	DOLLAR GENERAL
COST.O	COSTCO WHOLESALE CORP NEW	DFS.N	DISCOVER FINANCIAL SERVICES
COP.N	CONOCOPHILLIPS	ADS.N	ALLIANCE DATA SYSTEMS
COO.N	COOPER	DE.N	DEERE
COG.N	CABOT OIL & GAS	DAL.N	DELTA AIR LINES
ADM.N	ARCHER DANIELS MIDLAND	D.N	DOMINION ENERGY
A.N	AGILENT	CXO.N	CONCHO RESOURCES
CVS.N	CVS HEALTH	CVX.N	CHEVRON
WTB.L	WHITBREAD	NOVN.SIX	NOVARTIS AG-REG SHS
WPP.L	WPP	NESN.SIX	NESTLE SA-REG
VOD.L	VODAFONE	LONN.SIX	LONZA AG-REG
ULVR.L	UNILEVER	LHN.SIX	HOLCIM
TSCO.L	TESCO	GIVN.SIX	GIVAUDAN-REG
SVT.L	SEVERN TRENT	GEBN.SIX	GEBERIT
STJ.L	ST. JAMES'S PLACE	CSGN.SIX	CREDIT SUISSE GROUP-REG
STAN.L	STANDARD CHARTER	ADEN.SIX	ADECCO SA-REG
SSE.L	SSE	ZURN.SIX	ZURICH FINANCIAL SERVICES
SMT.L	SCOT MORTGAGE IT	UHR.SIX	SWATCH GROUP AG/THE-BR
SMIN.L	SMITHS	SREN.SIX	SWISS RE AG
AZN.L	ASTRAZENECA	SLHN.SIX	SWISS LIFE HOLDING AG-REG
SMDS.L	SMITH(DS)	SGSN.SIX	SGS SOC GEN SURVEILLANCE-R
SGE.L	SAGE	SCMN.SIX	SWISSCOM AG-REG
SDR.L	SCHRODERS	ROG.SIX	ROCHE HOLDING AG-GENUSSS
SBRY.L	SAINSBURY	ABBN.SIX	ABB
RTO.L	RENTOKIL INITIAL	DB1.DF	DEUTSCHE BOERSE
RSA.L	RSA INSURANCE	DAI.DF	DAIMLER

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Security code	Security name	Security code	Security name
AVV.L	AVEVA	CON.DF	CONTINENTAL
RMV.L	RIGHTMOVE	BMW.DF	BAY.MOTOREN WERKE
RIO.L	RIO TINTO	BEI.DF	BEIERSDORF
REL.L	RELX	BAYN.DF	BAYER
RDSB.L	ROYAL DUTCH SH-B	BAS.DF	BASF
RDSA.L	ROYAL DUTCH SH-A	WDI.DF	WIRECARD
RBS.L	ROYAL BANK OF SCOTLAND GROUP	SIE.DF	SIEMENS
PSON.L	PEARSON	SAP.DF	SAP
PSN.L	PERSIMMON	RWE.DF	RWE
PRU.L	PRUDENTIAL	MUV2.DF	MUENCHENER RUECKVERSICHERUNGS
POLY.L	POLYMETAL INTERNATIONAL	MTX.DF	MTU AERO ENGINES
PNN.L	PENNON	ALV.DF	ALLIANZ
NXT.L	NEXT	MRK.DF	MERCK
MRW.L	WM MORRISON	LHA.DF	DEUTSCHE LUFTHANSA
MNDI.L	MONDI	IFX.DF	INFINEON TECHNOLOGIES
MGGT.L	MEGGITT	HEI.DF	HEIDELBERGCEMENT
LSEG.L	LON STK EXCH	FRE.DF	FRESENIUS
LLOY.L	LLOYDS BANKING	FME.DF	FRESENIUS MEDICAL CARE
ANTO.L	ANTOFAGASTA	EOAN.DF	E.ON
LGEN.L	LEGAL & GEN	DTE.DF	DEUTSCHE TELEKOM
JMAT.L	JOHNSON MATTHEY	DPW.DF	DEUTSCHE POST
ITV.L	ITV	DBK.DF	DEUTSCHE BANK
ITRK.L	INTERTEK	ADS.DF	ADIDAS
INF.L	INFORMA	CABK.MA	CAIXABANK S.A
III.L	3I	BKT.MA	BANKINTER SA
IHG.L	INTERCONTINENTAL HOTELS	BKIA.MA	BANKIA
ICP.L	INTERMEDIATE CAPITAL	BBVA.MA	BANCO BILBAO VIZCAYA ARGENTA
AHT.L	ASHTEAD	ANA.MA	ACCIONA SA
IAG.L	INTL CONSOLIDATED AIRLINES	VIS.MA	VISCOFAN SA
HSBA.L	HSBC	TL5.MA	MEDIASET ESPANA COMUNICACION
HLMA.L	HALMA	AMS.MA	AMADEUS IT HOLDING SA-A SHS
HIK.L	HIKMA PHARMACEUTICALS	TEF.MA	TELEFONICA SA
GSK.L	GLAXOSMITHKLINE	SGRE.MA	SIEMENS GAMESA RENEWABLE ENERGY
GLEN.L	GLENCORE	SAN.MA	BANCO SANTANDER SA
FRES.L	FRESNILLO	SAB.MA	BANCO DE SABADELL SA
FLTR.L	FLUTTER ENTERTAINMENT	REP.MA	REPSOL SA
FERG.L	FERGUSON	REE.MA	RED ELECTRICA CORPORACION SA
ADM.L	ADMIRAL	NTGY.MA	NATURGY ENERGY GROUP
EZJ.L	EASYJET	MTS.MA	ARCELORMITTAL
EXPN.L	EXPERIAN	MEL.MA	MELIA HOTELS INTERNATIONAL
EVR.L	EVRAZ	MAP.MA	MAPFRE SA
DGE.L	DIAGEO	ACX.MA	ACERINOX SA
DCC.L	DCC	ITX.MA	INDITEX
CRH.L	CRH	IDR.MA	INDRA SISTEMAS SA
CRDA.L	CRODA INTERNATIONAL	IBE.MA	IBERDROLA SA
CPG.L	COMPASS	IAG.MA	INTL CONSOLIDATED AIRLINE-DI

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Security code	Security name	Security code	Security name
CNA.L	CENTRICA	GRF.MA	GRIFOLS SA
CCL.L	CARNIVAL	FER.MA	FERROVIAL SA
ABF.L	ASSOC BRIT FOODS	ENG.MA	ENAGAS SA
BRBY.L	BURBERRY	ENC.MA	ENCE ENERGIA Y CELULOSA SA
BNZL.L	BUNZL	ELE.MA	ENDESA SA
BKG.L	BERKELEY	COL.MA	INMOBILIARIA COLONIAL SOCIMI SA
BHP.L	BHP	ACS.MA	ACS ACTIVIDADES CONS Y SERV
BDEV.L	BARRATT DEVELOPMENTS	MT.AS	ARCELORMITTAL
BATS.L	BRITISH AMERICAN TOBACCO	ML.PA	MICHELIN (CGDE)
BARC.L	BARCLAYS	MC.PA	LVMH MOET HENNESSY LOUIS VUI
AAL.L	ANGLO AMER	LR.PA	LEGRAND SA
CAP.PA	CAPGEMINI	ACA.PA	CREDIT AGRICOLE SA
CA.PA	CARREFOUR SA	KER.PA	KERING
BNP.PA	BNP PARIBAS	HO.PA	THALES SA
BN.PA	Danone Group	GLE.PA	SOCIETE GENERALE SA
ATO.PA	ATOS	FP.PA	TOTAL
AIR.PA	AIRBUS GROUP NV	ENGI.PA	ENGIE
VIV.PA	VIVENDI	EN.PA	BOUYGUES SA
VIE.PA	VEOLIA ENVIRONNEMENT SA	EL.PA	ESSILORLUXOTTICA
UG.PA	PEUGEOT SA	DSY.PA	DASSAULT SYSTEMES SA
SW.PA	SODEXO	DG.PA	VINCI
SU.PA	SCHNEIDER ELECTRIC SE	CS.PA	AXA SA
STM.PA	STMICROELECTRONICS NV	AC.PA	ACCOR SA
SGO.PA	COMPAGNIE DE SAINT-GOBAIN	RMS.PA	HERMES INTERNATIONAL
SAN.PA	Sanofi	RI.PA	PERNOD RICARD SA
SAF.PA	SAFRAN SA	PUB.PA	PUBLICIS GROUPE
AI.PA	AIR LIQUIDE SA	ORA.PA	ORANGE
RNO.PA	RENAULT SA	OR.PA	L'OREAL

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