Short-run disequilibrium adjustment and long-run equilibrium in the international stock markets: A network-based approach

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Abstract: In this paper, we propose a network-based analytical framework that exploits cointegration and the error correction model to systematically investigate the directions and intensities in terms of the short-run disequilibrium adjustment towards long-run equilibrium affecting the international stock markets during the period of 5 January 2007 to 30 June 2017. Under this setting, we investigate whether and how the cross-border directional interconnectedness within the world's 23 developed and 23 emerging stock markets altered during the entire period of 2007–2017, and two specific periods of 2007–2009 Global Financial Crisis and 2010–2012 European Sovereign Debt Crisis. The main results indicate that the magnitude of the short-run disequilibrium adjustment towards long-run equilibrium for individual stock markets is not homogeneous over different time scales. We report that the changes in directional interconnectedness within stock markets worldwide did occur under the impact of the recent financial crises. The derived networks of stock markets interconnectedness allow us to visually characterize how specific stock markets from different regions form interconnected groups when exhibiting similar behaviours, which none the less provides significant information for strategic portfolio and risk management.

JEL classification: G15; C12; G01

Keywords: International Stock Markets; Cointegration; Error Correction Model; Complex Network Theory; Financial Crisis

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1 Introduction

In an increasingly volatile and interconnected world, understanding and analysing the complex behaviours in financial markets is critical to assessing and monitoring systemic risk (e.g., Acemoglu et al., 2015; Stavroglou et al., 2019). Although a considerably high volume of heterogeneous and interacting entities has already been identified in international financial markets, their continuously and increasingly fluctuating connectivity requires from the decision maker to rethink the implications of complex interdependence, and consequently to further explore the interconnectedness affecting the most these markets (Elliott et al., 2014; Roukny et al., 2018).

Economists, and financial economists in particular, have long been interested in understanding whether and how the cross-border dependencies within the world's developed and emerging stock markets alters during periods of crisis (e.g., Kasa, 1992; Bekaert and Harvey, 1995; Lehkonen, 2015). In this paper, we try to shed new light on this topic. Specifically, we develop an analytical framework to identify and monitor changes that occur in the directional interconnectedness structure concerning the short-run disequilibrium adjustments, which maintain stable long-run equilibrium relations, among the global stock markets over time. We expect that the proposed analytical framework, and thus our better understanding of the direction and intensity of the international stock market long-run interconnectedness, may play an increasingly important role in the effective design of the different intermediate steps involved in the decision-making process under risk and uncertainty than previously realised (Roukny et al., 2018).

In this direction, complex network theory has been a leading tool for analysing the interdependencies between different economic or financial variables since the seminal work of Mantegna (1999). Over the last two decades, correlation-based measures have been broadly utilized to characterize financial markets as complex networks (e.g., Tola et al., 2008; Chi et al., 2010; Tumminello et al., 2010; Kenett et al., 2010; Kenett and Havlin, 2015; Kenett et al., 2015; Sensoy et al., 2016; Stavroglou et al., 2017). From network theory perspective, various financial entities (i.e., assets, stock exchanges, financial institutions) are perceived as network nodes, and interdependencies across them are usually assessed by correlation measures (Newman, 2003; Schweitzer et al., 2009). More recently, in the relevant literature, a set of papers that combines econometric techniques and network theory clarifies the interrelations of different entities in financial markets (e.g., Billio et al., 2012; Diebold and Yilmaz, 2014, 2015; Wang et al., 2017; Stavroglou et al., 2017; Geraci and Gnabo, 2018). Notably, under the vector auto-regression (VAR) framework, Billio et al. (2012) and Diebold and Yilmaz (2014) introduce the Granger-causality and variance decomposition networks for understanding the mean and volatility spillover effects in financial systems. Thus, in their setting, the network interconnectedness between different financial entities can be viewed as a channel of shock transmission, which provides a considerable contribution to detect systemic risk in the financial literature (e.g., Fernández-Rodríguez et al., 2016; Lyócsa et al., 2019; Brunetti et al., 2019; Song et al., 2019; Hamill et al., 2021). However, an important limitation still remains in the corresponding literature that is the use of stationary financial variables/time series, which does not take the potential cointegration structure of the variables into account. When the financial variables under consideration are non-stationary at levels, but stationary in first differences (i.e., integrated of order one, $I(1)$), the standard VAR model is no longer suitable for modelling them at levels.

Engle and Granger (1987) and Granger et al. (2000) claim that cointegration stipulates the long-run equilibrium relationships, or equivalently the existence of common stochastic trends among non-stationary financial variables, which allows for short-run deviations that might occur because of a transitory shock in financial market volatility. However, such divergence is temporary, and the occurrence of common factors such as investors' preferences (e.g., arbitrage activity), market forces and government regulations will lead to short-run deviations between the non-stationary financial variables converging to their long-run equilibrium steady state, i.e., tending to be cointegrated and having long-run co-movements (e.g., Masih and Masih, 2001; Alexander, 2001; Chen et al., 2002; Syriopoulos, 2007; Yu et al., 2010; Narayan et al., 2011). Thus, cointegration should be considered when modelling a financial complex network as it can reflect the instantaneous interconnectedness and synergy of different non-stationary financial variables and signals the existence of similar trends (e.g., Kasa, 1992; Arshanapalli and Doukas, 1993).

Motivated by this, we attempt to utilize the bivariate error correction model (ECM) (Engle and Granger, 1987) as it captures such a self-regulating disequilibrium mechanism that can automatically calibrate the short-run departures from long-run equilibrium across the non-stationary financial variables. Our research is close to Billio et al. (2012) who use the bivariate VAR models to conduct for pairwise Granger-causality tests among stationary time series, but we incorporate the error correction term to restrict the long-run behaviours across non-stationary financial variables. This specification is not only elegant, but it provides insight for identifying stable long-run interdependency structures among non-stationary financial variables over time. In particular, a faster speed of short-run disequilibrium adjustment towards re-equilibrium can be further viewed as an indication of a higher degree of cointegration (e.g., Pascual, 2003; Mylonidis and Kollias, 2010).

To the best of our knowledge, the long-run inter-linkages within the international stock markets that may be captured via cointegration and the ECM model along with tools from complex network theory have not yet been investigated thoroughly. To bridge this gap in the relevant literature, we propose a network-based analytical framework that exploits cointegration and the ECM model so as to systematically recognize the magnitude and direction of adjustment to deviations from the long-run equilibrium, and the degree of long-run interconnectedness across stock markets in a global context.

In the framework of complex systems, interdependencies across the world's stock markets are often considered as self-organized without accounting for the influence of external forces (Sornette, 2017). Yet the recent financial crises have promoted new research directions to revisit their role as a critical element to determine the growing interdependencies affecting the global stock markets (e.g., Bekaert et al., 2014; Lehkonen, 2015; Mobarek et al., 2016). Further, the application of tools from network theory to the highly interconnected financial markets provides us with important new insights into understanding system-wide effects and the mechanisms underlying the transition of financial stress to the stock markets across the world (e.g., Anufriev and Panchenko, 2015; Rossi et al., 2018).

Our main contribution is developing a network-based analytical framework to identify and monitor the changes in the directional long-run interconnectedness structure, concerning the short-run disequilibrium adjustment towards long-run equilibrium across the international stock markets, during long-term time horizon and financial crisis episodes. Equipped with the statistical validation test[1], this network-based analytical framework is powerful to reveal the underlying critical directional long-run interconnectedness among the global stock markets (Curme et al., 2015). More specifically, our data sample ranges from January 2007 to June 2017, which covers the rising number of financial crises, e.g., the 2007–2009 Global Financial Crisis (GFC) and 2010–2012 European Sovereign Debt Crisis (ESDC), that have occurred in recent times around the globe. Thus, over the long-run period of 2007–2017, it enables us to investigate the patterns of pairwise directional network interconnectedness across the international stock markets from a systematic perspective. Also, we endeavour to answer the question: "*in the presence of a distress or uncertain situation how the international stock market interconnectedness changes?*"

Besides, following the MSCI market classification[2] by grouping the 23 developed and 23 emerging stock markets worldwide into geographical regions, we aim to identify whether there are substantial differences among distinct regions and countries/areas, and how such interconnectedness was affected during the financial crises. Also, to shed more light on portfolio diversification and risk management within the international stock markets, we contribute by employing the ForecAtlas2 network layout algorithm (Jacomy et al., 2014) to classify and group sets of stock markets that share similar interconnectedness characteristics in terms of adjustments of short-run disequilibrium back to long-run equilibrium in times of financial crises. This is crucial for investors who hold globally diversified portfolios, as the presence of network clusters of highly interconnected stock markets implies a potential limitation of diversification within these long-run intercon-

[1] For more applications of the statistical validation tests in finance (see, Barras et al., 2010; Bajgrowicz and Scaillet, 2012; Psaradellis et al., 2019).

[2] MSCI included China A-shares in the Emerging Markets Index in May 2018. Saudi Arabia and Argentina were moved from the Frontier Markets Index to the Emerging Markets Index in May 2019.

nected markets (e.g., Gupta and Guidi, 2012; Dimpfl, 2014; Chen et al., 2014). By contrast, the absence of interconnectedness across stock markets provides supportive evidence of the existence of possible benefits from an international portfolio diversification (e.g. Bai and Green, 2010; Christoffersen et al., 2012; Ghysels et al., 2016).

The key findings can be summarized as follows. First, our network analysis confirms that the magnitudes of short-run disequilibrium adjustments toward long-run equilibrium shows quite dramatic differences across stock markets in 46 countries/areas, during the longer horizon period of 2007–2017, and two specific crisis periods of the 2007–2009 GFC and 2010–2012 ESDC. In particular, compared to the entire 2007–2017 period and ESDC, distortions in the long-run equilibrium will be corrected quickly among the 46 stock markets in times of GFC (Donadelli and Paradiso, 2014; Christoffersen et al., 2012; Lehkonen, 2015). To be specific, over the period of the GFC, stock markets in the world's advanced economies and particularly most of the European ones (including both developed and emerging markets), tend to be densely interconnected as a component in the network associated with faster adjustments of short-run disequilibrium to achieve long-run equilibrium, relative to the ESDC and 2007–2017 period (Christoffersen et al., 2012; Ghysels et al., 2016). Particularly, the level of directional interconnectedness across the US stock market and several core-European stock markets (e.g., Finland, the UK, France, Italy, Ireland, Switzerland, Belgium etc.) rose markedly, associated with the higher short-run disequilibrium corrections back to long-run equilibrium, over the GFC period (Bartram and Bodnar, 2009; Diebold and Yilmaz, 2012). The resulted groupings not only help identify the underlying risk transmission originating from the US stock market, but also imply the limitations of the benefits of international diversification within the group (Lehkonen, 2015; Mollah et al., 2016). In contrast, most emerging stock markets, especially from the Asia-Pacific and the MENA[3], were likely to be more globally segmented during the GFC, which provides evidence in support of international diversification opportunities (Dooley and Hutchison, 2009; Longstaff, 2010). However, the reverse results are found within the emerging stock markets from Latin Americas over the period of the GFC.

Remarkably, our results also demonstrate that the interconnectedness patterns in European stock markets during the two financial crises are divergent. In particular, all major Eurozone stock markets experienced a much more pronounced increase of intra-regional interconnectedness during the ESDC compared to that during the GFC and the entire period of 2007–2017, and a further decrease in the rewards from diversification (Mollah et al., 2016; Virk and Javed, 2017; Niţoi and Pochea, 2019). Meanwhile, the directional interconnectedness within and across the stock markets of the US, Germany, core non-Eurozone (i.e., the UK, Sweden, Denmark, Switzerland) as well as most emerging

[3]It is also known as MENAP referring to the Middle East, North Africa, Afghanistan, and Pakistan, which corresponds to the Greater Middle East.

stock markets in Asia-Pacific and Latin America, appear to be strongly interconnected and grouped as an individual component in the network during the ESDC. It is evident that those two components are inter-linked through Israel and a set of dominant stock markets in Asia-Pacific, such as Hong Kong, Australia, and Japan.

More importantly, the obtained results relate to the high degree of directional interconnectedness within emerging stock markets around the globe over the longer horizon between 2007 and 2017, which quite differs from that during the GFC and ESDC, and decreases the possible diversification benefits (Guidi and Ugur, 2014). Our results further show that, over the 2007–2017 period, European stock markets are clustered into different sub-groups, i.e., "GIPSI"[4] stock markets and most EMU[5] stock markets, which decreases the rewards from diversification (Mensi et al., 2018). However, the stock markets of Denmark, Switzerland, Germany, Sweden and Norway appear to be interconnected with the world's other stock markets, which highlights potential diversification gains.

Last but not least, a noteworthy finding of our study is the time-varying interconnectedness of the stock market in the US, see when comparing the results during the full-sample period of 2007–2017 and the GFC and ESDC sub-periods. Over the longer horizon of 2007–2017, we show evidence of a striking decrease of directional interconnectedness between the US and most of the world's other stock markets except for those in Germany, Japan, Denmark and Pakistan, compared to the periods of the GFC and the ESDC. Our results therefore signal that, between 2007 and 2017, the US stock market can be regarded as a safer haven than the world's other stock markets, especially those in Europe, as the low international co-movements may make the portfolio diversification possible. As expected, the US stock market is risk contagious to the world's stock markets during the GFC, which provides us with the first evidence on how the crisis spread. However, the decrease in directional interconnectedness between the US and most stock markets in the Eurozone during the onset of the ESDC, tends to be more pronounced compared to the GFC period.

The remainder of this study is organized as follows. In Section 2, we provide a brief review of the relevant literature. Section 3 describes the data and the preliminary statistical analysis of each individual stock market. Section 4 then outlines the methodology adopted for the analysis. Section 5 presents the main empirical findings. Finally, conclusions and directions for future research are drawn in Section 6.

[4]The acronym of "GIPSI" refers to Greece, Ireland, Portugal, Spain and Italy (Ahmad et al., 2013; Mensi et al., 2018).

[5]This refers to the Economic and Monetary Union (EMU) of the European Union.

2 Related literature

To recognise the critical relevance of the intensity of interdependence or the degree of co-movement among stock markets, numerous studies have focused on investigating the spillover effects across different stock returns and/or returns' volatility (Bekaert and Harvey, 1995; Forbes and Rigobon, 2002). From an econometric viewpoint, the co-movement of stock markets can be studied by means of spillover dynamic, in which the movement and price changes of one market may affect the movement of another market (Ahmed and Huo, 2019). In this respect, for example, the generalised autoregressive conditional heteroskedastic (GARCH)-family models (Ng, 2000; Koulakiotis et al., 2012), Granger-causality tests (Lin, 2012; Neaime, 2016), the variance decomposition in the underlying VARs or structural VARs (Diebold and Yilmaz, 2009; Chevallier et al., 2018; Huang et al., 2018), etc., are increasingly popular. Particularly, in times of crisis, the increased intensity of the mean or volatility spillover effect can be explained as financial contagion (Jayech, 2016).

Another group of researchers investigate the long-run co-movement and the degree of integrations across the non-stationary stock market prices, using the notion of cointegration (Engle and Granger, 1987; Johansen, 1988). Accordingly, several studies document the presence of long-run equilibrium relationships in regional stock markets, such as in Latin America (Chen et al., 2002), Asia (Awokuse et al., 2009; Gupta and Guidi, 2012; Yu et al., 2010), Europe (Guidi and Ugur, 2014; Caporale et al., 2016). In the context of international stock markets, a partial list of such work includes Kasa (1992), Arshanapalli and Doukas (1993), Masih and Masih (1997), Masih and Masih (2001), Dimpfl (2014), among others. More importantly, according to Engle and Granger (1987) the presence of cointegration implies that the dynamics of stock prices changes can be described by an ECM model to capture the short-run error correction towards the long-run equilibrium (Eun and Sabherwal, 2003). In this regard, by incorporating error correction mechanism, Masih and Masih (1997) find that changes in the stock markets of Canada, the UK, and France respond to the disequilibrium of the US stock market during the pre-crash period. However, over the post-crash era, the UK and German stock markets react much more significant to the US stock market equilibrium error. Mylonidis and Kollias (2010) apply rolling cointegration and ECM models to reflect the dynamic process of convergence among four stock markets in Europe (i.e., Germany, France, Spain and Italy). Their findings show that stock market prices for Germany and France adjust towards their long-run level faster than other stock markets, forcing these markets to co-move in the long term. In Chien et al. (2015)'s study, they investigate the dynamic long-run cointegration relationships across stock markets in China and ASEAN-5 countries. According to their findings, China and Indonesia, the two largest economies among the six studied, appear to correct the deviations from the long-run equilibrium level.

To better illustrate the intensity and the asymmetry of bilateral relations, complex network theory permits visualization and interpretation of the intricate structural dependency among a set of variables in economic and financial systems (see Mantegna, 1999; Arthur, 1999; Schweitzer et al., 2009, among others). It is also worth noting that network analysis is a powerful graphical statistical approach for simplifying complex financial systems and overcoming the "dimension barrier" of multivariate econometric models (Chi et al., 2010; Vỳrost et al., 2019; Zhang et al., 2020). Recent crises, in particular, have reminded us that the failure of an individual financial entity may cause similar failures in interconnected entities that propagate throughout the entire financial system or entire market and resulting in systemic instability, which can be captured by the property of complex systems (Sornette, 2017). For this reason, Diebold and Yilmaz (2014, 2015) construct variance decomposition networks based on VAR models to measure the total and directional volatility spillovers across financial firms, in which the aggregate financial interconnections can quantify "systemic risk" in collective fluctuations. Granger-causality networks proposed by Billio et al. (2012) is constructed based on examining mean spillover effects in complex financial system, network-based connectedness measures thus can be viewed as systemic risk indicators. Using these two networks, Chowdhury et al. (2019) explore stock market linkages between Asia and the rest of the world, discovering that the connections have grown stronger over the last two decades. Mensi et al. (2018) discover strengthened volatility spillover among "GIPSI" stock markets and the US, European and Asian regional markets as a result of the GFC and ESDC crises based on Diebold and Yilmaz (2014)'s spillover network. Through network centrality measures, Anufriev and Panchenko (2015) detect systemically important financial institutions in connectedness network. In study of clustering effects in financial networks, several studies, such as those of Fenn et al. (2012); Birch et al. (2016); Lee and Nobi (2018); Vỳrost et al. (2019) apply approaches of minimal spanning tree (MST), planar maximally filtered graph (PMFG) for better understanding the connecting structure in financial market (Mantegna and Stanley, 2000; Tumminello et al., 2005; Birch et al., 2015).

Starting from these prior studies, characterising the network of stock market interdependencies is key. The lack of consensus, especially with regard to international stock market co-movements, call for further studies to figure out the long-run interconnectedness among the stock markets worldwide, particularly in the context of network analysis.

3 Data and Descriptive Statistics

3.1 Data Description

Our empirical data consist of weekly[6] closing price indices of 23 developed and 23 emerging stock markets according to the MSCI market classification[2], from 5 January 2007 until 30 June 2017. All weekly data were collected from Thomson Reuters Datastream. In order to investigate how and to what extent the short-run error correction effects and long-run equilibrium relationships occur across the 46 stock market indices globally during two important times of financial turbulence, the data are divided into two sets[7]:

(i) 3 August 2007 to 26 June 2009 (the period of the GFC);

(ii) 1 January 2010 to 28 December 2012 (the period of the ESDC).

For comparative purposes, the 46 stock market indices are all expressed in common currency, the US dollars,[8] to mitigate the impacts of local inflation and national currency fluctuation on each stock market index (Bekaert and Harvey, 1995; Pukthuanthong and Roll, 2009). The chosen list of countries/areas and the corresponding stock market indices in the study are given in Table 1.

[Table 1 about here.]

Since the 46 stock market indices have different scales, we rescale them with a common starting point so as to be comparable (Forbes and Rigobon, 2002). The first step is to calculate the percentage change in each stock market index, which is given by

$$\Delta_i(t) = \frac{P_i(t)}{P_i(t-1)}, \text{ for all t} \geq 2, \tag{1}$$

where $P_i(t)$ is the price of stock market index i in week t. For the rescaled stock market index series $R_i(t)$, we set the first entry in each index series to be $R_i(1) = 1$ on 5 January 2007, and then $R_i(t)$ is expressed, for all subsequent entries in each index series, by

$$R_i(t) = R_i(t-1) * \Delta_i(t), \text{ for all t} \geq 2. \tag{2}$$

After rescaling all the original stock market index series, we finally transform them into their natural logarithms.[9]

[6] According to Eun and Shim (1989) and Kadlec and Patterson (1999), the use of weekly data can avoid the "non-synchronous trading effect", therefore the adverse effects of belonging to different time zones and having different operating days are minimized.

[7] We specify the intervals of the 2007–2009 GFC and 2010–2012 ESDC according to Billio et al. (2012); Lehkonen (2015) among others.

[8] For comparison purpose, in previous study of Chen et al. (2018), we conduct stock markets integration analysis under common and domestic currency terms, respectively, and conclude that the estimation under the local currency terms shows more interactions between stock markets.

[9] The cointegration test is based on a logarithmic transformation of stock market index series to minimize the heteroscedasticity in the values of the level series.

3.2 Descriptive Statistics

To underline the different characteristics of each individual stock market index considered in this paper, we present the descriptive statistics for the weekly return series of the 46 stock market indices during the entire 2007–2017 time period, and two crisis periods of 2007–2009 GFC and 2010–2012 ESDC, in Tables 2–4, respectively.

For the full sample period of 2007–2017, Table 2 shows that developed stock markets of Denmark (0.123%), the US (0.099%), Germany (0.091%), and emerging stock markets of Pakistan (0.180%), Thailand (0.179%), Qatar (0.173%), Philippines (0.170%), both posted the highest positive mean returns, while the lowest are found in Greece (-0.337%), Portugal (-0.167%), Italy (-0.152%), and Norway (-0.133%) with high volatilities confirmed by standard deviations. However, except for Qatar (0.048%), each stock market posted a negative mean return associated with high volatility level during the 2007–2009 GFC (see Table 3). As expected, all European stock markets appear to have negative mean returns and high volatilities during the onset of 2010–2012 ESDC (see Table 4). Also, as shown in Tables 2–4, all sample stock market returns exhibit negative skewness, and the kurtosis values are above three for all return series in the full-sample period while excepting the stock markets of Norway, Russia, South Africa, and Taiwan in 2007–2009 GFC period and Peru, Qatar, and India in 2010–2012 ESDC period. This result indicates that the distributions of the global stock market returns are non-normal but leptokurtic. It is also worth noting that the Jarque-Bera tests rejected normality for all stock markets at the 1% level regardless of the full-sample period or the crisis periods of 2007–2009 GFC (with the exception of Australia, India, Malaysia, and Taiwan) and 2010–2012 ESDC (with the US, Norway, Spain, the United Arab Emirates, India, and Thailand being the exceptions).

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

4 Methodology

This section outlines the methodology of our empirical analysis framework, used to estimate the possibility of the short-run error correction effects and long-run equilibrium relationships within international stock markets via *cointegration*, the *ECM model*, and *network-based treatment*. Further, since statistical significance requires multiple comparison tests, the powerful *False Discovery Rate* (hereafter referred to as FDR) correction is utilized to control data snooping bias.

4.1 Cointegration and Error Correction Effects

Cointegration analysis enables us to examine the existence of the long-run equilibrium relationship among the stock market indices. It implies that, even if two non-stationary $I(1)$[10] price series might drift apart in the short run, they will maintain an equilibrium relationship in the long run (Engle and Granger, 1987). As a result, if two non-stationary stock market indices are cointegrated, it means that they share a common stochastic trend and tend to co-move in the long term. In our bivariate case, the Engle and Granger (1987) cointegration test is applied.[11] We assume that the two $I(1)$ series x_t and y_t are respectively the log-levels of stock price indices (after being rescaled) in time t, and the bivariate cointegration relationship between x_t and y_t is given by the following equations:

$$y_t = \alpha + \beta x_t + \varepsilon_t, \tag{3}$$

$$x_t = \alpha' + \beta' y_t + \varepsilon'_t, \tag{4}$$

where Eqs. (3) and (4) are the forward and reverse cointegrating regression equations respectively (Granger, 2001). Specifically, ε_t (ε'_t) denotes the mean-zero stationary residuals, i.e., $I(0)$ variable. β (β') is the cointegration coefficient that reflects the effect of the independent variable x_t (y_t) on the dependent variable y_t (x_t) that occurs over the future time period. Once the existence of cointegration between x_t and y_t has been derived in the long term, we then confirm that x_t and y_t are forced to move around the common stochastic trend, at the same time experiencing short-run transitory deviations from this long-run equilibrium relationship. Then, the short-run disequilibrium can be captured by the ECM model, to guarantee that the two observed variables do not drift too far apart when they deviate from the long-run equilibrium (Engle and Granger, 1987; Granger, 1988). According to the Granger Representation Theorem (Engle and Granger, 1987; Granger, 1988), if the cointegration regression equation holds, a bivariate ECM model can be presented by

$$\Delta y_t = \alpha_0 + \delta ECT_{t-1} + \sum_{i=1}^{L} \theta_i \Delta y_{t-i} + \sum_{i=1}^{L} \gamma_i \Delta x_{t-i} + \eta_t, \tag{5}$$

where

$$ECT_{t-1} = \hat{\varepsilon}_{t-1} = y_{t-1} - [\hat{\alpha} + \hat{\beta} x_{t-1}]. \tag{6}$$

The intuition arising from the bivariate ECM model is that, the current changes in stock market index y_t (i.e. Δy_t) is a function of the lagged error correction term δECT_{t-1}[12]

[10] The variable is non-stationary in log level, while the first log difference of the variable is stationary.

[11] In the literature, two common tests are employed for cointegration, which are the Engle and Granger (1987) and Johansen (1991) tests. In the multivariate case, the Johansen (1991) test is preferred, since it identifies the space spanned by the cointegration vectors.

[12] The error correction term has to be included with lag 1 since the deviation from the long-run

(i.e., $\hat{\varepsilon}_{t-1}$, reflects the degree to which two stock market indices y_t and x_t are outside of their equilibrium in the previous period $t-1$), the lagged changes in y_t (i.e., $\sum_{i=1}^{L} \theta_i \Delta y_{t-i}$), x_t (i.e., $\sum_{i=1}^{L} \gamma_i \Delta x_{t-i}$),[13] the drift α_0, and the white noise series η_t. By definition, the statistical significance of the term δECT_{t-1} demonstrates that the stock market indices x_t and y_t shares a long-run equilibrium relationship at time t, as y_t tends to change and correct the previous disequilibrium between x_{t-1} and y_{t-1}. The estimated parameter δ, i.e., error correction coefficient, should be statistically significant and negative, and denotes how fast deviations from the long-run equilibrium are dissipated following changes in y_t. According to early studies (Pascual, 2003; Mylonidis and Kollias, 2010), to the extent that the greater the magnitude of the short-run error adjustment coefficients for re-equilibrium, can be viewed as an indicator of a higher degree of cointegration. With regard to the terms $\sum_{i=1}^{L} \theta_i \Delta y_{t-i}$ and $\sum_{i=1}^{L} \gamma_i \Delta x_{t-i}$, for example, if we assume the coefficient of γ_i in the latter term is statistically significant through F-tests, once the stock market index x_t sees change in the period $t-1$, then the stock market index y_t will response immediately to the lagged change in x_t (i.e., short-term effect). This is consistent with the standard bivariate Granger-causality test (Granger, 1988; Billio et al., 2012). However, in our case, we are most interested in the respective short-run error correction terms δECT_{t-1}. Conversely, if Eq. (4) holds, we can identify whether and how the stock market index x_t experiences changes to correct the short-run disequilibrium and converge to the long-run equilibrium with y_t.

Generally, before undertaking cointegration and ECM models, *unit root tests* should be conducted on each individual stock market index to confirm their integration order. If two stock market indices are integrated at the same order (i.e., $I(1)$, non-stationary in log level while being stationary when taken in first difference), unit root tests will further help us to confirm whether the two stock market indices are indeed cointegrated. Here, we employ the well known Augmented Dickey-Fuller (hereafter referred to as the ADF) and Phillips-Perron (hereafter referred to as the PP) unit root tests (Dickey and Fuller, 1979; Phillips and Perron, 1988), with a null hypothesis that each stock market index series is non-stationary and possesses a unit root under inspection.

4.2 Statistical Validation Tests

When we conduct cointegration and the ECM model for the pairwise stock indices, determining whether an observed result is statistically significant requires multiple comparison tests (Curme et al., 2015). However, as the number of hypotheses increases, so does the probability of incorrect rejections of false positives. Therefore, a multiple hypothesis test correction needs to be considered. In the finance literature, several methods for miti-

equilibrium in the period $t-1$ starts the adjustment process in period t.

[13] L is lag length and the determination of the optimal lag length is based on the Akaike information criterion (AIC).

gating data snooping bias have been proposed. The FDR introduced by Benjamini and Hochberg (1995) describes the proportion of false discoveries among total rejections in a multiple comparison. To control and correct the FDR of a family of hypothesis tests, we utilize the Benjamini and Hochberg (hereafter referred to as BH) procedure (Benjamini and Hochberg, 1995; Benjamini and Yekutieli, 2001).

We first denote the obtained p-values by $P_1, ..., P_m$ and associated null hypotheses by $H_1, ..., H_m$ for the m simultaneous hypothesis tests. Then, we sort the p-values in ascending order as $0 \leq P_{(1)} \leq ... \leq P_{(m)}$, where $i = 1, 2, ..., m$ are the indices of the ordered p-values, and $H_{(i)}$ is the null hypothesis corresponding to $P_{(i)}$. For a pre-specified FDR at level α ($0 \leq \alpha \leq 1$), the BH procedure rejects all hypotheses of which $P_{(i)} \leq P_{(k)}$, where

$$k = \max \left\{ 0 \leq k \leq m : P_{(k)} \leq \frac{k}{m}\alpha \right\}. \tag{7}$$

Finally, the BH procedure is valid when the m tests are independent, and controls the FDR at level

$$\mathrm{E(FDR)} \leq \frac{m_0}{m}\alpha \leq \alpha, \tag{8}$$

where m_0 is the number of true null hypotheses.

The FDR controlling procedure is both adaptive and scalable (Benjamini, 2010), and it depends on the number of hypotheses tested and the predefined FDR at level α. In our study, we will require very strong evidence before we reject the null hypothesis, thus the pre-specified FDR at level $\alpha = 0.01$ is considered in cointegration test and the ECM setting. However, in the *online supplementary materials*, see Section **A**, the case of $\alpha = 0.05$ is also provided and compared with the main FDR controlling procedure developed here.

4.3 Interconnectedness Network Construction

The bivariate ECM test is the econometric tool at the core of the network construction and what we are most interested in are the respective magnitudes of the short-run disequilibrium adjustment coefficients δs across the N stock markets under study (see Eq. (5)). If the estimated δs among pairs of cointegrated stock markets are *statistically significant* and *negative* (as expected, implementing the statistical validation tests described in Section 3.2), then the structure of a network[14] with N stock markets can be described as a $N \times N$ asymmetric adjacency matrix $\mathbf{W} = \{w_{ij}\}$ $(i, j = 1, 2, ..., N)$ (Newman, 2003; Barabasi, 2014). Consider if a stock market i exhibits the short-run disequilibrium adjustment to achieve long-run equilibrium relationship with stock market j associated with corresponding magnitude w_{ij} (the corresponding δ), then a directed edge

[14] A network can be represented by means of a graph $G = (V, E)$ that consists of a set V of N vertices and a set E of M edges (Barabasi, 2014).

would be drawn from i to j and vice versa. Meanwhile, $w_{ij} = 0$ indicates the absence of short-run disequilibrium correction from i towards j for reaching stable long-run equilibrium, and therefore no directed long-run linkage (Schweitzer et al., 2009; Billio et al., 2012; Diebold and Yilmaz, 2014). Thus, in this directed-weighted network, the directions and extents of short-run disequilibrium adjustments between stock market pairs, as well as and the number of corresponding long-run equilibrium relationships, can be intuitively explored.[15]

In the network setting, the aggregate magnitudes of short-run aggregate disequilibrium adjustments for reaching long-run interconnectedness from others toward the stock market i, can be defined as in-strength ($S_{i\leftarrow\bullet}$). Correspondingly, the aggregate intensities of short-run aggregate disequilibrium adjustments for reaching long-run interconnectedness toward others from the stock market j, is described as out-strength ($S_{\bullet\leftarrow j}$).

$$S_{i\leftarrow\bullet} = \sum_{j=1,j\neq i}^{N} w_{ij},\ S_{\bullet\leftarrow j} = \sum_{i=1,i\neq j}^{N} w_{ij}. \tag{9}$$

Note that, a stock market with a higher level of in-strength is indicative of the faster speed that other stock markets adjust the deviations from long-run equilibrium toward it within the system. Conversely, a stock market with a higher out-strength is more likely to correct the disequilibrium toward other stock markets for reaching long-run stable equilibrium associated with very rapid speed in the system. Then, the number of inward and outward linkages of each stock market are defined as in-degree ($D_{i\leftarrow\bullet}$) and out-degree ($D_{\bullet\leftarrow j}$), respectively.

$$D_{i\leftarrow\bullet} = \sum_{j=1,j\neq i}^{N} w_{ij},\ D_{\bullet\leftarrow j} = \sum_{i=1,i\neq j}^{N} w_{ij}. \tag{10}$$

Moreover, to clarify the central stock market or say its relative importance in the network, the basic and simplest strength-centrality (i.e., total strength) of a stock market is calculated by the sum of its in-strength and out-strength (Stavroglou et al., 2017). Similarly, the degree-centrality of a stock market (i.e., total degree) measure is calculated by the sum of its in-degree and out-degree (Billio et al., 2012; Anufriev and Panchenko, 2015; Rossi et al., 2018).

5 Network Analysis of International Stock Markets

As explained in Section 4.1, prior to the cointegration test, the ADF and PP unit root tests were conducted on the investigated 46 stock market indices to estimate the order of

[15] In the *online supplementary materials*, see Section **B**, the degree and strength distributions of three international stock market networks at FDR significance levels of $\alpha = 0.01$ and $\alpha = 0.05$ are also provided and discussed.

integration. The outcomes of the ADF and PP tests on each individual stock market index for the entire 2007–2017 period, two sub-sample periods of 2007–2009 and 2010–2012, can be found in Tables A.1–A.3 in Appendix A. The derived results indicate that all stock market indices are non-stationary at levels but stationary when taken in first differences, thus indicating that each stock market index follows an $I(1)$ process, during the three studied periods. Given the fact that the 46 stock market indices are not stationary and are integrated of order one, it is possible to carry out the cointegration analysis in the bivariate setting taking the log-form of each stock market index. If the residuals from estimating the cointegration equations (Eqs. (3) and (4)) are stationary, this will indicate the existence of long-run equilibrium relationships between the pairs of stock market indices. To conserve space, only a summary is reported here.[16] Once the variables included are found to be cointegrated, we proceed to conduct the ECM model for all pairs of cointegrated stock markets.

We then characterize the directed-weighted networks of the 46 stock markets based on the statistically significant and negative results for the error correction terms in the ECM models, where the detailed results are displayed as the corresponding asymmetric adjacency matrices in Tables B.1–B.3 (see Appendix B). Figures 1, 3 and 5 visualize the international networks of stock markets directional long-run interconnectedness over the entire period 2007–2017, and two specific criss periods of 2007–2009 GFC, 2010–2012 ESDC, respectively. Nodes (stock markets) are coloured according to their geographical locations, with orange for stock markets in Europe, blue for the Americas, green for the Asia-Pacific region, yellow for the Middle East, and red for Africa. In the network, the greater the magnitudes of the statistically significant short-run error correction coefficients (in absolute value), the thicker the width of the edge (or the bigger the size of the arrow), which further implies a faster short-run disequilibrium correction speed to restore the long-run equilibrium relationship between the two stock markets in question. The directionality of each edge in the network reveals the direction in which one stock market adjusts the short-run disequilibrium towards a long-run equilibrium relationship with the other stock market. Note also that, in Figures 1, 3 and 5, we illustrate the pairwise directional interconnectedness within global stock markets by applying the ForceAtlas2 layout algorithm (Jacomy et al., 2014). It allows us to visually depict the groups of 46 stock markets that share similar characteristics in terms of their adjustments of short-run disequilibrium to achieve long-run equilibrium. Therefore, we can infer that the directionally interconnected stock markets are perceived as subject to common stochastic trends of co-movement in the long term, which provides us with the first bit of evidence on how the world's stock markets respond to common risks. Besides, in Figures 2, 4 and 6 we display the magnitudes of the in-, out- and total strength (degree) of each stock market

[16]The detailed results of the stationarity tests for the estimated residuals from the cointegration equations are not presented here but are available upon request.

in the sample, over the three different periods, respectively.

5.1 The Full-sample Period of 2007–2017

We start our analysis for the directed and weighted network of the international stock markets over the entire 2007–2017 period (see Figure 1). As can be seen, the global stock markets form diverse sub-groups with similar interconnectedness characteristics, although there are multiple interconnections between these sub-groups. An important finding is that, emerging stock markets in Asia-Pacific, Latin America, the Middle East, and Africa are mostly grouped closer to each other, with a considerably high degree of directional interconnectedness. These significantly intensified interconnections associated with the faster short-run disequilibrium corrections toward long-run equilibrium among emerging stock markets worldwide, highlights the presence of common trends that are strongly driving those emerging markets to become interconnected in the long run, throughout the whole sample period of 2007–2017. It can be interpreted as evidence that, over the 2007–2017 period, the series of severe financial crises and subsequent QEs and QE tapering policies implemented by advanced economies in the US, Europe, and Japan significantly affected the movements of capital flows in emerging economies worldwide (Ahmed et al., 2017; Yang and Zhou, 2017). According to several prior studies (e.g., Froot and Ramadorai, 2008; Bekaert et al., 2011), capital flows from advanced countries were a potential determinant of the greater synchronization of stock markets in emerging economies. Note also that after the outbreak of the GFC, several regional initiatives, for instance, in Asia-Pacific region, Chiang Mai Initiative Multilateralization (CMIM) set to start in March 2010, ASEAN Comprehensive Investment Agreement (ACIA) took effect in 2012, etc., which further strengthened regional cooperation and integration among emerging Asia-Pacific stock markets (Caporale et al., 2019).

Moreover, as Figures 1 and 2 show, the prominent Asia-Pacific stock markets of Hong Kong, Australia, New Zealand, and South Korea, as expected, appear to be strongly internally interconnected with faster short-run disequilibrium correction speed and significantly interconnected to other Asia-Pacific stock markets and the rest of the world's advanced markets over the full period 2007–2017 period (Chevallier et al., 2018)

[Figure 1 about here.]

[Figure 2 about here.]

Besides, a notable observation in Figure 1 shows that the European stock markets are likely to be tightly internally interconnected and formed as individual sub-groups within the network, which signals heterogeneity within and across the European stock markets and the world's other stock markets. The most visible finding is that the stock markets in troubled "GIPSI" countries appear to form a separated, highly interconnected sub-group. Meanwhile, the stock markets of Austria, the Netherlands, Belgium, Finland, Ireland, France, Poland, the UK, and the Czech Republic in the EMU are grouped as another tightly interconnected component associated with faster adjustments of short-run disequilibrium to achieve long-run equilibrium (Bracker et al., 1999). The remaining European stock markets, namely those in Norway, Russia, Sweden, Switzerland, Denmark, and Germany, tend to be regionally segmented from those two European sub-groups but appear to significantly interconnected with the world's other stock markets during the same time period. The different sub-groups of European stock markets shown in our analysis strongly indicate the heterogeneous intra-regional co-movement behaviours that emerged when the European stock markets were buffeted by a series of negative shocks between 2007 and 2017.

Nevertheless, over the entire period of 2007–2017, it can be witnessed that the absence of long run co-movements between the US stock market and most of the rest of the world's stock markets (except for Japan, Germany, Denmark, and Pakistan). In Figures 1 and 2, it is apparent that the degree of directional interconnectedness between the US stock market and the world's other stock markets has highly decreased. More importantly, with the exception of the stock markets of Germany and Denmark, the directional interconnectedness between the US and the rest of the European stock markets has begun to disappear. The observed increased divergence of the US stock market (i.e., the S&P 500) mostly reflects the fact that it has experienced the strongest recovery path (the longest and best bull market ever) since March 2009, of all the world's stock markets.

5.2 The 2007-2009 GFC Period

For the specific crisis period of 2007–2009 GFC, several interesting observations emerge in Figure 3. One immediately striking result is that tightly directional interconnectedness is observed within and across most of the European stock markets and a set of developed stock markets from Asia-Pacific (i.e., New Zealand, Japan, Australia, Singapore, and Hong Kong), the Americas (i.e., the US and Canada), and the Middle East (i.e., Israel) (Bartram and Bodnar, 2009; Baur, 2012). Consisting with the findings in Figure 4, this highly interconnected component of the network highlights the presence of the faster short-run disequilibrium adjustments, which maintain the higher degree of long-run equilibrium relationships amongst these world's advanced economies and most of the European ones (including both developed and emerging markets) during the GFC period. In fact, in line with the observations made by early studies (e.g., Bekaert et al., 2014; Lehkonen, 2015; Mobarek et al., 2016), the GFC originated from the largest and most influential economy, the US market, was an international crisis that swept over financial markets worldwide at varying degrees. The developed stock markets and all major stock markets in Europe were seriously negatively affected and experienced significantly higher volatility levels than the rest of world's stock markets, leading to increasing dramatical cross-market co-movements in the long-run. Another important finding observed in Figure 3 is that the US stock market and several core developed European stock markets, including Finland, the UK, France, Italy, Ireland, Switzerland, Belgium etc., tend to be closer directionally interconnected and appear as a hairball within this component (Bartram and Bodnar, 2009; Lehkonen, 2015; Mollah et al., 2016). It confirms that their greater exposure to the US stock market is accompanied by the faster short-run disequilibrium adjustment rates toward long-run equilibrium to co-move, highlighting that these core European stock markets are more responsive to the shock of the US-originated GFC, and further providing insight into the underlying transmission of crisis through the global network of stock market interconnectedness.

Conversely, there are quite dramatic differences for the world's emerging stock markets, particularly in Asia-Pacific and the MENA region, during the time of the 2007–2009 GFC. From Figure 3 it is observed that the directional interconnectedness of these emerging stock markets with other stock markets across the globe is loosely visible compared with that between the developed stock markets and most of the European ones. It is evident that several emerging Asia-Pacific stock markets, namely the Philippines, India, Malaysia, Pakistan, and Indonesia, appear to be separated from the central component of the network (Dooley and Hutchison, 2009; Longstaff, 2010). Despite the presence of intra-regional interconnectedness with relatively weak short-run disequilibrium correction rates across these emerging Asia-Pacific stock markets, the evidence of the lower globally interconnectivity (also see Figure 4) demonstrates the absence of the common trends driving them to be long-run interconnected with the world's advantaged stock markets and most of the European stock markets, over the period 2007–2009 GFC. Our results support the view that the aforementioned emerging markets in Asia-Pacific experienced a much more robust and speedy recovery in contrast to the fragile and stuttering recovery of advanced economies, and in particular the majority European economies, possibly leading to lower global interconnectivity as they followed divergent trends (e.g., Kose and Prasad, 2010).

At the same time, Figure 3 also suggests that emerging markets from the MENA zone, namely the stock markets of Qatar, Egypt, and the United Arab Emirates, are highly independent and separated from the central component of the network. A notable observation in Figure 4 is that they appear to be characterized by the relatively lowest degree of directional interconnectedness associated with a weaker adjustment of the short-run disequilibrium towards long-run equilibrium with the world's other stock markets (with the exception of Israel and Mexico). This finding highlights the fact that, even though the MENA economies are becoming increasingly integrated with other global stock markets, while their modest exposure to trade and financial flows from advanced economies, which helped them to relatively mitigate the impact of the global shock (Kose and Prasad, 2010; Bekaert et al., 2014).

As is shown in Figure 3, the remaining emerging stock markets in the region of Asia-Pacific, i.e., South Korea, Taiwan, and Thailand, are mostly grouped closer to the central component of the network. The results emerge from Figure 3 and 4 reflect that most of them appear to exhibit dense global interconnectedness associated with faster adjustments of the short-run disequilibrium back to long-run equilibrium to co-move with the world's advanced economies, and in particular with the European economies. Our results concur with the stylized fact that these relatively higher exposures of the emerging Asia-Pacific stock markets were hit harder by the GFC than others in the same geographical region, as the significant exporters of capital and durable consumer goods contribute to greater co-movements within the world market. Note also that, among the emerging Latin American stock markets, we find that Chile, Peru, Columbia, Brazil, and Mexico appear to be tightly interconnected with the central component of the network. As Figure 3 displays, not only do they have closer intra-regional interconnectedness but they also exhibit tight pairwise directional interconnectedness with the world's other stock markets. The results reveal clearly that the effect of the GFC on the Latin American stock markets was more significant than that on emerging stock markets in Asia-Pacific and the MENA (see Figure 4). In line with Ocampo (2009), we conclude from our results that the emerging stock markets from Latin America were hit harder during the GFC, and a possible reason seems to be important continental market factors linking the Latin American and the US stock markets more closely than those from Asia-Pacific and the MENA (Dooley and Hutchison, 2009; Longstaff, 2010). It is also noteworthy that the adverse impact of the US-originated GFC was not the same across all emerging Latin American stock markets (Dufrénot et al., 2011). Particularly, as it is shown in Figures 3 and 4, Mexico, Columbia, Peru, and Chile economies, with their low levels of export diversification, were particularly affected and exhibit relatively faster speed of short-run disequilibrium correction and more directional interconnectedness with the world's other stock markets during the GFC (Chambet and Gibson, 2008).

[Figure 3 about here.]

[Figure 4 about here.]

5.3 The 2010–2012 ESDC Period

Finally, we consider the crisis period of the ESDC, and especially during its most severe phase between January 2010 and December 2012. The structure of the directional interconnectedness of the global network of stock markets, shown in Figure 5, captures some interesting signs. It appears that the directional interconnectedness within the European stock markets is substantially different from how it was during the 2007–2009 GFC period. By comparison, the most visible difference is that most of the European stock markets form distinct structural components within the network, which are characterized by highly directional interconnectedness associated with faster short-run disequilibrium adjustment inside and are significantly linked externally.

To be specific, in Figure 5, the first structural component contains ten stock markets from the Eurozone countries (i.e., Spain, Greece, Italy, Portugal, Finland, Belgium, France, Austria, and the Netherlands), three from the EU economies (i.e., the Czech Republic, Hungary, and Poland), and Norway (Virk and Javed, 2017; Niţoi and Pochea, 2019). This tightly intensified and interconnected group highlights the presence of faster adjustments of the short-run disequilibrium toward long-run equilibrium within these European stock markets. This evidence further supports the view that the risk of the 2010–2012 ESDC mainly concentrated in the European countries (Mollah et al., 2016; Virk and Javed, 2017). As the greater synchronization of monetary and fiscal policies, closer trade links, and financial integration within the European area, it is more likely for those economies to be exposed to common shocks, which led the European stock markets to be the most responsive and to be the most severely hit by the shocks that occurred during the period 2010–2012 ESDC. Another interesting finding in Figure 5 is that the emerging stock markets of India, the United Arab Emirates, Turkey, Egypt, and Brazil are particularly close to the aforementioned European stock markets, with a high degree of interconnectedness accompanied by sizeable short-run disequilibrium correction coefficients (see Figure 6).

Figure 5 also shows that Germany and most of the non-Eurozone economies (i.e., the UK, Denmark, Switzerland, and Sweden) are grouped together with a high level of interconnectedness, and are externally interconnected to the stock market of Israel and a set of core Asia-Pacific stock markets (i.e., Australian, Japan, Hong Kong, and South Korean) (e.g., Jayech, 2016). It is particularly evident in Figure 6 where these dominant Asia-Pacific stock markets appear to have faster short-run disequilibrium correction speed toward more long-run interconnectedness with other markets. Besides that, here, we see that several emerging stock markets, including five from the Asia-Pacific (i.e., Thailand, Malaysia, Indonesia, Pakistan, and the Philippines), four from the Americas (i.e., Peru, Mexico, Chile, and Columbia), one from the Middle East (i.e., Qatar) and one from Africa (i.e., South Africa), are also grouped in this component within the US, the five core European, and a set of dominant Asia-Pacific stock markets. This result is in striking contrast to the findings from the 2007–2009 GFC period, where most emerging stock markets in the regions of Asia-Pacific and the MENA were relatively separated from all major world's advanced markets and European ones. In contrast, they show a tendency to be highly interconnected globally during the 2010–2012 ESDC period. This comes as no surprise, as our results strongly suggest that the post-crisis boom in the emerging markets associated large capital inflows from advanced economies after the recent GFC, resulted in greater co-movements between the emerging and the rest of world's stock markets.

It should also be noted that, results emerge from Figures 5 and 6 signal a lower degree of directional interconnectedness associated with slower short-run disequilibrium correction speed across the US stock market and the group of the Eurozone stock markets in the network compared to that during the GFC period. Our finding supports the fact that the US stock market has experienced a strong recovery path compared to other markets after the GFC, especially relative to the Eurozone stock markets whose performance lagged behind that of the US as European countries mired in the ESDC. Besides of this, the stock market heterogeneous reactions to unconventional monetary policy might be another reason for the reduction in co-movements between the US and most Eurozone stock markets. For instance, the very prompt adoption of a series large-scale asset purchases programmes (LSAP), i.e., the quantitative easing (QE) polices, by the US Federal Reserve (Fed) after the GFC outbreak, in contrast to the relatively limited and short-lived European Central Bank (ECB)'s measures over 2010–2012 period, may led to divergent growth experiences in the two regions (Fawley and Neely, 2013; Caporale et al., 2016; Chen et al., 2018).

[Figure 5 about here.]

[Figure 6 about here.]

5.4 Discussion

To sum up, our findings clearly show that the intensity of the short-run disequilibrium adjustment towards long-run equilibrium for individual stock markets differs widely during the entire sample period of 2007–2017, and two specific crisis periods of 2007–2009 GFC and 2010–2012 ESDC. Particularly, compared to the entire 2007–2017 period and ESDC, distortions in the long-run equilibrium will be corrected quickly among the 46 stock markets in times of GFC. These results are consistent with Donadelli and Paradiso (2014), Christoffersen et al. (2012), and Lehkonen (2015), who claim that network interconnections have become stronger by the onset of GFC. More importantly, our network analysis is meaningful since the visualization of directions and intensities of the global stock market interconnectedness highlights which specific stock markets form interconnected groups or components, when exhibiting similar behaviours in their adjustment of short-run disequilibrium to maintain long-run equilibrium (Guidi and Ugur, 2014; Vỳrost et al., 2019).

Based on the longer investment horizon between 2007 and 2017, our results highlight substantial difference from the periods of the GFC and ESDC. The presence of the strong long-run interconnectedness among a diverse set of emerging stock markets worldwide implies that investors may be exposed to common shocks in the underlying market over 2007–2017, thereby making it necessary for them to be indifferent among investment choices. Similarly, the high degree of long-run interconnectedness within a set of EMU stock markets, and among "GIPSI" stock markets, indicates the absence of potential diversification benefits (Mensi et al., 2018). Conversely, the observed low level of long-run interconnectedness (1) among the US and the majority world's developed and emerging stock markets; (2) between Norway, Russia, Sweden, Switzerland, Germany, Denmark, and the several local European stock markets; (3) between the "GIPSI" stock markets and most emerging stock markets, etc., thereby may offer potential arbitrage from diversification for the entire sample period of 2007–2017.

Consistent with the observations made by many previous studies (e.g. Christoffersen et al., 2012; Ghysels et al., 2016), our sub-periods network analysis confirms that, during the 2007–2009 GFC, the directional interconnectedness within and across stock markets in developed countries and most of the European ones is extremely high, compared to that during the ESDC and the entire period of 2007–2017, suggesting that international investors had a difficult task in setting up their portfolios in this component of the network. In particular, the group consisting of the stock markets within the US and several core European stock markets (i.e., Finland, the UK, France, Italy, Ireland, Switzerland, Belgium etc.) further provides supportive evidence of the extremely small diversification opportunities when investing in these markets (Bartram and Bodnar, 2009; Diebold and Yilmaz, 2012). In striking contrast, emerging stock markets in Asia-Pacific and the MENA offer significant diversification benefits because of their lower degree of interconnectedness with the rest of the world's stock markets during the period of the GFC. These results are in accord with the findings of Dooley and Hutchison (2009) and Longstaff (2010) that emerging markets, especially in Asia and the MENA regions, have not been entirely affected by the US sub-prime crisis that has exploded since August 2007.

Likewise, the presence of high level of interconnectedness among the Eurozone stock markets during the onset of the ESDC, suggests that Eurozone-based diversification strategies seem to be inefficient from the international investors' perspective, which is consistent with arguments made by Virk and Javed (2017), Niţoi and Pochea (2019) and Mollah et al. (2016), among others. At the same time, the potential benefits of international diversification are decreasing for the US, the core European stock markets, and a set of emerging stock markets worldwide (i.e., from Asia-Pacific, Latin-Americas, South Africa, and Qatar), as the degree of interconnectedness increased throughout the period of the ESDC.

Finally, most importantly, what our analysis implies for financial economists in particular is that the sub-periods analysis, which includes two major global shocks, the GFC and ESDC, of our findings is much different than we realise. Comparing with the whole sample period of 2007 till 2017, the interdependency only lives on for a little while. After that, we might have to erase the board and start over again with the next crisis, and again. And yet again.

6 Conclusions and Perspectives

In this paper, we investigate the short-run disequilibrium adjustment effects and long-run equilibrium relationships affecting the international stock markets, based on our empirical framework which makes use of the methods of cointegration, the error correction model and network theory, during the period from January 2007 to June 2017. For this purpose, we conduct a comparative network analysis of the entire 2007–2017 period, and two recent financial crises, i.e., the 2007–2009 GFC and the 2010–2012 ESDC, to assess how extreme financial stress has shaped the stock markets interconnectedness in a global context, which has received little attention in previous studies.

To be specific, the empirical results obtained by studying a sample of 23 developed and 23 emerging stock markets worldwide over different time scales suggest substantial differences in the extent of short-run disequilibrium adjustment towards long-run equilibrium for individual stock markets, throughout the the entire period of 2007–2017, and crisis periods of the GFC and ESDC. Our findings confirm the changes in the pair-wise directional interconnectedness within the world's stock markets did occur under the impact of the recent financial crises. Particularly, compared to the entire 2007–2017 period and ESDC, distortions in the long-run equilibrium will be corrected quickly among the 46 stock markets in times of GFC. More importantly, the comparison of the network structure analysis highlights heterogeneous behaviours, in terms of the degree of directional interconnectedness and the adjustment rates of the short-run disequilibrium towards long-run equilibrium, across the world's stock markets. The formulated groups have significant implications for portfolio and risk management during financial crises, as well as for buy-and-hold investors.

The present paper has focused on the pre-specified sample period of an event, namely static network analysis within the international stock markets. In follow-up work, it would be useful to extend dynamic network analysis to a time-varying perspective across the global stock markets through rolling window approach[17], to give a full picture of their dynamic interconnectedness structure, in both tranquil and crisis times. In this direction, the pattern causality method developed by Stavroglou et al. (2019, 2020) will be considered.

[17]Early studies by Pascual (2003); Mylonidis and Kollias (2010); Guidi and Ugur (2014) among others, have pointed out that the rolling window analysis is helpful in taking into account the structural breaks in underlying interconnectedness in financial markets.

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References

D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi. Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608, 2015.

W. Ahmad, S. Sehgal, and N. R. Bhanumurthy. Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling*, 33:209–225, 2013.

A. D. Ahmed and R. Huo. Impacts of China's crash on Asia-Pacific financial integration: Volatility interdependence, information transmission and market co-movement. *Economic Modelling*, 79:28–46, 2019.

S. Ahmed, B. Coulibaly, and A. Zlate. International financial spillovers to emerging market economies: How important are economic fundamentals? *Journal of International Money and Finance*, 76:133–152, 2017.

C. Alexander. *Market models: A guide to financial data analysis.* John Wiley & Sons, 2001.

M. Anufriev and V. Panchenko. Connecting the dots: Econometric methods for uncovering networks with an application to the australian financial institutions. *Journal of Banking & Finance*, 61:S241–S255, 2015.

B. Arshanapalli and J. Doukas. International stock market linkages: Evidence from the pre-and post-october 1987 period. *Journal of Banking & Finance*, 17(1):193–208, 1993.

W. B. Arthur. Complexity and the economy. *Science*, 284(5411):107–109, 1999.

T. O. Awokuse, A. Chopra, and D. A. Bessler. Structural change and international stock market interdependence: Evidence from asian emerging markets. *Economic Modelling*, 26(3):549–559, 2009.

Y. Bai and C. J. Green. International diversification strategies: Revisited from the risk perspective. *Journal of Banking & Finance*, 34(1):236–245, 2010.

P. Bajgrowicz and O. Scaillet. Technical trading revisited: False discoveries, persistence tests, and transaction costs. *Journal of Financial Economics*, 106(3):473–491, 2012.

A.-L. Barabasi. *Linked-how Everything is Connected to Everything Else and what it Means F.* Perseus Books Group, 2014.

L. Barras, O. Scaillet, and R. Wermers. False discoveries in mutual fund performance: Measuring luck in estimated alphas. *The Journal of Finance*, 65(1):179–216, 2010.

S. M. Bartram and G. M. Bodnar. No place to hide: The global crisis in equity markets in 2008/2009. *Journal of International Money and Finance*, 28(8):1246–1292, 2009.

D. G. Baur. Financial contagion and the real economy. *Journal of Fanking & Finance*, 36(10):2680–2692, 2012.

G. Bekaert and C. R. Harvey. Time-varying world market integration. *The Journal of Finance*, 50(2):403–444, 1995.

G. Bekaert, C. R. Harvey, C. T. Lundblad, and S. Siegel. What segments equity markets? *The Review of Financial Studies*, 24(12):3841–3890, 2011.

G. Bekaert, M. Ehrmann, M. Fratzscher, and A. Mehl. The global crisis and equity market contagion. *The Journal of Finance*, 69(6):2597–2649, 2014.

Y. Benjamini. Discovering the false discovery rate. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 72(4):405–416, 2010.

Y. Benjamini and Y. Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1):289–300, 1995.

Y. Benjamini and D. Yekutieli. The control of the false discovery rate in multiple testing under dependency. *The Annals of Statistics*, 29(4):1165–1188, 2001.

M. Billio, M. Getmansky, A. W. Lo, and L. Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559, 2012.

J. Birch, A. A. Pantelous, and K. Zuev. The maximum number of 3-and 4-cliques within a planar maximally filtered graph. *Physica A: Statistical Mechanics and its Applications*, 417:221–229, 2015.

J. Birch, A. A. Pantelous, and K. Soramäki. Analysis of correlation based networks representing dax 30 stock price returns. *Computational Economics*, 47(4):501–525, 2016.

K. Bracker, D. S. Docking, and P. D. Koch. Economic determinants of evolution in international stock market integration. *Journal of Empirical Finance*, 6(1):1–27, 1999.

C. Brunetti, J. H. Harris, S. Mankad, and G. Michailidis. Interconnectedness in the interbank market. *Journal of Financial Economics*, 133(2):520–538, 2019.

G. M. Caporale, L. A. Gil-Alana, and J. C. Orlando. Linkages between the US and European stock markets: a fractional cointegration approach. *International Journal of Finance & Economics*, 21(2):143–153, 2016.

G. M. Caporale, K. F. You, and L. Chen. Global and regional stock market integration in Asia: A panel convergence approach. *International Review of Financial Analysis*, 65:101381, 2019.

A. Chambet and R. Gibson. Financial integration, economic instability and trade structure in emerging markets. *Journal of International Money and Finance*, 27(4):654–675, 2008.

G. M. Chen, M. Firth, and O. M. Rui. Stock market linkages: evidence from Latin America. *Journal of Banking & Finance*, 26(6):1113–1141, 2002.

M. P. Chen, P. F. Chen, and C. C. Lee. Frontier stock market integration and the global financial crisis. *The North American Journal of Economics and Finance*, 29:84–103, 2014.

Y. H. Chen, R. N. Mantegna, A. A. Pantelous, and K. M. Zuev. A dynamic analysis of S&P 500, FTSE 100 and EURO STOXX 50 indices under different exchange rates. *PloS One*, 13(3):e0194067, 2018.

J. Chevallier, D. K. Nguyen, J. Siverskog, and G. S. Uddin. Market integration and financial linkages among stock markets in pacific basin countries. *Journal of Empirical Finance*, 46:77–92, 2018.

K. T. Chi, J. Liu, and F. C. M. Lau. A network perspective of the stock market. *Journal of Empirical Finance*, 17(4):659–667, 2010.

M. S. Chien, C. C. Lee, T. C. Hu, and H. T. Hu. Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. *Economic Modelling*, 51:84–98, 2015.

B. Chowdhury, M. Dungey, M. Kangogo, M. A. Sayeed, and V. Volkov. The changing network of financial market linkages: The Asian experience. *International Review of Financial Analysis*, 64:71–92, 2019.

P. Christoffersen, V. Errunza, K. Jacobs, and H Langlois. Is the potential for international diversification disappearing? a dynamic copula approach. *The Review of Financial Studies*, 25(12):3711–3751, 2012.

C. Curme, M. Tumminello, R. N. Mantegna, H. E. Stanley, and D. Y. Kenett. Emergence of statistically validated financial intraday lead-lag relationships. *Quantitative Finance*, 15(8):1375–1386, 2015.

D. A. Dickey and W. A. Fuller. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a): 427–431, 1979.

F. X. Diebold and K. Yilmaz. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534):158–171, 2009.

F. X. Diebold and K. Yilmaz. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66, 2012.

F. X. Diebold and K. Yilmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134, 2014.

F. X. Diebold and K. Yilmaz. Trans-atlantic equity volatility connectedness: US and European financial institutions, 2004–2014. *Journal of Financial Econometrics*, 14(1):81–127, 2015.

T. Dimpfl. A note on cointegration of international stock market indices. *International Review of Financial Analysis*, 33:10–16, 2014.

M. Donadelli and A. Paradiso. Is there heterogeneity in financial integration dynamics? Evidence from country and industry emerging market equity indexes. *Journal of International Financial Markets, Institutions and Money*, 32:184–218, 2014.

M. Dooley and M. Hutchison. Transmission of the us subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis. *Journal of International Money and Finance*, 28(8):1331–1349, 2009.

G. Dufrénot, V. Mignon, and A. Péguin-Feissolle. The effects of the subprime crisis on the Latin American financial markets: An empirical assessment. *Economic Modelling*, 28(5):2342–2357, 2011.

M. Elliott, B. Golub, and M. O. Jackson. Financial networks and contagion. *American Economic Review*, 104(10):3115–53, 2014.

R. F. Engle and C. W. J. Granger. Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55(2):251–276, 1987.

C. S. Eun and S. Sabherwal. Cross-border listings and price discovery: Evidence from US-listed Canadian stocks. *The Journal of Finance*, 58(2):549–575, 2003.

C. S. Eun and S. Shim. International transmission of stock market movements. *Journal of Financial and Quantitative Analysis*, 24(02):241–256, 1989.

B. W. Fawley and C. J. Neely. Four stories of quantitative easing. *Federal Reserve Bank of St. Louis Review*, 95(1):51–88, 2013.

D. J. Fenn, M. A. Porter, P. J. Mucha, M. McDonald, S. Williams, N. F. Johnson, and N. S. Jones. Dynamical clustering of exchange rates. *Quantitative Finance*, 12(10): 1493–1520, 2012.

F. Fernández-Rodríguez, M. Gómez-Puig, and S. Sosvilla-Rivero. Using connectedness analysis to assess financial stress transmission in emu sovereign bond market volatility. *Journal of International Financial Markets, Institutions and Money*, 43:126–145, 2016.

K. J. Forbes and R. Rigobon. No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, 57(5):2223–2261, 2002.

K. A. Froot and T. Ramadorai. Institutional portfolio flows and international investments. *The Review of Financial Studies*, 21(2):937–971, 2008.

M. V. Geraci and J. Y. Gnabo. Measuring interconnectedness between financial institutions with Bayesian time-varying vector autoregressions. *Journal of Financial and Quantitative Analysis*, 53(3):1371–1390, 2018.

E. Ghysels, A. Plazzi, and R. Valkanov. Why invest in emerging markets? The role of conditional return asymmetry. *The Journal of Finance*, 71(5):2145–2192, 2016.

C. W. J. Granger. Some recent development in a concept of causality. *Journal of Econometrics*, 39(1-2):199–211, 1988.

C. W. J. Granger. *Essays in econometrics: collected papers of Clive WJ Granger*, volume 32. Cambridge University Press, 2001.

C. W. J Granger, B. N Huangb, and C. W. Yang. A bivariate causality between stock prices and exchange rates: evidence from recent Asianflu. *The Quarterly Review of Economics and Finance*, 40(3):337–354, 2000.

F. Guidi and M. Ugur. An analysis of south-eastern european stock markets: Evidence on cointegration and portfolio diversification benefits. *Journal of International Financial Markets, Institutions and Money*, 30:119–136, 2014.

R. Gupta and F. Guidi. Cointegration relationship and time varying co-movements among Indian and Asian developed stock markets. *International Review of Financial Analysis*, 21:10–22, 2012.

P. A. Hamill, Y. W. Li, A. A. Pantelous, S. A. Vigne, and J. Waterworth. Was a deterioration in 'connectedness' a leading indicator of the european sovereign debt crisis? *Journal of International Financial Markets, Institutions and Money*, page 101300, 2021.

W. Huang, P. C. Lai, and D. A. Bessler. On the changing structure among Chinese equity markets: Hong Kong, Shanghai, and Shenzhen. *European Journal of Operational Research*, 264(3):1020–1032, 2018.

M. Jacomy, T. Venturini, S. Heymann, and M. Bastian. Forceatlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PloS One*, 9(6):e98679, 2014.

S. Jayech. The contagion channels of july–august-2011 stock market crash: a DAG-copula based approach. *European Journal of Operational Research*, 249(2):631–646, 2016.

S. Johansen. Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3):231–254, 1988.

S. Johansen. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6):1551–1580, 1991.

G. B. Kadlec and D. M. Patterson. A transactions data analysis of nonsynchronous trading. *The Review of Financial Studies*, 12(3):609–630, 1999.

K. Kasa. Common stochastic trends in international stock markets. *Journal of Monetary Economics*, 29(1):95–124, 1992.

D. Y. Kenett and S. Havlin. Network science: a useful tool in economics and finance. *Mind & Society*, 14(2):155–167, 2015.

D. Y. Kenett, M. Tumminello, A. Madi, G. Gur-Gershgoren, R. N. Mantegna, and E. Ben-Jacob. Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. *PloS One*, 5(12):e15032, 2010.

D. Y. Kenett, X. Q. Huang, I. Vodenska, S. Havlin, and H. E. Stanley. Partial correlation analysis: Applications for financial markets. *Quantitative Finance*, 15(4):569–578, 2015.

M. A. Kose and E. S. Prasad. Emerging markets come of age. *Finance and development*, page 7, 2010.

A. Koulakiotis, N. Kartalis, K. Lyroudi, and N. Papasyriopoulos. Asymmetric and threshold effects on comovements among germanic cross-listed equities. *International Review of Economics & Finance*, 24:327–342, 2012.

J. W. Lee and A. Nobi. State and network structures of stock markets around the global financial crisis. *Computational Economics*, 51(2):195–210, 2018.

H. Lehkonen. Stock market integration and the global financial crisis. *Review of Finance*, 19(5):2039–2094, 2015.

C. H. Lin. The comovement between exchange rates and stock prices in the asian emerging markets. *International Review of Economics & Finance*, 22(1):161–172, 2012.

F. A. Longstaff. The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics*, 97(3):436–450, 2010.

Š. Lyócsa, T. Vỳrost, and E. Baumöhl. Return spillovers around the globe: A network approach. *Economic Modelling*, 77:133–146, 2019.

R. N. Mantegna. Hierarchical structure in financial markets. *The European Physical Journal B*, 11(1):193–197, 1999.

R. N. Mantegna and H. E. Stanley. *An introduction to econophysics: correlation and complexity in finance*. Cambridge University Press, Cambridge, 2000.

A. M. M. Masih and R. Masih. Dynamic linkages and the propagation mechanism driving major international stock markets: an analysis of the pre-and post-crash eras. *The Quarterly Review of Economics and Finance*, 37(4):859–885, 1997.

R. Masih and A. M. M. Masih. Long and short term dynamic causal transmission amongst international stock markets. *Journal of International Money and Finance*, 20(4):563–587, 2001.

W. Mensi, F. Z. Boubaker, K. H. Al-Yahyaee, and S. H. Kang. Dynamic volatility spillovers and connectedness between global, regional, and GIPSI stock markets. *Finance Research Letters*, 25:230–238, 2018.

A. Mobarek, G. Muradoglu, S. Mollah, and A. J. Hou. Determinants of time varying co-movements among international stock markets during crisis and non-crisis periods. *Journal of Financial Stability*, 24:1–11, 2016.

S. Mollah, A. S. Quoreshi, and G. Zafirov. Equity market contagion during global financial and eurozone crises: Evidence from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money*, 41:151–167, 2016.

N. Mylonidis and C. Kollias. Dynamic european stock market convergence: Evidence from rolling cointegration analysis in the first euro-decade. *Journal of Banking & Finance*, 34(9):2056–2064, 2010.

P. K. Narayan, S. Mishra, and S. Narayan. Do market capitalization and stocks traded converge? new global evidence. *Journal of Banking & Finance*, 35(10):2771–2781, 2011.

S. Neaime. Financial crises and contagion vulnerability of mena stock markets. *Emerging Markets Review*, 27:14–35, 2016.

M. E. J. Newman. The structure and function of complex networks. *SIAM review*, 45 (2):167–256, 2003.

A. Ng. Volatility spillover effects from Japan and the US to the Pacific–Basin. *Journal of International Money and Finance*, 19(2):207–233, 2000.

M. Niţoi and M. M. Pochea. What drives European Union stock market co-movements? *Journal of International Money and Finance*, 97:57–69, 2019.

J. A. Ocampo. Latin America and the Global Financial Crisis. *Cambridge Journal of Economics*, 33(4):703–724, 2009.

A. G. Pascual. Assessing european stock markets (co) integration. *Economics Letters*, 78(2):197–203, 2003.

P. C. B. Phillips and P. Perron. Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346, 1988.

I. Psaradellis, J. Laws, A.A. Pantelous, and G. Sermpinis. Spread trading, technical analysis and data snooping: Mean reversion vs momentum. *Available at SSRN, http://dx.doi.org/10.2139/ssrn.3128788*, 2019.

K. Pukthuanthong and R. Roll. Global market integration: An alternative measure and its application. *Journal of Financial Economics*, 94(2):214–232, 2009.

A. G. Rossi, D. Blake, A. Timmermann, I. Tonks, and R. Wermers. Network centrality and delegated investment performance. *Journal of Financial Economics*, 128(1):183–206, 2018.

T. Roukny, S. Battiston, and J. E. Stiglitz. Interconnectedness as a source of uncertainty in systemic risk. *Journal of Financial Stability*, 35:93–106, 2018.

F. Schweitzer, G. Fagiolo, D. Sornette, F. Vega-Redondo, A. Vespignani, and D. R. White. Economic networks: The new challenges. *Science*, 325(5939):422–425, 2009.

A. Sensoy, K. Ozturk, E. Hacihasanoglu, and B. M. Tabak. Not all emerging markets are the same: A classification approach with correlation based networks. *Journal of Financial Stability*, 33:163–186, 2016.

Y. J Song, Q. Ji, Y. J Du, and J. B. Geng. The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energy Economics*, 84:104564, 2019.

D. Sornette. *Why stock markets crash: critical events in complex financial systems.* Princeton University Press, 2017.

S. K. Stavroglou, A. A. Pantelous, K. Soramäki, and K. Zuev. Causality networks of financial assets. *Journal of Network Theory in Finance*, 3(2):17–67, 2017.

S. K. Stavroglou, A. A. Pantelous, H. E. Stanley, and K. M. Zuev. Hidden interactions in financial markets. *Proceedings of the National Academy of Sciences of the United States of America*, 116(22):10646–10651, 2019.

S. K. Stavroglou, A. A. Pantelous, H. E. Stanley, and K. M. Zuev. Unveiling causal interactions in complex systems. *Proceedings of the National Academy of Sciences of the United States of America*, 117(14):7599–7605, 2020.

T. Syriopoulos. Dynamic linkages between emerging european and developed stock markets: Has the EMU any impact? *International Review of Financial Analysis*, 16(1): 41–60, 2007.

V. Tola, F. Lillo, M. Gallegati, and R. N. Mantegna. Cluster analysis for portfolio optimization. *Journal of Economic Dynamics and Control*, 32(1):235–258, 2008.

M. Tumminello, T. Aste, T. Di Matteo, and R. N. Mantegna. A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences of the United States of America*, 102(30):10421–10426, 2005.

M. Tumminello, F. Lillo, and R. N. Mantegna. Correlation, hierarchies, and networks in financial markets. *Journal of Economic Behavior and Organization*, 75(1):40 – 58, 2010.

N. Virk and F. Javed. European equity market integration and joint relationship of conditional volatility and correlations. *Journal of International Money and Finance*, 71:53–77, 2017.

T. Vỳrost, Š. Lyócsa, and E. Baumöhl. Network-based asset allocation strategies. *The North American Journal of Economics and Finance*, 47:516–536, 2019.

G. J. Wang, C. Xie, K. J. He, and H. E. Stanley. Extreme risk spillover network: application to financial institutions. *Quantitative Finance*, 17(9):1417–1433, 2017.

Z. H. Yang and Y. G. Zhou. Quantitative easing and volatility spillovers across countries and asset classes. *Management Science*, 63(2):333–354, 2017.

I. W. Yu, K. P. Fung, and C. S. Tam. Assessing financial market integration in Asia–equity markets. *Journal of Banking & Finance*, 34(12):2874–2885, 2010.

W. P. Zhang, X. T. Zhuang, J. Wang, and Y. Lu. Connectedness and systemic risk spillovers analysis of chinese sectors based on tail risk network. *The North American Journal of Economics and Finance*, 54:101248, 2020.

Tables

Table 1
The selected countries/areas and corresponding stock market indices used in the study.

Developed Markets				Emerging Markets			
No.	**Stock Market Index**	**Code**	**Continent**	**No.**	**Stock Market Index**	**Code**	**Continent**
1	Canada (S&P/TSX)	CAN	Americas	24	Brazil (BOVESPA)	BRA	
2	United States (S&P500)	US		25	Chile (IPSA)	CHI	
3	Austria (ATX)	AUS		26	Colombia (IGBC)	COL	Americas
4	Belgium (BEL20)	BEL		27	Mexico (IPC)	MEX	
5	Denmark (OMXC20)	DEN		28	Peru (IGBVL)	PER	
6	Finland (OMXH25)	FIN		29	Czech Republic (PX)	CR	
7	France (CAC40)	FRA		30	Egypt (EGX30)	EGY	
8	Germany (DAX30)	GER		31	Greece (ATHEX20)	GRE	
9	Ireland (ISEQ20)	IRE		32	Hungary (BUX)	HUN	Europe,
10	Israel (TA125)	ISR	Europe,	33	Poland (WIG20)	POL	Middle-
11	Italy (FTSE MIB)	ITA	Middle-	34	Qatar (DSM200)	QAT	East,
12	the Netherlands (AEX)	NET	East	35	Russia (RTS)	RUS	Africa
13	Norway (OSLO)	NOR		36	South Africa (FTSE/JSE)	SA	
14	Portugal (PSI20)	POR		37	Turkey (BIST)	TUR	
15	Spain (IBEX35)	SPA		38	United Arab Emirates (ADX)	UAE	
16	Sweden (OMXS30)	SWE		39	India (BSE100)	IND	
17	Switzerland (SMI)	SWI		40	Indonesia (IDX)	INDO	
18	United Kingdom (FTSE100)	UK		41	South Korea (KOSPI)	KOR	
19	Australia (ASX)	AUST		42	Malaysia (FTSE BURSA)	MAL	Asia-
20	Hong Kong (HSI)	HK	Asia-	43	Pakistan (KSE100)	PAK	Pacific
21	Japan (NIKKEI225)	JAP	Pacific	44	Philippines (PSEI)	PHI	
22	New Zealand (S&P/NZX 50)	NZ		45	Taiwan (TAIEX)	TW	
23	Singapore (ST)	SIN		46	Thailand (SET)	THA	

Table 2
The descriptive statistics of the weekly returns of the global stock market indices over the January 2007–June 2017 sample period.

	Mean (%)	**Max (%)**	**Min (%)**	**Std. dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Prob.**
Developed Markets								
CAN	0.018	16.372	-26.633	0.035	-1.313	12.902	2391.853	0.0000
US	0.099	11.356	-20.084	0.026	-0.967	11.805	1852.062	0.0000
AUS	-0.088	18.655	-36.343	0.043	-1.508	13.980	2954.966	0.0000
BEL	-0.050	10.247	-28.320	0.035	-1.543	12.528	2286.028	0.0000
DEN	0.123	13.221	-24.592	0.035	-1.460	11.230	1738.106	0.0000
FIN	-0.021	11.811	-20.185	0.036	-0.915	6.910	424.759	0.0000
FRA	-0.037	13.860	-27.259	0.037	-1.121	9.952	1216.116	0.0000
GER	0.091	14.505	-26.556	0.037	-1.057	9.954	1203.853	0.0000
IRE	-0.083	12.938	-33.945	0.038	-1.881	16.236	4315.562	0.0000
ISR	0.093	14.832	-17.406	0.032	-0.767	8.315	697.533	0.0000
ITA	-0.152	13.063	-26.568	0.042	-1.035	7.356	530.180	0.0000
NETH	-0.019	13.901	-30.963	0.036	-1.441	14.581	3246.327	0.0000
NOR	-0.133	8.639	-7.926	0.020	-0.104	4.608	59.911	0.0000
POR	-0.166	10.234	-22.779	0.036	-1.061	7.170	498.987	0.0000
SPA	-0.081	12.529	-26.036	0.041	-0.953	7.536	551.721	0.0000
SWD	0.026	16.154	-23.846	0.039	-0.715	8.074	633.287	0.0000
SWI	0.047	13.103	-24.329	0.028	-1.521	16.475	4349.265	0.0000
UK	-0.043	16.279	-27.820	0.032	-1.359	15.153	3534.532	0.0000
AUST	0.004	13.236	-35.515	0.039	-1.839	17.136	4862.505	0.0000
HK	0.044	11.897	-17.660	0.032	-0.269	5.870	194.281	0.0000
JAP	0.039	7.010	-21.976	0.027	-1.234	11.728	1875.265	0.0000
NZ	0.035	10.270	-23.702	0.029	-1.613	13.191	2603.984	0.0000
SIN	0.021	17.789	-20.754	0.030	-0.488	11.137	1530.757	0.0000
Emerging Markets								
BRA	-0.006	25.702	-33.118	0.053	-0.516	8.478	708.296	0.0000
CHI	0.064	17.122	-33.259	0.035	-1.727	18.863	6007.053	0.0000
COL	-0.055	12.419	-27.296	0.038	-1.185	9.532	1100.346	0.0000
MEX	0.026	23.913	-30.203	0.042	-0.598	12.454	2069.733	0.0000
PER	0.041	18.670	-37.072	0.041	-1.351	17.683	5079.959	0.0000
CR	-0.103	18.936	-32.782	0.040	-1.237	13.838	2816.421	0.0000
EGY	-0.095	14.664	-45.319	0.047	-2.503	21.597	8453.864	0.0000
GRE	-0.337	17.124	-25.758	0.053	-0.564	4.831	105.404	0.0000
HUN	0.009	20.158	-35.320	0.048	-0.966	10.586	1396.619	0.0000
POL	-0.002	24.932	-29.004	0.045	-0.883	10.967	1517.944	0.0000
QAT	0.172	14.930	-23.073	0.033	-1.351	12.245	2114.272	0.0000
RUS	-0.119	34.188	-23.729	0.051	-0.152	9.202	878.697	0.0000
SA	0.029	24.194	-20.054	0.042	-0.077	7.722	508.662	0.0000
TUR	0.012	24.599	-28.521	0.052	-0.450	6.632	319.095	0.0000
UAE	0.064	11.026	-18.493	0.028	-1.011	9.538	1067.551	0.0000
IND	0.092	19.929	-21.397	0.039	-0.287	6.403	271.416	0.0000
INDO	0.140	17.533	-27.743	0.038	-0.926	11.150	1591.863	0.0000
KOR	0.063	26.469	-28.768	0.040	-0.701	13.389	2504.469	0.0000
MAL	0.046	11.253	-10.084	0.024	-0.401	5.509	158.141	0.0000
PAK	0.179	9.469	-20.955	0.031	-1.472	9.904	1283.906	0.0000
PHI	0.170	12.750	-21.356	0.033	-0.870	8.151	673.672	0.0000
TW	0.064	9.572	-12.190	0.030	-0.630	4.728	104.244	0.0000
THA	0.179	11.065	-27.197	0.031	-1.279	13.744	2780.260	0.0000

Table 3
The descriptive statistics of the weekly returns of the global stock market indices over the August 2007–June 2009 sample period.

	Mean (%)	Max (%)	Min (%)	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
Developed Markets								
CAN	-0.358	16.372	-26.633	0.060	-1.100	6.760	78.299	0.0000
US	-0.449	11.356	-20.084	0.043	-0.692	7.148	78.886	0.0000
AUS	-0.801	18.655	-36.343	0.071	-1.254	8.835	166.387	0.0000
BEL	-0.740	10.247	-28.320	0.054	-1.400	8.676	165.220	0.0000
DEN	-0.554	13.221	-24.592	0.059	-1.090	6.213	62.173	0.0000
FIN	-0.670	11.811	-20.185	0.054	-0.583	4.153	11.084	0.0039
FRA	-0.565	13.860	-27.259	0.055	-1.120	7.858	118.020	0.0000
GER	-0.425	14.505	-26.556	0.057	-1.022	7.385	96.561	0.0000
IRE	-1.151	12.938	-33.945	0.065	-1.366	8.759	167.613	0.0000
ISR	-0.165	14.832	-17.406	0.053	-0.494	4.270	10.681	0.0048
ITA	-0.723	13.063	-26.568	0.059	-1.161	6.457	71.543	0.0000
NETH	-0.703	13.901	-30.963	0.058	-1.300	9.451	199.558	0.0000
NOR	-0.020	8.639	-7.287	0.025	0.403	4.553	12.636	0.0018
POR	-0.625	10.234	-22.779	0.049	-1.278	7.494	110.285	0.0000
SPA	-0.388	12.529	-26.036	0.056	-1.331	7.750	122.330	0.0000
SWD	-0.593	16.154	-23.846	0.062	-0.376	4.858	16.568	0.0003
SWI	-0.386	13.103	-24.329	0.046	-1.375	10.711	276.509	0.0000
UK	-0.600	16.279	-27.820	0.056	-1.029	8.468	140.802	0.0000
AUST	-0.505	13.236	-35.515	0.065	-1.754	10.563	286.697	0.0000
HK	-0.184	11.897	-17.660	0.052	-0.211	3.593	2.183	0.3357
JAP	-0.329	7.010	-21.976	0.039	-1.646	10.800	295.658	0.0000
NZ	-0.684	10.270	-23.702	0.049	-1.309	7.621	116.347	0.0000
SIN	-0.438	17.789	-20.754	0.053	-0.280	5.798	33.590	0.0000
Emerging Markets								
BRA	-0.057	25.702	-33.118	0.084	-0.696	5.977	44.544	0.0000
CHI	-0.079	17.122	-33.259	0.060	-1.745	11.790	368.949	0.0000
COL	-0.216	12.419	-27.296	0.056	-1.594	8.725	177.117	0.0000
MEX	-0.382	23.913	-30.203	0.069	-0.369	8.157	111.969	0.0000
PER	-0.511	18.670	-37.072	0.071	-1.325	9.871	223.704	0.0000
CR	-0.592	18.936	-32.782	0.069	-0.902	7.619	101.431	0.0000
EGY	-0.387	10.764	-26.064	0.061	-1.724	7.746	141.936	0.0000
GRE	-0.792	17.124	-25.758	0.059	-0.885	6.341	58.954	0.0000
HUN	-0.693	20.158	-35.320	0.075	-0.699	7.401	87.964	0.0000
POL	-0.871	24.932	-29.004	0.073	-0.492	6.939	67.982	0.0000
QAT	0.048	12.053	-23.073	0.058	-1.254	5.989	62.794	0.0000
RUS	-0.731	34.188	-23.729	0.082	0.128	6.366	47.001	0.0000
SA	-0.322	24.194	-20.054	0.069	0.243	4.927	16.286	0.0003
TUR	-0.518	24.599	-28.521	0.079	-0.068	5.088	18.068	0.0001
UAE	-0.295	11.026	-18.493	0.043	-1.074	6.560	71.324	0.0000
IND	-0.189	19.929	-21.397	0.064	-0.189	3.839	3.489	0.1747
INDO	-0.210	17.063	-27.743	0.066	-0.780	5.511	36.041	0.0000
KOR	-0.628	26.469	-28.768	0.071	-0.270	6.730	58.607	0.0000
MAL	-0.239	7.454	-9.773	0.033	-0.368	3.022	2.231	0.3277
PAK	-0.961	9.469	-20.955	0.052	-0.955	4.928	30.382	0.0000
PHI	-0.367	12.750	-21.356	0.051	-0.708	5.640	37.037	0.0000
TW	-0.342	9.572	-12.190	0.046	-0.288	2.700	1.740	0.4190
THA	-0.349	11.065	-27.197	0.048	-1.653	11.592	349.583	0.0000

Table 4
The descriptive statistics of the weekly returns of the global stock market indices over the January 2010–December 2012 sample period.

	Mean (%)	Max (%)	Min (%)	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
Developed Markets								
CAN	0.063	8.277	-11.028	0.030	-0.621	4.414	23.005	0.0000
US	0.147	7.128	-7.460	0.024	-0.317	3.929	8.229	0.0163
AUS	-0.077	11.050	-18.645	0.044	-0.994	5.296	59.987	0.0000
BEL	-0.064	9.027	-15.866	0.037	-0.914	4.885	44.822	0.0000
DEN	0.194	9.011	-15.309	0.033	-0.990	6.386	100.000	0.0000
FIN	-0.121	9.567	-16.469	0.041	-0.830	5.287	51.916	0.0000
FRA	-0.106	11.445	-16.765	0.041	-0.642	4.475	24.860	0.0000
GER	0.105	11.374	-15.034	0.039	-0.648	4.597	27.507	0.0000
IRE	0.027	8.788	-17.985	0.035	-1.265	7.237	158.336	0.0000
ISR	-0.009	9.800	-16.471	0.031	-0.796	7.770	164.386	0.0000
ITA	-0.281	11.679	-18.443	0.048	-0.590	3.914	14.475	0.0007
NETH	-0.040	10.395	-15.184	0.036	-0.686	4.903	35.789	0.0000
NOR	-0.241	3.989	-7.320	0.021	-0.356	3.199	3.562	0.1685
POR	-0.310	8.169	-16.166	0.038	-0.817	4.582	33.614	0.0000
SPA	-0.299	11.150	-19.808	0.049	-0.433	3.760	8.630	0.0134
SWD	0.155	12.819	-17.507	0.041	-0.856	5.893	73.459	0.0000
SWI	0.106	7.324	-10.777	0.027	-0.862	5.005	45.462	0.0000
UK	0.058	8.153	-12.217	0.029	-0.861	5.409	56.999	0.0000
AUST	0.066	11.951	-14.677	0.037	-0.871	6.128	83.318	0.0000
HK	0.023	10.716	-9.709	0.028	-0.013	4.324	11.393	0.0034
JAP	0.041	5.410	-9.949	0.024	-0.739	4.597	30.759	0.0000
NZ	0.127	6.635	-9.841	0.025	-0.892	4.774	41.136	0.0000
SIN	0.145	8.825	-7.973	0.026	-0.453	4.426	18.569	0.0001
Emerging Markets								
BRA	-0.178	12.122	-16.215	0.042	-0.470	4.878	28.669	0.0000
CHI	0.154	9.361	-14.374	0.032	-0.923	6.457	99.828	0.0000
COL	0.245	7.262	-11.370	0.029	-0.929	5.000	48.449	0.0000
MEX	0.201	11.031	-13.548	0.034	-0.662	5.146	41.331	0.0000
PER	0.324	11.860	-10.227	0.035	0.047	4.266	10.478	0.0053
CR	-0.067	9.082	-16.637	0.039	-0.885	4.830	42.136	0.0000
EGY	-0.168	14.664	-17.895	0.039	-0.256	6.364	75.238	0.0000
GRE	-0.623	14.107	-18.685	0.057	-0.164	3.104	0.769	0.6808
HUN	-0.200	12.545	-24.484	0.052	-0.863	5.561	61.974	0.0000
POL	0.058	9.403	-19.399	0.042	-1.043	5.811	79.680	0.0000
QAT	0.264	14.930	-11.249	0.023	0.700	16.572	1210.058	0.0000
RUS	0.036	10.024	-17.966	0.042	-0.937	5.914	78.034	0.0000
SA	0.136	10.525	-14.138	0.036	-0.516	4.845	29.038	0.0000
TUR	0.142	9.833	-16.993	0.042	-0.884	4.500	34.931	0.0000
UAE	-0.035	3.929	-5.545	0.017	-0.093	3.472	1.673	0.4333
IND	-0.035	8.404	-8.474	0.033	0.044	2.797	0.320	0.8523
INDO	0.325	7.262	-11.607	0.028	-1.125	6.479	111.596	0.0000
KOR	0.163	9.946	-12.921	0.036	-0.764	4.854	37.511	0.0000
MAL	0.250	6.055	-8.028	0.021	-0.734	5.269	47.479	0.0000
PAK	0.287	6.723	-7.235	0.022	-0.479	4.323	17.352	0.0002
PHI	0.489	7.582	-10.564	0.029	-0.847	4.751	38.575	0.0000
TW	0.022	7.347	-10.027	0.030	-0.685	4.138	20.612	0.0000
THA	0.465	8.097	-9.202	0.027	-0.197	3.839	5.589	0.0612

Figures

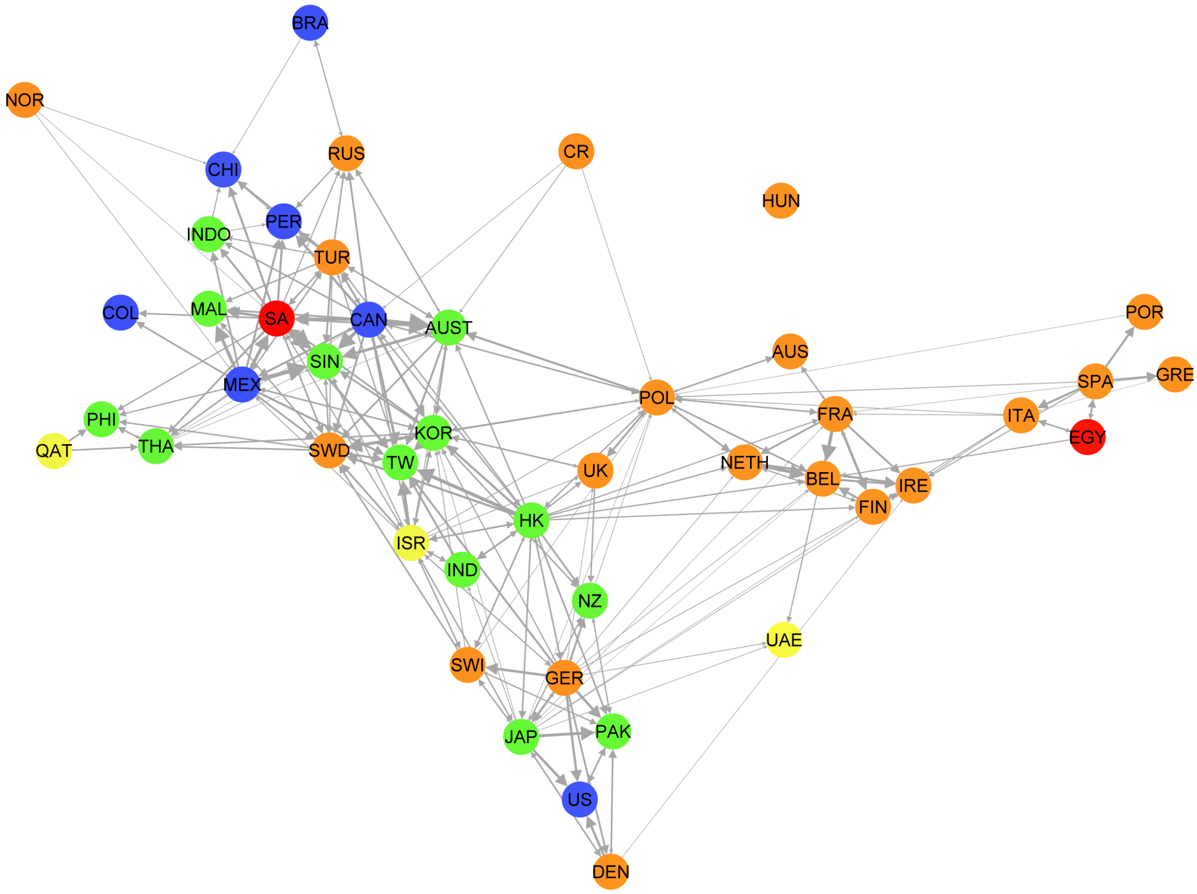
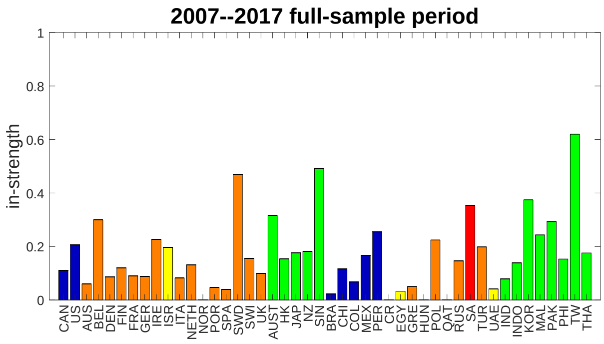
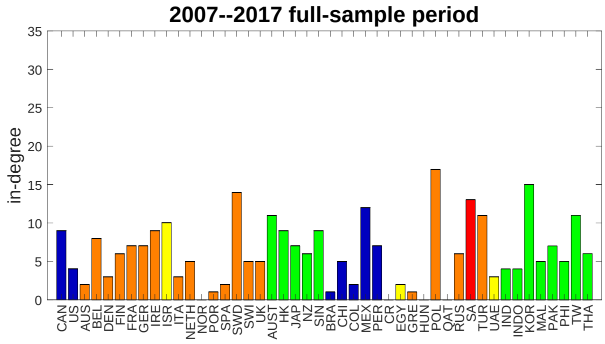


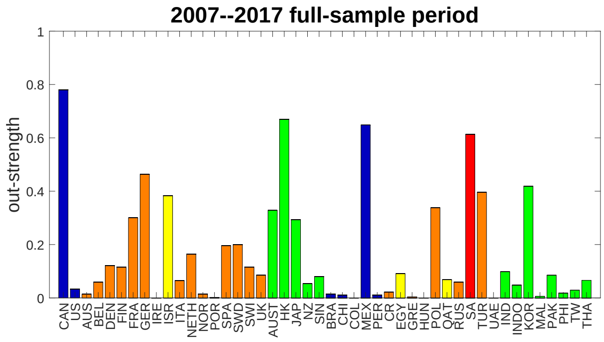
Figure 1. The international network of the investigated 46 stock markets over the January 2007–June 2017 full-sample period. Nodes (stock markets) are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker the width of an edge (or the bigger the size of an arrow), the greater magnitude of the short-run error adjustment coefficient between stock market pair. The directionality of each edge indicates the direction in which one stock market adjusts the short-run disequilibrium towards long-run equilibrium with the other.



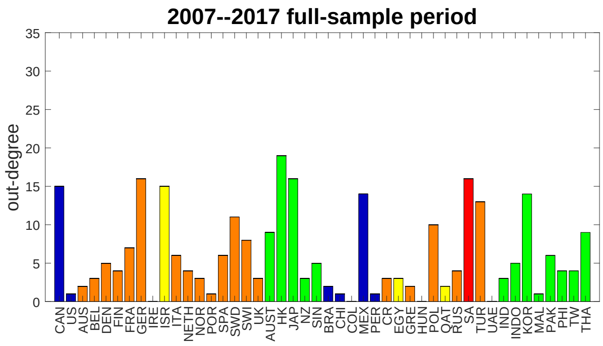
(a) In-strength



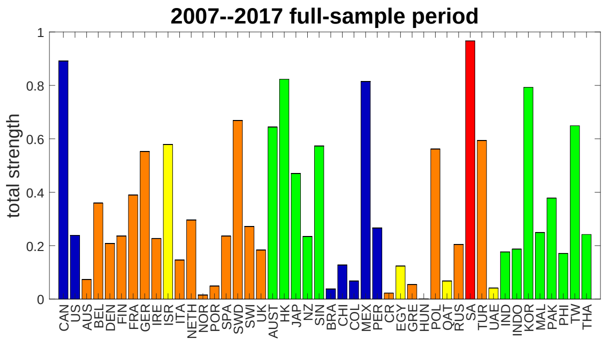
(b) In-degree



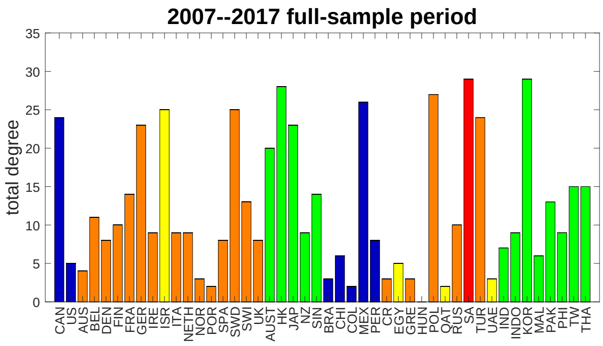
(c) Out-strength



(d) Out-degree



(e) Total strength



(f) Total degree

Figure 2. The magnitudes of the in-, out- and total strength and degree of the 46 stock markets over the January 2007–June 2017 full-sample period. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa.

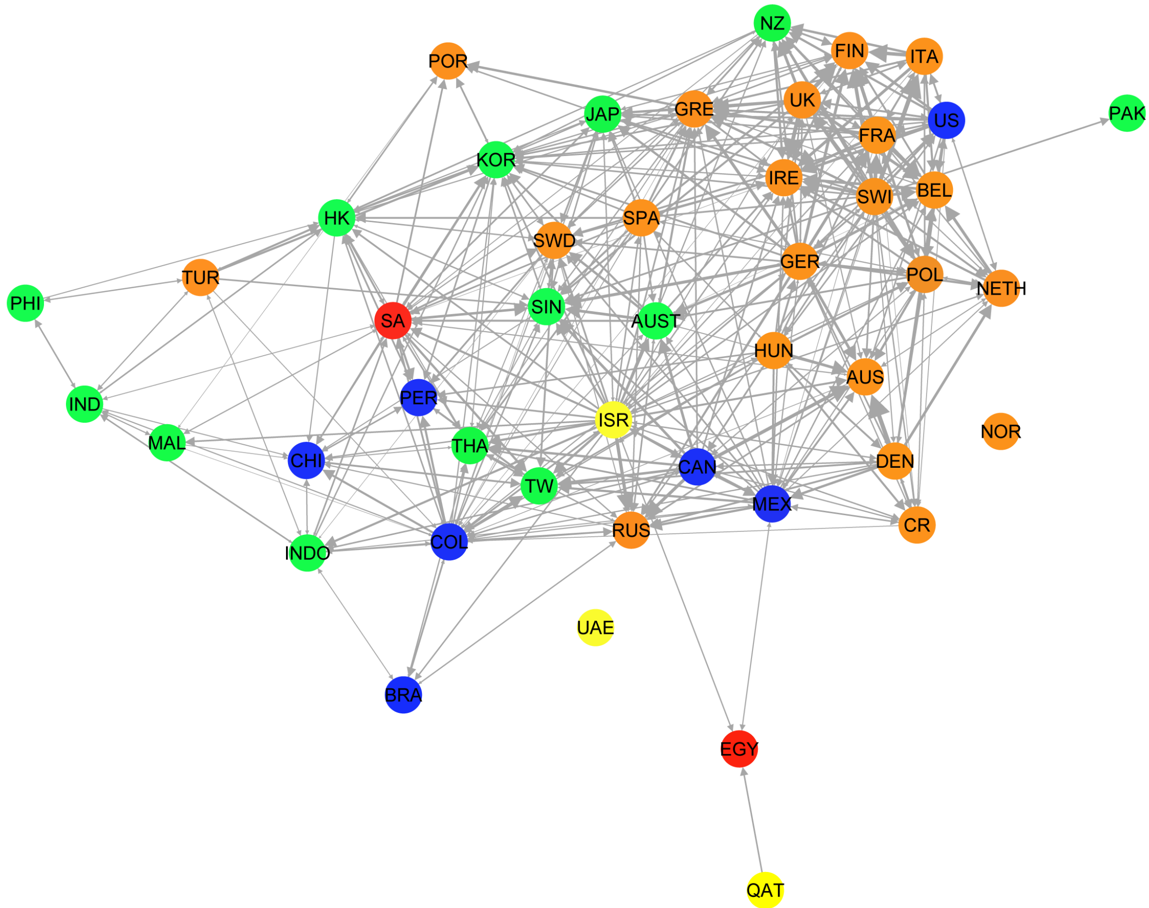
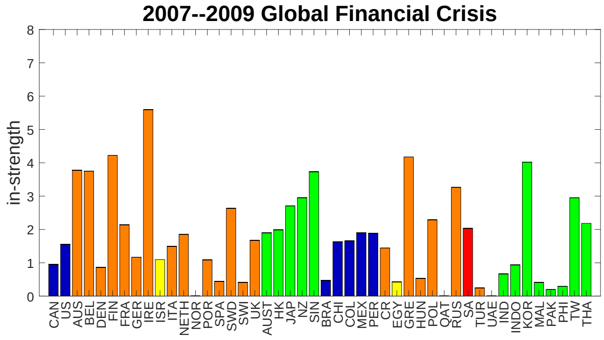
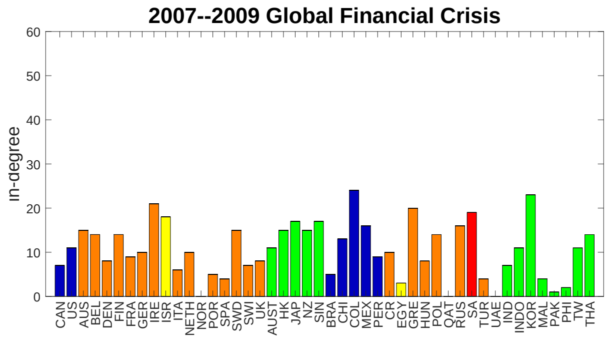


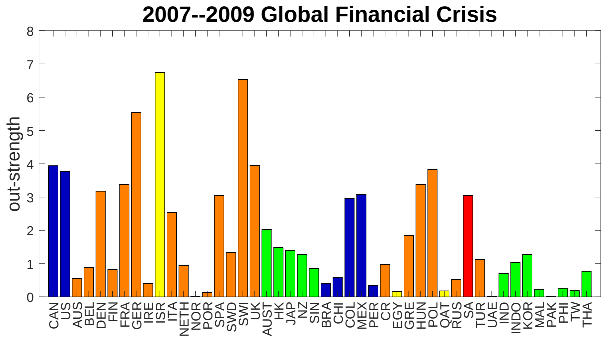
Figure 3. The international network of the investigated 46 stock markets over the August 2007–June 2009 sub-period. Nodes (stock markets) are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker the width of an edge (or the bigger the size of an arrow), the greater magnitude of the short-run error adjustment coefficient between stock market pair. The directionality of each edge indicates the direction in which one stock market adjusts the short-run disequilibrium towards long-run equilibrium with the other.



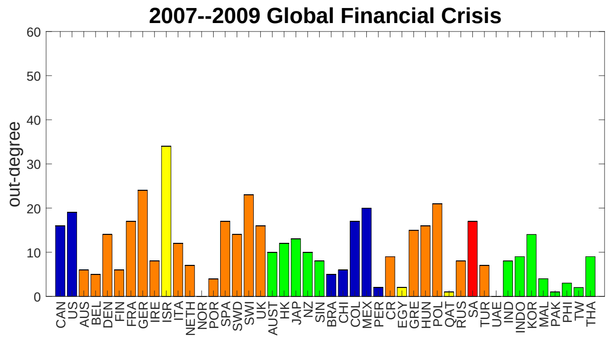
(a) In-strength



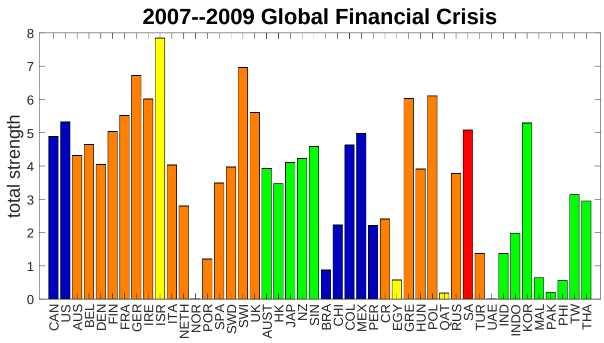
(b) In-degree



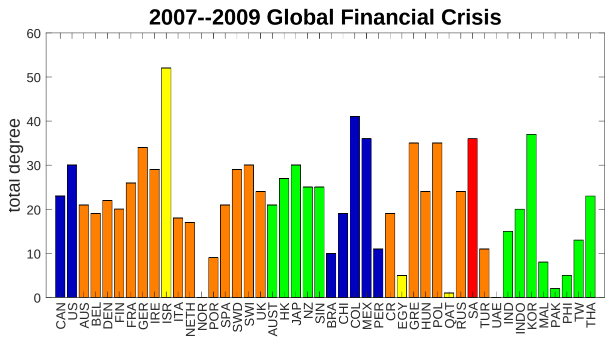
(c) Out-strength



(d) Out-degree



(e) Total strength



(f) Total degree

Figure 4. The magnitudes of the in-, out- and total strength and degree of the 46 stock markets over the August 2007–June 2009 sub-period. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa.

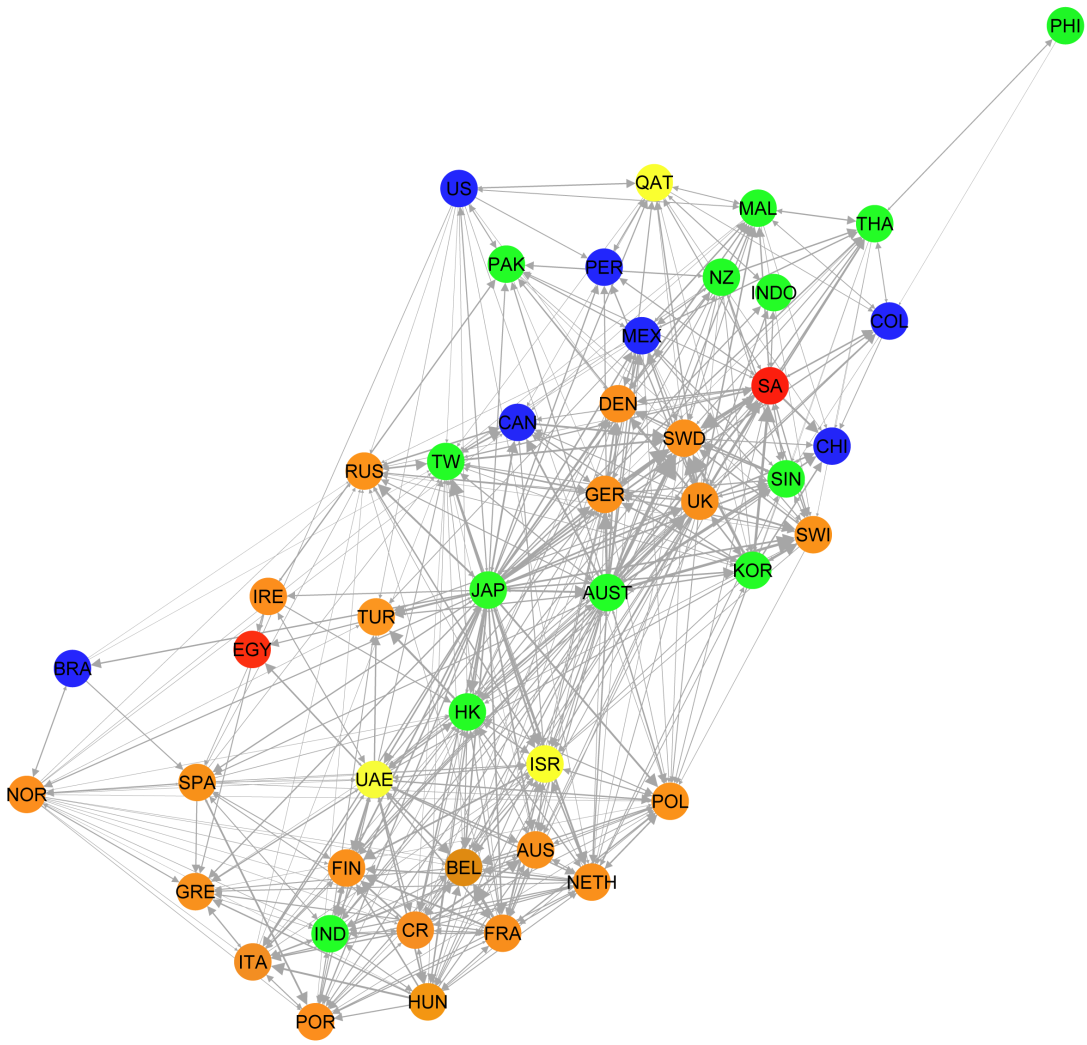
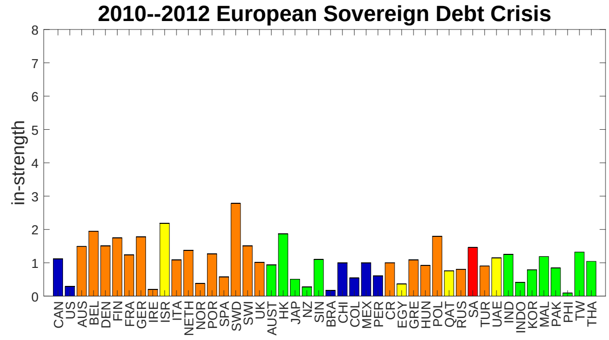
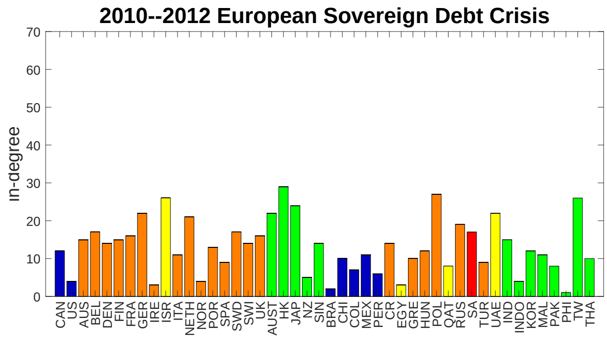


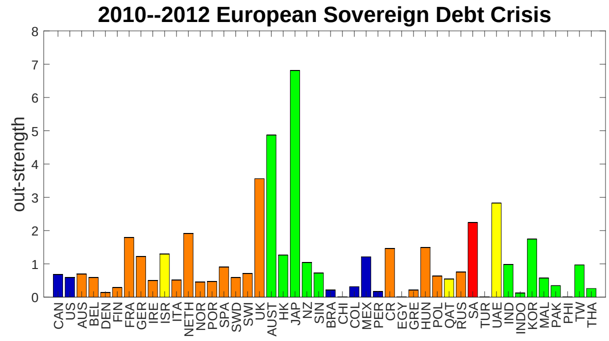
Figure 5. The international network of the investigated 46 stock markets over the January 2010–December 2012 sub-period. Nodes (stock markets) are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker the width of an edge (or the bigger the size of an arrow), the greater magnitude of the short-run error adjustment coefficient between stock market pair. The directionality of each edge indicates the direction in which one stock market adjusts the short-run disequilibrium towards long-run equilibrium with the other.



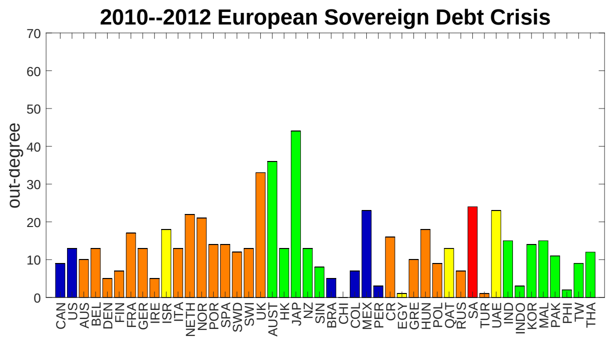
(a) In-strength



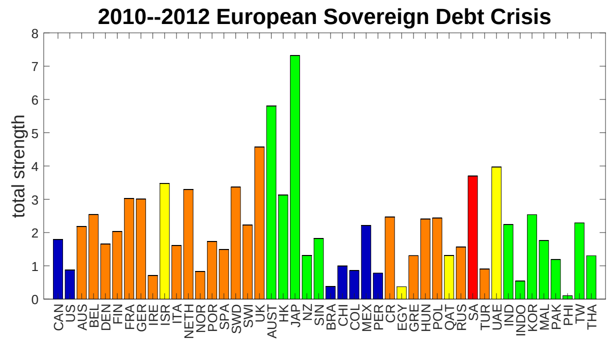
(b) In-degree



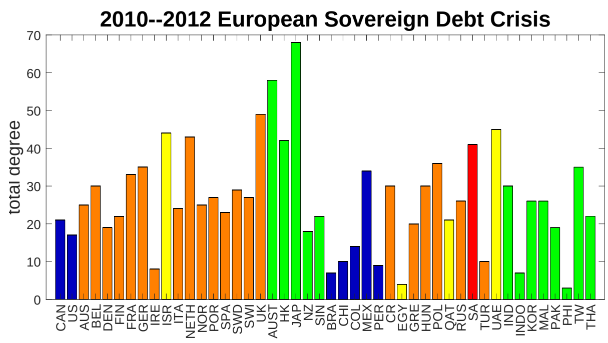
(c) Out-strength



(d) Out-degree



(e) Total strength



(f) Total degree

Figure 6. The magnitudes of the in-, out- and total strength and degree of the 46 stock markets over the January 2010–December 2012 sub-period. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa.

Appendix A Results of unit root tests

This Appendix reports the results of the unit root tests of all 46 stock market indices during the entire period of 2007–2017, and two crisis periods of 2007–2009 GFC and 2010–2012 ESDC, respectively.

Table A.1
The results of ADF and PP unit root tests on the 46 stock market indices over the full period 2007–2017.

	Log Level				First Log Difference			
	With Trend		Without Trend		With Trend		Without trend	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
Developed Markets								
CAN	-2.367	-2.526	-2.372	-2.533	-16.618∗	-25.065∗	-16.632∗	-25.086∗
US	-2.195	-2.164	-0.264	-0.302	-16.038∗	-24.933∗	-15.978∗	-24.866∗
AUS	-1.873	-2.102	-2.083	-2.207	-15.671∗	-23.493∗	-15.643∗	-23.479∗
BEL	-1.939	-1.999	-2.129	-2.175	-15.462∗	-23.538∗	-15.417∗	-23.505∗
DEN	-2.019	-2.207	-0.760	-0.943	-15.595∗	-24.716∗	-15.587∗	-24.719∗
FIN	-1.614	-1.794	-1.810	-1.949	-16.38∗	-24.516∗	-16.361∗	-24.510∗
FRA	-2.224	-2.297	-2.381	-2.427	-16.427∗	-24.688∗	-16.412∗	-24.676∗
GER	-2.361	-2.515	-1.606	-1.741	-15.479∗	-24.343∗	-15.484∗	-24.356∗
IRE	-1.880	-1.925	-1.868	-1.935	-16.615∗	-24.294∗	-16.419∗	-24.139∗
ISR	-2.358	-2.529	-1.832	-1.940	-17.250∗	-23.904∗	-17.265∗	-23.925∗
ITA	-2.112	-2.199	-2.153	-2.160	-15.710∗	-23.437∗	-15.685∗	-23.421∗
NETH	-2.076	-2.163	-2.163	-2.249	-15.523∗	-23.209∗	-15.502∗	-23.200∗
NOR	-2.779	-2.855	-1.345	-1.359	-16.679∗	-22.708∗	-16.688∗	-22.723∗
POR	-2.270	-2.470	-1.372	-1.398	-15.658∗	-22.964∗	-15.669∗	-22.981∗
SPA	-2.392	-2.593	-2.069	-2.161	-16.339∗	-24.83∗	-16.343∗	-24.841∗
SWD	-2.271	-2.373	-1.823	-1.921	-16.821∗	-25.338∗	-16.827∗	-25.351∗
SWI	-2.099	-2.267	-1.126	-1.300	-16.091∗	-27.651∗	-16.086∗	-27.649∗
UK	-2.144	-2.180	-2.179	-2.215	-16.913∗	-25.919∗	-16.910∗	-25.920∗
AUST	-2.272	-2.397	-2.274	-2.399	-15.912∗	-24.460∗	-15.927∗	-24.482∗
HK	-2.697	-2.875	-2.524	-2.670	-15.331∗	-23.119∗	-15.342∗	-23.139∗
JAP	-2.486	-2.573	-1.251	-1.318	-15.787∗	-24.421∗	-15.746∗	-24.380∗
NZ	-1.997	-2.043	-1.192	-1.282	-15.520∗	-23.232∗	-15.467∗	-23.197∗
SIN	-1.992	-2.173	-1.944	-2.115	-13.632∗	-21.624∗	-13.645∗	-21.642∗
Emerging Markets								
BRA	-2.508	-2.744	-1.561	-1.798	-15.394∗	-25.199∗	-15.388∗	-25.198∗
CHI	-1.819	-1.922	-1.877	-1.979	-16.831∗	-25.741∗	-16.834∗	-25.747∗
COL	-1.272	-1.435	-0.946	-1.136	-14.925∗	-24.534∗	-14.898∗	-24.517∗
MEX	-2.252	-2.472	-2.222	-2.427	-15.581∗	-26.242∗	-15.595∗	-26.264∗
PER	-1.880	-2.041	-1.779	-1.940	-13.695∗	-20.642∗	-13.699∗	-20.651∗
CR	-2.631	-2.816	-1.771	-1.868	-14.555∗	-21.780∗	-14.566∗	-21.798∗
EGY	-2.189	-2.384	-1.743	-1.916	-15.792∗	-24.150∗	-15.804∗	-24.170∗
GRE	-1.583	-1.716	-1.481	-1.478	-14.858∗	-22.023∗	-14.837∗	-22.016∗
HUN	-2.003	-2.150	-2.180	-2.308	-15.390∗	-22.401∗	-15.371∗	-22.395∗
POL	-2.010	-2.260	-2.071	-2.294	-15.629∗	-24.139∗	-15.628∗	-24.151∗
QAT	-1.950	-2.102	-1.826	-1.746	-15.908∗	-23.197∗	-15.880∗	-23.180∗
RUS	-2.173	-2.368	-1.902	-2.102	-15.167∗	-22.548∗	-15.181∗	-22.567∗
SA	-2.408	-2.551	-2.369	-2.511	-16.738∗	-25.470∗	-16.752∗	-25.492∗
TUR	-2.455	-2.656	-2.369	-2.577	-15.281∗	-23.837∗	-15.291∗	-23.850∗
UAE	-1.402	-1.532	-1.147	-1.216	-16.413∗	-23.259∗	-16.427∗	-23.277∗
IND	-2.390	-2.576	-2.098	-2.275	-13.768∗	-21.746∗	-13.778∗	-21.763∗
INDO	-1.664	-1.893	-1.687	-1.691	-15.357∗	-24.287∗	-15.361∗	-24.294∗
KOR	-2.393	-2.449	-2.117	-2.163	-15.465∗	-23.431∗	-15.478∗	-23.450∗
MAL	-1.422	-1.482	-1.727	-1.764	-15.58∗	-22.237∗	-15.555∗	-22.217∗
PAK	-1.558	-1.586	-0.064	-0.212	-13.797∗	-20.369∗	-13.723∗	-20.337∗
PHI	-1.529	-1.711	-1.035	-1.087	-15.872∗	-24.306∗	-15.884∗	-24.323∗
TW	-2.112	-2.462	-1.585	-1.898	-14.884∗	-23.883∗	-14.887∗	-23.894∗
THA	-1.582	-1.807	-1.341	-1.467	-14.692∗	-22.808∗	-14.700∗	-22.818∗

Note: ∗ indicates significance at the 1% level. When the observation sample $T = 548$, the critical values for the ADF test with trend are -3.96 (1%), -3.41 (5%), -3.12 (10%), and those without trend are -3.43 (1%), -2.86 (5%), -2.57 (10%). The critical values for the PP test with trend are -3.979 (1%), -3.420 (5%), -3.132 (10%), and those without trend are -3.445 (1%), -2.867 (5%), -2.570 (10%).

Table A.2
The results of ADF and PP unit root tests on 46 stock market indices over the sub-period of 2007–2009.

	Log Level				First Log Difference			
	With Trend		Without Trend		With Trend		Without Trend	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
Developed Markets								
CAN	-1.528	-1.685	-0.887	-0.986	-6.574∗	-10.784∗	-6.610∗	-10.838∗
US	-1.941	-2.152	-0.846	-0.846	-6.255∗	-10.381∗	-6.289∗	-10.435∗
AUS	-1.482	-1.525	-0.728	-0.827	-6.100∗	-9.793∗	-6.133∗	-9.841∗
BEL	-1.785	-1.692	-0.673	-0.754	-5.699∗	-8.889∗	-5.727∗	-8.931∗
DEN	-1.571	-1.682	-0.809	-0.939	-6.235∗	-10.598∗	-6.273∗	-10.652∗
FIN	-1.894	-1.788	-0.608	-0.649	-6.788∗	-9.548∗	-6.818∗	-9.594∗
FRA	-1.978	-2.039	-0.739	-0.834	-6.489∗	-10.599∗	-6.520∗	-10.651∗
GER	-1.989	-2.061	-0.877	-0.953	-6.043∗	-10.264∗	-6.073∗	-10.314∗
IRE	-1.263	-1.243	-0.794	-0.836	-6.881∗	-9.855∗	-6.915∗	-9.897∗
ISR	-1.544	-1.720	-0.898	-0.898	-7.501∗	-10.264∗	-7.538∗	-10.319∗
ITA	-1.859	-1.993	-0.716	-0.794	-5.970∗	-10.044∗	-6.002∗	-10.093∗
NETH	-1.842	-1.826	-0.681	-0.781	-5.866∗	-9.407∗	-5.887∗	-9.450∗
NOR	-2.532	-2.537	-2.546	-2.551	-7.329∗	-9.531∗	-7.334∗	-9.574∗
POR	-1.243	-1.390	-0.850	-0.962	-6.160∗	-10.272∗	-6.197∗	-10.312∗
SPA	-1.565	-1.839	-0.868	-1.014	-6.042∗	-11.054∗	-6.074∗	-11.106∗
SWD	-1.444	-1.559	-1.045	-1.173	-6.731∗	-10.573∗	-6.758∗	-10.612∗
SWI	-1.880	-2.250	-0.705	-0.858	-6.606∗	-12.978∗	-6.640∗	-13.041∗
UK	-1.641	-1.754	-0.737	-0.835	-7.037∗	-11.676∗	-7.076∗	-11.737∗
AUST	-1.489	-1.524	-0.857	-0.922	-6.793∗	-10.249∗	-6.835∗	-10.301∗
HK	-1.624	-1.625	-0.955	-1.041	-6.207∗	-9.718∗	-6.242∗	-9.766∗
JAP	-1.564	-1.666	-1.292	-1.325	-6.151∗	-9.391∗	-6.174∗	-9.400∗
NZ	-1.296	-1.425	-0.907	-0.990	-7.129∗	-10.623∗	-7.185∗	-10.659∗
SIN	-1.114	-1.186	-0.969	-1.061	-5.773∗	-9.071∗	-5.814∗	-9.095∗
Emerging Markets								
BRA	-1.417	-1.520	-1.033	-1.175	-6.522∗	-11.174∗	-6.551∗	-11.228∗
CHI	-0.864	-1.190	-1.232	-1.441	-7.597∗	-11.856∗	-7.587∗	-11.832∗
COL	-0.946	-1.396	-1.281	-1.558	-6.147∗	-11.375∗	-6.199∗	-11.364∗
MEX	-1.554	-1.826	-1.002	-1.165	-5.888∗	-11.282∗	-5.921∗	-11.336∗
PER	-0.690	-0.755	-1.287	-1.356	-5.856∗	-8.767∗	-5.814∗	-8.699∗
CR	-1.752	-1.728	-0.783	-0.810	-5.697∗	-8.973∗	-5.717∗	-9.012∗
EGY	-1.581	-1.603	-0.572	-0.679	-5.204∗	-9.718∗	-5.191∗	-9.729∗
GRE	-1.642	-1.484	-0.719	-0.775	-5.818∗	-8.232∗	-5.852∗	-8.275∗
HUN	-1.482	-1.465	-1.045	-1.102	-6.212∗	-8.977∗	-6.251∗	-9.013∗
POL	-1.681	-1.704	-0.643	-0.744	-6.939∗	-10.426∗	-6.972∗	-10.477∗
QAT	-1.710	-1.704	-1.115	-1.166	-6.395∗	-9.505∗	-6.330∗	-9.477∗
RUS	-1.409	-1.337	-0.815	-0.834	-6.054∗	-8.705∗	-6.092∗	-8.753∗
SA	-1.519	-1.651	-1.054	-1.155	-6.539∗	-10.787∗	-6.577∗	-10.837∗
TUR	-1.485	-1.564	-1.096	-1.199	-6.123∗	-9.750∗	-6.156∗	-9.783∗
UAE	-1.828	-1.839	-0.349	-0.329	-7.197∗	-9.238∗	-6.958∗	-9.082∗
IND	-1.205	-1.271	-0.970	-1.047	-5.062∗	-8.930∗	-5.096∗	-8.963∗
INDO	-0.988	-1.099	-0.965	-1.076	-6.579∗	-9.714∗	-6.633∗	-9.743∗
KOR	-1.571	-1.590	-1.107	-1.158	-6.625∗	-9.742∗	-6.672∗	-9.780∗
MAL	-1.276	-1.148	-0.865	-0.953	-6.464∗	-8.755∗	-6.514∗	-8.797∗
PAK	-1.917	-1.785	-0.500	-0.592	-5.498∗	-8.237∗	-5.515∗	-8.271∗
PHI	-1.299	-1.363	-0.960	-1.036	-7.700∗	-10.464∗	-7.764∗	-10.505∗
TW	-0.747	-0.942	-1.004	-1.105	-5.994∗	-9.817∗	-6.030∗	-9.820∗
THA	-0.892	-1.002	-0.918	-1.058	-6.113∗	-9.651∗	-6.157∗	-9.674∗

Note: ∗ indicates significance at the 1% level. When the observation sample $T = 100$, the critical values for the ADF test with trend are -4.04 (1%), -3.45 (5%), -3.15 (10%), and those without trend are -3.51 (1%), -2.89 (5%), -2.58 (10%). The critical values for the PP test with trend are -4.053 (1%), -3.455 (5%), 3.153 (10%), and those without trend are -3.497 (1%), -2.891 (5%), -2.582 (10%).

Table A.3
The results of ADF and PP unit root tests on 46 stock market indices over the sub-period of 2010–2012.

	Log Level				**First Log Difference**			
	With Trend		**Without Trend**		**With Trend**		**Without Trend**	
	ADF	**PP**	**ADF**	**PP**	**ADF**	**PP**	**ADF**	**PP**
Developed Markets								
CAN	-2.059	-2.199	-2.089	-2.247	-9.472	-14.276	-9.491	-14.312
US	-2.753	-2.980	-1.415	-1.586	-8.902	-13.724	-8.931	-13.769
AUS	-1.624	-1.763	-1.666	-1.676	-9.038	-12.963	-9.023	-12.976
BEL	-1.841	-2.204	-1.924	-2.084	-9.178	-14.564	-9.174	-14.570
DEN	-1.760	-2.184	-1.547	-1.990	-8.305	-14.351	-8.330	-14.394
FIN	-1.776	-2.187	-1.428	-1.601	-8.262	-14.266	-8.286	-14.305
FRA	-2.230	-2.405	-2.306	-2.344	-9.005	-13.252	-8.989	-13.245
GER	-2.032	-2.379	-1.850	-2.208	-8.084	-13.265	-8.096	-13.283
IRE	-2.793	-2.984	-2.590	-2.852	-8.867	-13.948	-8.804	-13.903
ISR	-2.021	-2.278	-1.819	-1.947	-8.337	-12.670	-8.364	-12.711
ITA	-2.100	-2.334	-1.870	-1.868	-9.036	-13.155	-9.020	-13.153
NETH	-2.318	-2.528	-2.395	-2.528	-8.836	-13.306	-8.834	-13.315
NOR	-2.531	-2.753	-1.431	-1.388	-9.571	-13.216	-9.565	-13.224
POR	-1.727	-1.822	-1.737	-1.600	-8.301	-12.363	-8.278	-12.340
SPA	-2.298	-2.511	-2.022	-2.017	-9.191	-13.451	-9.179	-13.448
SWD	-2.227	-2.519	-2.168	-2.449	-8.749	-14.137	-8.779	-14.182
SWI	-2.170	-2.439	-1.716	-1.991	-8.297	-13.584	-8.301	-13.600
UK	-2.792	-2.922	-2.393	-2.526	-8.694	-12.959	-8.711	-12.991
AUST	-2.636	-2.793	-2.512	-2.692	-8.567	-13.629	-8.585	-13.665
HK	-2.051	-2.102	-2.165	-2.182	-8.349	-12.643	-8.355	-12.649
JAP	-2.854	-3.107	-2.881	-3.114	-8.796	-13.025	-8.812	-13.063
NZ	-2.844	-2.690	-1.371	-1.377	-8.118	-12.081	-8.086	-12.053
SIN	-2.170	-2.249	-1.930	-2.029	-7.382	-11.532	-7.404	-11.566
Emerging Markets								
BRA	-2.475	-2.691	-1.682	-1.737	-7.991	-13.073	-8.016	-13.116
CHI	-1.909	-2.123	-2.007	-2.294	-8.203	-12.305	-8.212	-12.320
COL	-2.139	-2.375	-2.162	-2.411	-8.614	-13.684	-8.618	-13.688
MEX	-2.456	-2.770	-1.764	-2.081	-8.334	-13.788	-8.357	-13.826
PER	-1.881	-2.033	-1.467	-1.930	-7.919	-11.917	-7.924	-11.958
CR	-1.863	-2.017	-1.568	-1.578	-8.368	-12.098	-8.390	-12.135
EGY	-1.699	-1.830	-1.586	-1.539	-7.437	-11.168	-7.420	-11.180
GRE	-1.225	-1.381	-1.844	-1.680	-7.414	-11.861	-7.323	-11.752
HUN	-2.332	-2.476	-1.792	-1.758	-8.279	-12.457	-8.303	-12.496
POL	-1.675	-1.958	-1.722	-1.956	-7.031	-12.825	-7.038	-12.852
QAT	-2.014	-2.162	-1.766	-1.776	-9.882	-14.437	-9.757	-14.340
RUS	-2.105	-2.260	-2.033	-2.197	-7.527	-12.850	-7.558	-12.880
SA	-2.380	-2.536	-2.149	-2.282	-9.141	-13.931	-9.172	-13.980
TUR	-1.411	-1.794	-1.547	-1.846	-7.847	-13.389	-7.843	-13.399
UAE	-2.512	-2.654	-2.503	-2.574	-9.051	-12.702	-9.078	-12.713
IND	-2.265	-2.439	-1.813	-1.861	-7.541	-11.508	-7.566	-11.545
INDO	-1.802	-2.208	-2.156	-2.421	-8.200	-14.655	-8.136	-14.550
KOR	-2.367	-2.487	-2.097	-2.235	-8.078	-12.735	-8.105	-12.779
MAL	-2.157	-2.405	-1.770	-2.003	-8.508	-13.018	-8.521	-13.031
PAK	-2.229	-2.456	-0.710	-0.995	-8.342	-11.798	-8.341	-11.820
PHI	-2.369	-2.834	-0.715	-0.850	-8.291	-14.537	-8.319	-14.582
TW	-1.822	-2.026	-1.829	-2.031	-8.028	-13.245	-8.054	-13.287
THA	-1.971	-2.135	-1.165	-1.233	-7.642	-12.440	-7.667	-12.474

Note: $*$ indicates significance at the 1% level. When the observation sample $T = 157$, the critical values for the ADF test with trend are -3.99 (1%), -3.43 (5%), -3.13 (10%), and those without trend are -3.46 (1%), -2.88 (5%), -2.57 (10%). The critical values for the PP test with trend are -4.019 (1%), -3.439 (5%), -3.144 (10%), and those without trend are -3.473 (1%), -2.880 (5%) -2.577 (10%).

Appendix B Results of ECM tests

In this Appendix, the results of ECM tests for the pairwise international stock markets during the entire 2007–2017 period, and two crisis periods of 2007–2009 GFC and 2010–2012 ESDC, are respectively displayed by adjacent asymmetric matrices in Tables B.1–B.3.

Table B.1

The asymmetric adjacent matrix for the directed and weighted international stock market network during the full-sample period of 2007–2017.

	CAN	US	AUS	BEL	DEN	FIN	FRA	GER	IRE	ISR	ITA	NETH	NOR	POR	SPA	SWD	SWI	UK	AUST	HK	JAP	NZ	SIN	BRA	CHI	COL	MEX	PER	CR	EGY	GRE	HUN	POL	QAT	RUS	SA	TUR	UAE	IND	INDO	KOR	MAL	PAK	PHI	TW	THA	To
CAN	0	0	0	0	0	0	0	0	0	0.025	0	0	0	0	0	0.044	0	0	0.115	0.029	0	0	0.087	0	0	0	0.043	0.06	0	0	0	0	0.033	0	0.041	0.071	0.043	0	0	0.031	0.055	0.042	0	0	0.061	0	
US	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.033	0	0	0	
AUS	0	0	0	0	0	0	0.007	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.007	0	0	0	0	0	0	0	0	0	0	0	0	0	
BEL	0	0	0	0	0	0.003	0	0	0.048	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.009	0	0	0	0	0	0	0	0	0	0	0	0	0	
DEN	0	0.055	0	0	0	0	0	0.002	0.003	0	0	0	0	0	0	0	0	0	0	0	0.023	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.038	0	0	0	
FIN	0	0	0	0.049	0	0	0.015	0	0.031	0	0	0.021	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
FRA	0	0	0.027	0.08	0	0.059	0	0	0.044	0	0	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.029	0	0	0	0	0.021	0	0	0	0	0	0	0	0	
GER	0	0.055	0	0.008	0.04	0	0	0	0.012	0.019	0	0.006	0	0	0	0	0.059	0.007	0	0.016	0.051	0.045	0	0	0	0	0	0	0	0	0	0	0.008	0	0	0	0	0.012	0	0	0.022	0	0.06	0	0.043	0	
IRE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
ISR	0.008	0	0	0	0	0	0	0.023	0	0	0	0	0	0	0	0.042	0.028	0.011	0.014	0.03	0.028	0	0.023	0	0	0	0.013	0	0	0	0	0	0.011	0	0	0.023	0	0	0.026	0	0.028	0	0	0	0.075	0	
ITA	0	0	0	0	0	0.013	0.009	0	0.015	0	0	0	0	0	0.002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.014	0	0	0.012	0	0	0	0	0	0	0	0	0	0	0	0	0	
NETH	0	0	0	0.078	0	0.018	0	0	0.051	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.017	0	0	0	0	0	0	0	0	0	0	0	0	0	
NOR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.005	0	0.005	0	0	0	0	0	0	0	0	0.005	0	0	0	0	0	0	0	0	0	0	
POR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.002	0	0	0	0	0	0	0	0	0	0	0	0	0	
SPA	0	0	0	0	0	0	0	0	0.017	0	0.048	0	0	0.047	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.019	0.05	0	0.015	0	0	0	0	0	0	0	0	0	0	0	0	0	
SWD	0	0	0	0	0	0	0	0	0	0.011	0	0	0	0	0	0	0	0	0	0.002	0	0	0.019	0	0	0	0.006	0	0	0	0	0	0	0	0	0.012	0.011	0	0	0	0.002	0.028	0	0.03	0.046	0.033	
SWI	0	0	0	0	0	0	0	0.003	0	0.013	0	0	0	0	0	0.033	0	0	0	0.011	0.012	0	0	0	0	0	0	0	0	0	0	0	0.003	0	0	0	0	0	0	0	0.014	0	0.027	0	0	0	
UK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.029	0	0	0	0	0	0	0	0	0	0	0.023	0	0	0	0	0	0	0	0.033	0	0	0	0	0	
AUST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.036	0	0	0	0	0	0	0.072	0	0	0	0.024	0	0	0	0	0	0.012	0	0.03	0.041	0.03	0	0	0	0.039	0	0	0	0.044	0	
HK	0.023	0	0	0.027	0	0.024	0.022	0.035	0	0.036	0	0.026	0	0	0	0.052	0.033	0.025	0.028	0	0.034	0.04	0	0	0	0	0	0	0	0	0	0	0.023	0	0	0	0.024	0	0.041	0	0.053	0	0.037	0	0.087	0	
JAP	0	0.059	0	0.001	0.033	0.003	0.002	0.015	0.005	0.015	0	0	0	0	0	0	0.028	0	0	0.006	0	0.027	0	0	0	0	0	0	0	0	0	0	0.003	0	0	0	0	0.008	0.009	0	0.008	0	0.071	0	0	0	
NZ	0	0	0	0	0	0	0	0.009	0	0	0	0	0	0	0	0	0	0	0	0	0.017	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.027	0	0	0	
SIN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.028	0	0	0	0	0	0	0	0	0	0	0.005	0	0	0	0	0	0	0	0	0.029	0.009	0	0	0	0.009	0	0	0	0	0	
BRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.005	0	0	0	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0	0	0	
CHI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.011	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
COL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
MEX	0.015	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.042	0	0	0.033	0	0	0	0.103	0	0	0.035	0	0.047	0	0	0	0	0	0	0	0.078	0.029	0	0	0.042	0.034	0.082	0	0.027	0.047	0.034	
PER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.011	0	0	0	0	0	0	0	0	0	0	0	
CR	0.007	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.009	0	0	0	0	0	0	0	0	0	0	0	0	0	0.006	0	0	0	0	0	0	0	0	0	0	0	0	0	
EGY	0	0	0	0.02	0	0	0	0	0	0	0.033	0	0	0	0.038	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GRE	0	0	0	0	0	0	0.003	0	0	0	0.001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
HUN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
POL	0.029	0	0.033	0.036	0	0	0.032	0	0	0	0	0.039	0	0	0	0.028	0	0.044	0.047	0.025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.025	0	0	0	0	0	
QAT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.036	0	0.032	
RUS	0.001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.008	0	0	0	0	0.023	0	0	0	0.027	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
SA	0	0	0	0	0	0	0	0	0	0.02	0	0	0	0	0	0.038	0	0	0.014	0	0	0	0.103	0	0.046	0.033	0.018	0.046	0	0	0	0	0	0	0.022	0	0.022	0	0	0.043	0.025	0.063	0	0.027	0.058	0.035	
TUR	0.022	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.022	0	0	0.031	0	0	0	0.039	0	0.043	0	0.026	0.053	0	0	0	0	0	0	0.032	0.03	0	0	0	0.023	0.022	0.028	0	0	0.025	0	
UAE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
IND	0	0	0	0	0	0	0	0	0	0.026	0	0	0	0	0	0	0	0	0	0.027	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.045	0	
INDO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.018	0	0.003	0.011	0	0	0	0	0	0	0	0.01	0.006	0	0	0	0	0	0	0	0	0	
KOR	0.004	0	0	0	0	0	0	0	0	0.029	0	0	0	0	0	0.076	0	0.012	0.014	0.007	0	0.029	0.042	0	0	0	0.019	0	0	0	0	0	0.011	0	0	0.041	0.014	0	0	0	0	0	0	0	0.089	0.032	
MAL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.006	0	0	0	0	0	0	0	0	0	0	
PAK	0	0.037	0	0	0.014	0	0	0.002	0	0	0	0	0	0	0	0	0.008	0	0	0	0.012	0.012	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
PHI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.003	0	0	0	0	0	0	0	0	0	0	0.002	0	0	0	0	0	0	0	0	0.003	0	0	0	0	0	0	0	0	0	0.01	
TW	0	0	0	0	0	0	0	0	0	0.002	0	0	0	0	0	0.018	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.006	0	0.003	0	0	0	0	0	0	0	
THA	0.002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.006	0	0	0.003	0	0	0	0.005	0	0	0	0.003	0	0	0	0	0	0	0	0	0.005	0.004	0	0	0	0.005	0	0	0.033	0	0	
From																																															

Note: The numerical values in the matrix represent the magnitudes of the statistically significant short-run error correction coefficients (in absolute values) of stock market pairs at the pre-specified FDR $\alpha = 0.01$.

We define the nodes listed in the first column as the source nodes, and those listed in the first row as the destination nodes.

"From" refers to the outgoing linkages from source nodes to the corresponding destination nodes; "To" refers to the reverse direction.

Table B.2

The asymmetric adjacent matrix for the directed and weighted international stock market network during the sub-period of 2007–2009.

	CAN	US	AUS	BEL	DEN	FIN	FRA	GER	IRE	ISR	ITA	NETH	NOR	POR	SPA	SWD	SWI	UK	AUST	HK	JAP	NZ	SIN	BRA	CHI	COL	MEX	PER	CR	EGY	GRE	HUN	POL	QAT	RUS	SA	TUR	UAE	IND	INDO	KOR	MAL	PAK	PHI	TW	THA	To
CAN	0	0	0.477	0	0.138	0	0	0	0.194	0.203	0	0	0	0	0	0	0	0	0.364	0	0	0	0.365	0	0	0.171	0.28	0	0.139	0	0.201	0.039	0.098	0	0.446	0	0	0	0	0.17	0	0	0	0	0.341	0.308	
US	0	0	0.174	0.268	0.032	0.341	0.22	0.058	0.372	0	0.238	0.164	0	0	0	0.244	0.062	0.247	0	0	0.238	0.305	0	0	0	0	0	0	0.073	0	0.274	0.048	0.24	0	0	0	0	0	0	0	0.173	0	0	0	0	0	
AUS	0	0	0	0	0	0	0	0	0	0	0	0.062	0	0	0	0	0	0	0.095	0	0	0	0	0	0	0.061	0.013	0	0	0	0	0	0	0	0.187	0.122	0	0	0	0	0	0	0	0	0	0	
BEL	0	0	0	0	0	0.233	0	0	0.377	0	0	0	0	0	0	0	0	0	0.002	0	0	0.16	0	0	0	0	0	0	0	0	0.119	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
DEN	0.163	0.162	0.611	0.305	0	0	0	0.186	0	0.083	0	0.349	0	0	0	0	0	0	0	0	0	0	0	0	0	0.135	0.31	0	0.175	0	0	0.084	0.145	0	0.235	0	0	0	0	0	0	0	0	0	0.239	0	
FIN	0	0	0	0	0	0	0	0	0.293	0	0	0	0	0	0	0	0	0	0	0	0.083	0.139	0	0	0	0.018	0	0	0	0	0.16	0	0	0	0	0	0	0	0	0	0.129	0	0	0	0	0	
FRA	0	0.121	0.148	0.451	0	0.483	0	0	0.376	0.003	0.073	0.156	0	0	0	0	0	0.163	0	0	0.202	0.261	0	0	0	0	0.041	0	0.033	0	0.376	0	0.182	0	0.125	0	0	0	0	0	0.177	0	0	0	0	0	
GER	0	0.17	0.372	0.35	0.034	0.394	0.405	0	0.286	0.052	0.16	0.293	0	0	0	0	0.036	0.201	0.335	0	0.298	0.211	0.414	0	0	0.109	0.129	0	0.141	0	0.411	0.044	0.226	0	0.233	0	0	0	0	0	0.239	0	0	0	0	0	
IRE	0	0	0	0	0	0.034	0	0	0	0	0	0	0	0.174	0	0.031	0	0	0	0	0.013	0.045	0	0	0	0	0	0	0	0	0.027	0	0	0	0	0.018	0	0	0	0	0.071	0	0	0	0	0	
ISR	0.234	0	0.262	0.176	0.145	0	0.133	0.153	0.146	0	0	0.156	0	0	0.165	0.214	0.066	0.115	0.321	0.217	0.153	0.134	0.283	0.147	0.164	0.222	0.174	0.22	0.147	0.138	0.203	0.097	0.105	0	0.469	0.273	0	0	0	0.274	0.215	0.202	0	0	0.319	0.302	
ITA	0	0.165	0	0.271	0	0.497	0.204	0.027	0.401	0.027	0	0	0	0	0	0	0	0.122	0	0	0	0.309	0	0	0	0	0.058	0	0	0	0.264	0	0.195	0	0	0	0	0	0	0	0	0	0	0	0	0	
NETH	0	0.05	0.095	0.401	0	0	0.021	0	0.291	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0	0	0	0	0.062	0	0	0	0	0	0	0	0	0	0	0	0	0	
NOR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
POR	0	0	0	0	0	0	0	0	0.021	0	0	0	0	0	0	0	0	0	0	0.042	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.042	0.016	0	0	0	0	
SPA	0	0	0	0.223	0	0.254	0	0	0.237	0.021	0	0	0	0	0	0	0	0	0.186	0.242	0.222	0.187	0.256	0	0	0.078	0	0	0	0	0.261	0.005	0.111	0	0.148	0.203	0	0	0	0	0.198	0	0	0	0	0.214	
SWD	0	0	0	0	0	0	0	0	0.156	0	0	0	0	0	0	0	0	0	0	0.048	0.098	0.018	0.079	0	0	0.016	0	0.215	0	0	0.075	0	0	0	0.087	0.007	0	0	0	0.007	0.195	0	0	0	0.231	0.1	
SWI	0	0.318	0.226	0.379	0.105	0.489	0.53	0.221	0.403	0.068	0.623	0.262	0	0	0	0	0	0.377	0	0	0.243	0.334	0.222	0	0	0	0.139	0	0.162	0	0.317	0.189	0.4	0	0.155	0	0	0	0	0	0.185	0	0.197	0	0	0	
UK	0	0.155	0.125	0.398	0	0.587	0.168	0.021	0.559	0.011	0.207	0.11	0	0	0	0	0	0	0	0	0.272	0.403	0.251	0	0	0	0	0	0	0	0.411	0	0.054	0	0	0	0	0	0	0	0.213	0	0	0	0	0	
AUST	0	0	0.071	0	0	0	0	0	0.205	0	0	0	0	0	0	0.312	0	0	0	0	0	0	0.378	0	0	0.061	0.01	0	0	0	0.268	0	0	0	0.198	0.252	0	0	0	0	0.266	0	0	0	0	0	
HK	0	0	0	0	0	0	0	0	0	0	0	0	0	0.168	0	0.161	0	0	0	0	0.114	0	0.16	0	0.123	0.025	0	0.215	0	0	0.122	0	0	0	0	0.102	0	0	0.001	0	0.209	0	0	0	0	0.074	
JAP	0	0.005	0	0	0	0.143	0	0	0.206	0.045	0	0	0	0	0.017	0.216	0	0	0	0.104	0	0	0.178	0	0	0.051	0.024	0	0	0	0.168	0	0	0	0	0.097	0	0	0	0	0.154	0	0	0	0	0	
NZ	0	0	0	0.041	0	0.238	0	0	0.299	0.002	0	0	0	0	0	0.119	0	0	0	0.115	0	0	0	0	0	0	0	0	0	0	0.185	0	0	0	0	0.082	0.038	0	0	0	0.155	0	0	0	0	0	
SIN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.231	0	0	0	0.041	0.097	0	0	0	0.099	0.019	0	0	0	0	0	0	0	0	0	0.079	0	0	0	0	0.188	0	0	0	0	0.099	
BRA	0	0	0	0	0	0	0	0	0	0.005	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	0	0.134	0	0	0	0	0.08	0	0	0	0	0	0.133	
CHI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.177	0	0	0	0	0	0	0	0.033	0	0	0	0.048	0.069	0	0	0	0.234	0.035	
COL	0.067	0	0	0	0	0	0	0	0	0.092	0	0	0	0	0	0	0	0	0.096	0.172	0.108	0	0.178	0.218	0.283	0	0.101	0.281	0	0	0	0	0	0	0.215	0.232	0	0	0.124	0.119	0.129	0	0	0	0.354	0.201	
MEX	0.046	0	0.232	0.148	0	0	0	0.028	0.172	0.093	0	0.104	0	0	0	0.195	0	0	0.159	0	0.149	0	0.197	0	0	0.119	0	0	0.174	0.109	0.152	0	0.101	0	0.305	0	0	0	0	0.095	0	0	0	0	0.287	0.211	
PER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.082	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.253	0	
CR	0.103	0	0.288	0	0.065	0	0	0.072	0	0.093	0	0	0	0	0	0	0.015	0	0	0	0	0	0	0	0	0.081	0.151	0	0	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	
EGY	0	0	0	0	0	0	0	0	0	0.086	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.069	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GRE	0	0.002	0	0.067	0	0.177	0	0	0.224	0	0	0	0	0.307	0	0.163	0	0	0.056	0.077	0.111	0.206	0.126	0	0	0.014	0	0	0	0	0	0	0	0	0	0.053	0	0	0	0	0.171	0	0	0	0	0.099	
HUN	0.219	0.183	0.386	0	0.235	0	0.223	0.26	0	0.126	0	0	0	0	0.153	0	0.093	0.201	0	0	0	0	0	0	0	0.133	0.259	0.187	0.261	0	0	0	0.268	0	0	0	0	0	0	0	0	0	0	0	0.19	0	
POL	0.122	0.225	0.292	0.276	0.114	0.288	0.239	0.144	0.25	0.071	0.192	0.191	0	0	0.113	0.211	0.131	0.243	0.238	0	0	0.207	0	0	0	0	0.115	0	0.136	0	0	0.025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
QAT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.178	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
RUS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.089	0	0	0.05	0	0	0	0	0.025	0.117	0.013	0	0	0	0	0	0	0	0	0	0.049	0	0	0	0.019	0	0	0	0	0	0.152	
SA	0	0	0.017	0	0	0	0	0	0	0	0	0	0	0.218	0	0.24	0	0	0	0.235	0.193	0	0.344	0	0.196	0.06	0	0.276	0	0	0.116	0	0	0	0.132	0	0	0	0.076	0.015	0.315	0.115	0	0	0.299	0.196	
TUR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.265	0	0	0.2	0	0	0.081	0	0	0	0	0	0	0	0	0	0	0	0	0.106	0.085	0.267	0	0	0.125	0	0	
UAE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
IND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.18	0	0	0	0	0.096	0.024	0	0	0	0	0	0	0	0	0	0.078	0.05	0	0	0.027	0	0.078	0	0.17	0	0	
INDO	0	0	0	0	0	0	0	0	0	0.014	0	0	0	0	0	0	0	0	0	0	0	0	0	0.072	0.138	0.094	0	0	0	0	0	0	0	0	0.141	0.192	0.067	0	0.165	0	0.157	0	0	0	0	0	
KOR	0	0	0	0	0	0.062	0	0	0.126	0	0	0	0	0.219	0	0.147	0	0	0	0.07	0.109	0.038	0.029	0	0.1	0.017	0	0.201	0	0	0.065	0	0	0	0	0.028	0	0	0	0	0	0	0	0	0	0.059	
MAL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.053	0.008	0	0	0	0	0	0	0	0	0	0.057	0	0	0.114	0	0	0	0	0	0	0	
PAK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
PHI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.094	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.088	0	0.079	0	0	0	0	0	0	0	
TW	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.079	0	0	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
THA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.061	0	0	0	0.091	0	0	0.071	0.009	0.097	0	0	0	0	0	0	0	0	0	0.05	0.076	0	0	0	0	0.106	0	0	0	0.205	0	
From																																															

Note: The numerical values in the matrix represent the magnitudes of the statistically significant short-run error correction coefficients (in absolute values) of stock market pairs at the pre-specified FDR $\alpha = 0.01$.

We define the nodes listed in the first column as the source nodes, and those listed in the first row as the destination nodes.

"From" refers to the outgoing linkages from source nodes to the corresponding destination nodes; "To" refers to the reverse direction.

Table B.3

The asymmetric adjacent matrix for the directed and weighted international stock market network during the sub-period of 2010–2012.

	CAN	US	AUS	BEL	DEN	FIN	FRA	GER	IRE	ISR	ITA	NETH	NOR	POR	SPA	SWD	SWI	UK	AUST	HK	JAP	NZ	SIN	BRA	CHI	COL	MEX	PER	CR	EGY	GRE	HUN	POL	QAT	RUS	SA	TUR	UAE	IND	INDO	KOR	MAL	PAK	PHI	TW	THA	To
CAN	0	0	0	0	0	0	0	0.094	0	0.092	0	0	0	0	0	0.2	0	0	0.028	0	0.037	0	0	0	0	0	0	0	0	0	0	0	0	0	0.057	0.072	0	0	0	0	0.027	0	0	0	0.068	0	
US	0	0	0	0	0.011	0	0	0	0	0	0	0.025	0	0	0.049	0	0	0	0	0.025	0.016	0	0	0	0	0	0	0.075	0	0	0	0	0.026	0.127	0.02	0	0.029	0	0	0	0	0.079	0.091	0	0.019	0	
AUS	0	0	0	0.156	0	0	0.077	0	0	0.099	0	0.062	0	0	0	0	0	0	0	0.083	0.004	0	0	0	0	0	0	0	0	0	0	0	0.065	0	0	0	0	0.039	0.092	0	0	0	0	0	0.019	0	
BEL	0	0	0.028	0	0	0	0	0	0	0.062	0	0.026	0	0	0	0	0	0	0.024	0.087	0.011	0	0	0	0	0	0	0	0.021	0	0.086	0.031	0.049	0	0	0	0	0.043	0.088	0	0	0	0	0	0.029	0	
DEN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.019	0.003	0.034	0	0	0.001	0	0	0	0.081	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
FIN	0	0	0	0	0	0	0	0	0	0	0.07	0	0	0.067	0.049	0	0	0	0.006	0.016	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.018	0.061	0	0	0	0	0	0	0	
FRA	0	0	0.146	0.298	0	0.195	0	0	0	0.137	0	0.092	0	0.099	0	0	0	0	0.04	0.104	0.017	0	0	0	0	0	0	0	0.095	0	0.103	0.082	0.117	0	0.036	0	0	0.071	0.109	0	0	0	0	0	0.051	0	
GER	0.077	0	0	0	0.198	0	0	0	0	0.051	0	0	0	0	0	0.295	0.097	0	0.045	0.069	0	0	0.119	0	0	0	0	0	0	0	0	0	0.052	0	0.016	0.097	0	0	0	0	0.067	0	0	0	0.041	0	
IRE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.095	0	0	0	0	0	0	0	0	0	0.094	0.093	0	0	0	0	0	0	0.095	0	0	0	0	0.127	0	0	0	
ISR	0.031	0	0.125	0.127	0	0.179	0.095	0.034	0	0	0	0.089	0	0.092	0	0	0	0	0.024	0.081	0.014	0	0	0	0	0	0	0	0.081	0	0	0.062	0.107	0	0.028	0.036	0	0.059	0	0	0	0	0	0	0.032	0	
ITA	0	0	0	0	0	0.074	0	0	0	0.031	0	0.004	0	0.059	0	0	0	0	0.025	0.036	0.016	0	0	0	0	0	0	0	0	0	0.125	0	0.02	0	0.014	0	0	0.033	0.062	0	0	0	0	0	0.023	0	
NETH	0	0	0.101	0.133	0.074	0.141	0.076	0.051	0	0.15	0.101	0	0	0.095	0	0	0	0	0.042	0.124	0.029	0	0.072	0	0	0	0	0	0.087	0	0.099	0.071	0.137	0	0.032	0	0	0.082	0.105	0	0.058	0	0	0	0.059	0	
NOR	0.017	0	0	0.017	0	0.03	0.014	0	0	0.016	0.017	0.018	0	0.025	0.004	0	0	0	0	0.021	0.015	0	0	0.029	0	0	0	0	0.015	0	0.09	0.009	0.016	0	0.015	0	0.023	0.017	0.033	0	0	0	0	0	0.017	0	
POR	0	0	0	0.033	0	0.067	0.014	0	0	0.029	0.091	0.017	0	0	0.009	0	0	0	0	0.032	0.015	0	0	0	0	0	0	0	0.03	0	0	0	0.029	0	0.015	0	0	0.028	0.063	0	0	0	0	0	0	0	
SPA	0	0	0	0	0	0.081	0	0	0	0.046	0	0	0.115	0.187	0	0	0	0	0.032	0.042	0.023	0	0	0	0	0	0	0	0.051	0	0.112	0	0.04	0	0.03	0	0	0.042	0.073	0	0	0	0	0	0.033	0	
SWD	0	0	0	0	0.066	0	0	0	0	0.058	0	0.038	0	0	0	0	0.002	0	0	0.055	0.002	0	0.024	0	0.091	0	0.051	0	0	0	0	0	0.041	0	0	0	0	0	0	0	0	0.084	0	0	0	0.078	
SWI	0	0	0	0	0	0	0	0.079	0	0.04	0	0	0	0	0	0.139	0	0.038	0	0.044	0	0.014	0.078	0	0	0	0.101	0	0	0	0	0	0.036	0	0.018	0.06	0	0	0	0	0.041	0	0	0	0.023	0	
UK	0.08	0	0.068	0.067	0.169	0.074	0.063	0.115	0	0.075	0	0.058	0	0	0	0.29	0.199	0	0	0.073	0.029	0	0.137	0	0.138	0.14	0.158	0.127	0.072	0	0	0.07	0.072	0.118	0.053	0.162	0.093	0.074	0.075	0.111	0.126	0.155	0.115	0	0.067	0.135	
AUST	0.186	0	0.093	0.103	0.179	0.098	0.096	0.259	0	0.122	0.089	0.118	0	0.089	0.089	0.395	0.29	0.264	0	0.106	0.026	0.078	0.159	0	0.156	0	0.154	0.11	0.088	0	0	0.085	0.133	0.108	0.098	0.201	0.12	0.087	0.092	0	0.136	0.13	0.102	0	0.108	0.119	
HK	0	0	0.075	0.095	0.092	0.089	0.073	0.072	0	0.123	0	0.102	0	0	0	0.099	0	0	0	0	0	0	0	0	0	0	0	0	0.062	0	0	0	0.099	0	0	0	0.213	0.066	0	0	0	0	0	0	0	0	
JAP	0.179	0.11	0.172	0.167	0.144	0.163	0.176	0.188	0.107	0.197	0.13	0.193	0.114	0.131	0.13	0.191	0.18	0.173	0.213	0.203	0	0.121	0.165	0.144	0.159	0.129	0.148	0.124	0.148	0.114	0.12	0.135	0.199	0.112	0.197	0.183	0.155	0.157	0.147	0.115	0.158	0.123	0.113	0	0.259	0.119	
NZ	0	0	0	0	0.087	0	0	0.052	0	0	0	0	0	0	0	0.072	0.125	0	0	0	0.008	0	0.07	0	0	0	0.11	0	0	0	0	0	0.031	0	0	0	0	0	0	0	0.062	0.135	0.119	0	0.03	0.139	
SIN	0	0	0	0	0.165	0	0	0.069	0	0	0	0	0	0	0	0.161	0.077	0.039	0	0	0	0	0	0	0	0	0.106	0	0	0	0	0	0.044	0	0	0.066	0	0	0	0	0	0	0	0	0	0	
BRA	0	0	0	0	0	0	0	0	0	0	0	0	0.102	0	0.1	0	0	0	0	0	0.006	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001	0	0	0	0	0	0	0	0	0	0.003	0	
CHI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
COL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.024	0	0.043	0	0	0.024	0	0.06	0	0	0	0	0	0	0	0	0	0	0.017	0	0	0	0	0	0.07	0	0	0	0.075	
MEX	0	0	0.044	0.045	0.123	0	0.043	0.04	0	0.044	0	0.039	0	0	0	0.085	0.066	0.025	0	0.036	0.018	0.021	0.036	0	0	0	0	0	0	0	0	0	0.041	0	0.021	0	0.056	0.049	0	0	0.002	0.132	0.104	0	0.018	0.126	
PER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.098	0	0.038	0	0	0	0	0	0	0	0	0	0	
CR	0	0	0.204	0.153	0	0.183	0.107	0.029	0	0.09	0.139	0.07	0	0.105	0.074	0	0	0	0	0.06	0.015	0	0	0	0	0	0	0	0	0	0	0.108	0.061	0	0	0	0	0.041	0	0	0	0	0	0	0.025	0	
EGY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	
GRE	0	0	0	0.018	0	0	0.014	0	0	0	0.024	0.017	0.044	0	0	0	0	0	0	0.023	0	0	0	0	0	0	0	0	0	0	0	0.006	0.019	0	0	0	0	0.02	0.028	0	0	0	0	0	0	0	
HUN	0	0	0.099	0.142	0	0.154	0.096	0.032	0	0.079	0.201	0.065	0	0.115	0	0	0	0	0.029	0.055	0.023	0	0	0	0	0	0	0	0.065	0	0.136	0	0.046	0	0	0	0	0.037	0.088	0	0	0	0	0	0.029	0	
POL	0	0	0.061	0.13	0	0	0.078	0.037	0	0.09	0	0.098	0	0	0	0	0	0	0.01	0.091	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.041	0	0	0	0	0	0	0	0	
QAT	0.024	0.033	0	0	0	0	0	0	0	0	0	0	0	0	0	0.03	0	0.03	0.026	0	0	0	0	0	0.033	0.05	0	0.074	0	0	0	0	0	0	0	0.037	0	0	0	0.088	0.028	0.071	0	0	0.022	0	
RUS	0.157	0	0	0	0	0	0	0.101	0	0.138	0	0	0	0	0	0	0	0	0.076	0	0.072	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.044	0	0	0	0.169	0	
SA	0.06	0	0.062	0	0.14	0	0	0.097	0	0.071	0	0	0	0	0	0.277	0.124	0.054	0.011	0.065	0.012	0	0.121	0	0.193	0.155	0	0.102	0	0	0	0	0.067	0.09	0.032	0	0	0	0	0.102	0.043	0.146	0.075	0	0.023	0.121	
TUR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.007	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
UAE	0	0	0.142	0.181	0	0.133	0.156	0.087	0.085	0.115	0.129	0.134	0	0.113	0	0	0.088	0	0.091	0.132	0.075	0	0.085	0	0	0	0	0	0.122	0.154	0.127	0.172	0.143	0	0	0	0.136	0	0.138	0	0	0	0	0	0.086	0	
IND	0	0	0.066	0.086	0	0.09	0.059	0	0	0.046	0.094	0.045	0	0.088	0.078	0	0	0	0	0.025	0	0	0	0	0	0	0	0	0.067	0	0	0.086	0.041	0	0	0	0.076	0.038	0	0	0	0	0	0	0	0	
INDO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.043	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.044	0	0.04	0	0	0	0	0	0	0	0	0	0	
KOR	0.125	0	0	0	0	0	0	0.166	0	0.063	0	0.068	0	0	0	0.271	0.191	0.148	0.096	0	0.022	0	0	0	0.136	0	0	0	0	0	0	0	0.068	0	0.053	0.284	0	0	0	0	0	0	0	0	0.053	0	
MAL	0.016	0.051	0	0	0.041	0	0	0.029	0	0	0	0	0	0	0	0.04	0.035	0.024	0.014	0	0	0	0	0	0.026	0.047	0.03	0	0	0	0	0	0	0.066	0	0.015	0	0	0	0	0	0	0	0	0.016	0.124	
PAK	0	0.095	0	0	0.024	0	0	0.013	0.012	0	0	0	0	0	0	0.021	0.029	0.024	0.014	0	0	0.04	0	0	0	0	0.051	0	0	0	0	0	0	0	0	0.022	0	0	0	0	0	0	0	0	0	0	
PHI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.003	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.007	
TW	0.167	0	0	0	0	0	0	0.119	0	0.121	0	0	0	0	0	0.197	0	0.075	0.088	0	0.004	0	0	0	0	0	0	0	0	0	0	0	0	0	0.072	0.126	0	0	0	0	0	0	0	0	0	0	
THA	0	0	0	0	0	0	0	0.015	0	0	0	0	0	0	0	0.017	0.011	0.009	0.006	0	0	0	0.006	0	0.009	0.019	0.013	0	0	0	0	0	0	0	0	0.002	0	0	0	0	0	0.061	0	0.093	0	0	
From																																															

Note: The numerical values in the matrix represent the magnitudes of the statistically significant short-run error correction coefficients (in absolute values) of stock market pairs at the pre-specified FDR $\alpha = 0.01$.

We define the nodes listed in the first column as the source nodes, and those listed in the first row as the destination nodes.

"From" refers to the outgoing linkages from source nodes to the corresponding destination nodes; "To" refers to the reverse direction.

Online Supplementary Materials: "Short-run disequilibrium adjustment and long-run equilibrium in the international stock markets: A network-based approach"

Version: August 1, 2021

A FDR $\alpha = 0.05$ significance level

The choice of different pre-specified FDR significance levels α in *statistical validation tests* leads to different network structures of stock markets around the globe as the smaller is α, the more less reliable interconnections are eliminated. By choosing an FDR significance level of $\alpha = 0.05$, as expected, we obtain denser international stock market networks during the 2007–2009 GFC, 2010–2012 ESBC, and the entire period of 2007–2017, which are visualized in Figures A.1–A.3. The corresponding adjacent asymmetric matrices are displayed in Tables A.1–A.3. Specifically, in the case of the 2007–2009 period, Figure A.1 depicts the network of the global stock market, with a core-peripheral structure. A remarkable feature of the derived global stock market network is that it exhibits a strongly interconnected component, comprised of the US and most of the developed stock markets, while a set of emerging stock markets are located at the periphery. This result is similar to the results obtained using an FDR significance level of $\alpha = 0.01$. Meanwhile, for the cases of the 2010–2012 ESBC and the full period of 2007–2017, as shown in Figures A.2 and A.3, the network topological structure of the global stock market is very similar to a random graph as the FDR statistical significance level of $\alpha = 0.05$ yields more interconnections than did $\alpha = 0.01$.

In comparison, the network analysis at the FDR statistical significance level of $\alpha =$

0.01 provides the most important results for the analysis conducted in the main part of the paper, as the higher significance level filters out weak directional interconnectedness and highlights the most significant pairwise similarity and dissimilarity across the global stock markets. Conversely, when we choose a lower significance level, we obtain global stock market networks with denser topological structures, which provides more information for investors seeking to apply international portfolio diversification. However, it should be noted that choosing the appropriate statistical significance level is crucial for capturing the core part of the global stock market networks.

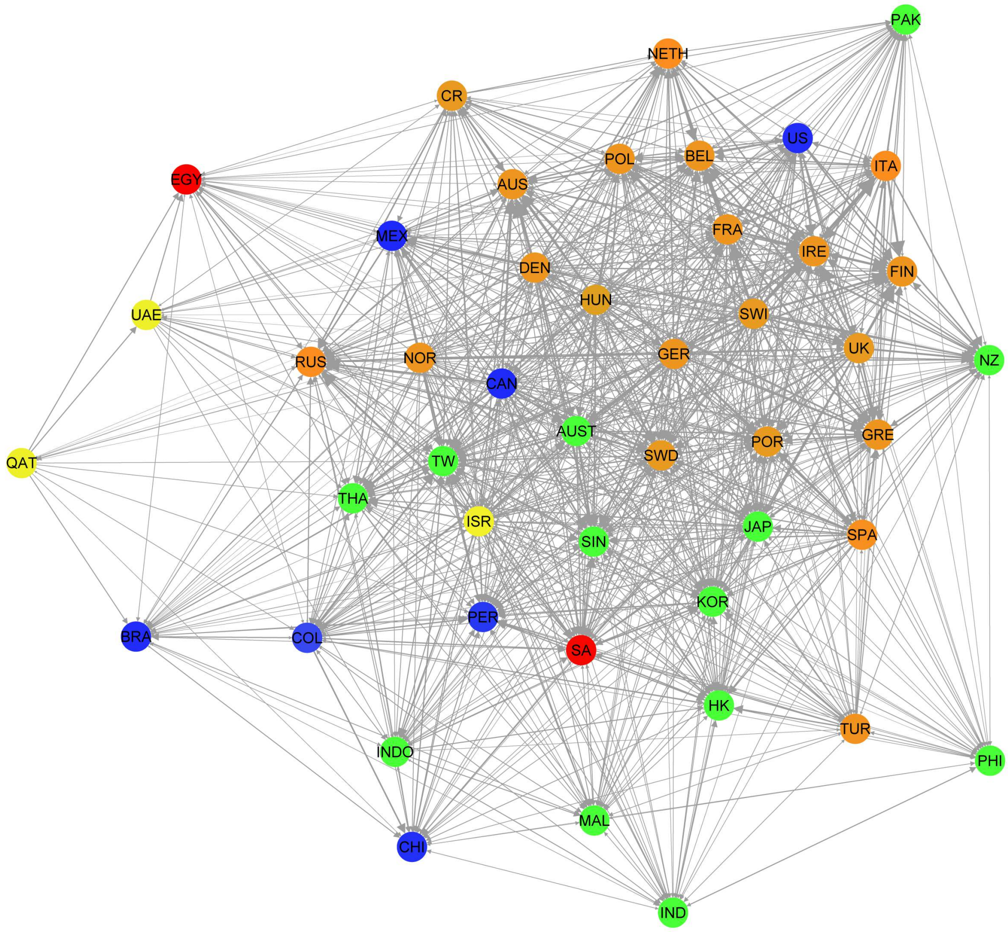


Figure A.1. The international network of the 46 stock markets at an FDR significance level of $\alpha = 0.05$ over the sub-period of 2007–2009. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker is the width of an edge (or the bigger an arrow), the greater is the magnitude of the short-run error adjustment coefficient between the stock market pair. The directionality of each arrow indicates the direction in which one stock market adjusts the short-run disequilibrium towards a long-run equilibrium relationship with the other one.

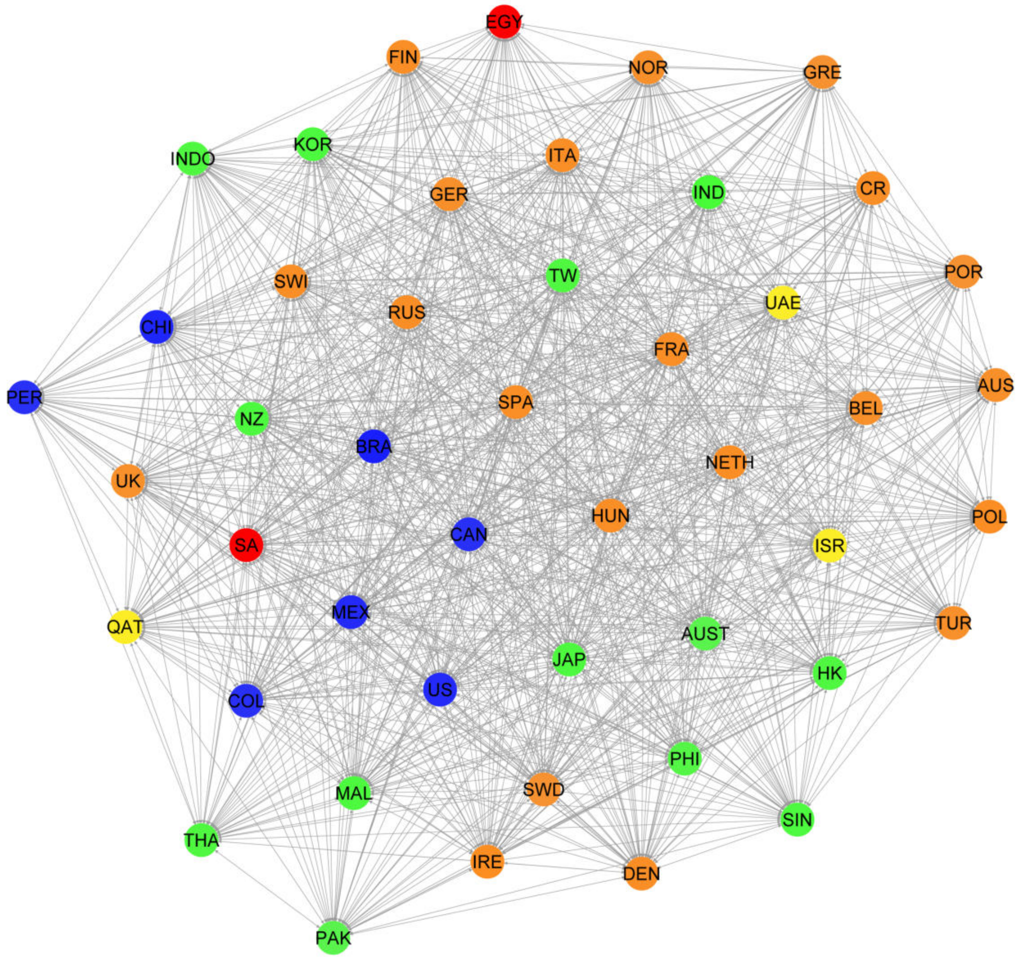


Figure A.2. The international network of the 46 stock markets at an FDR significance level of $\alpha = 0.05$ over the sub-period of 2010–2012. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker is the width of an edge (or the bigger an arrow), the greater is the magnitude of the short-run error adjustment coefficient between the stock market pair. The directionality of each arrow indicates the direction in which one stock market adjusts the short-run disequilibrium towards a long-run equilibrium relationship with the other one.

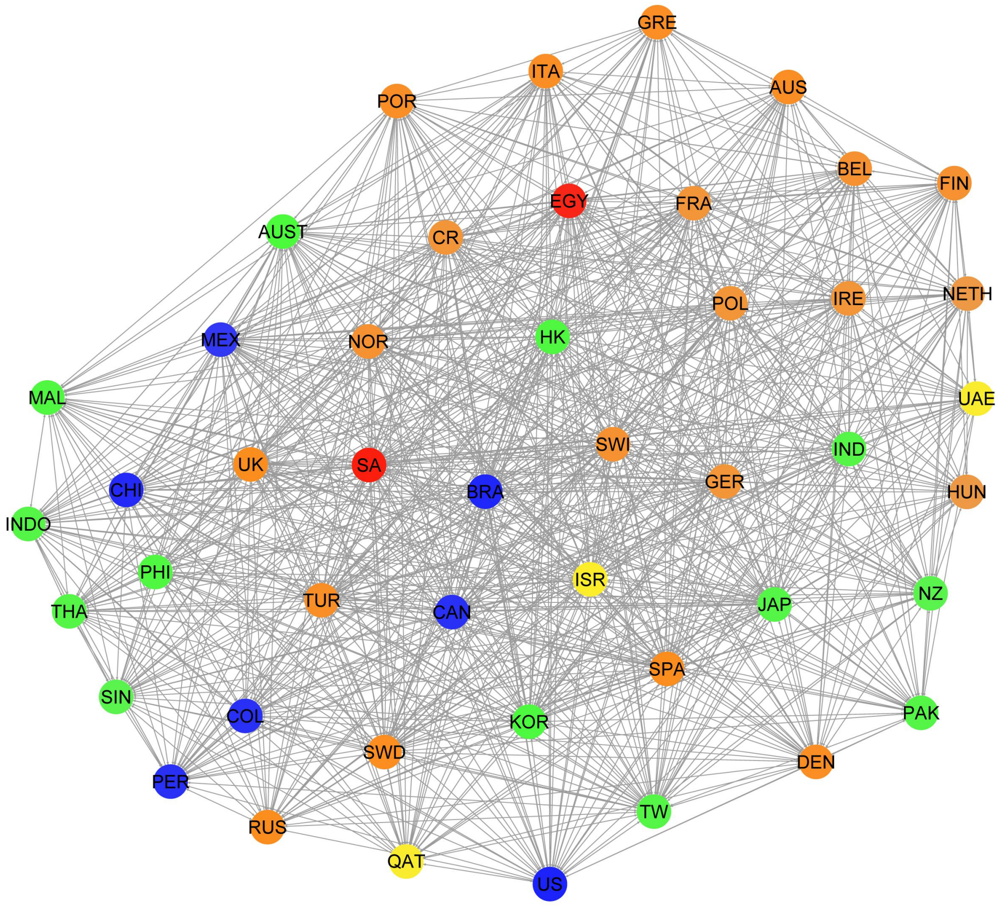


Figure A.3. The international network of the 46 stock markets at an FDR significance level of $\alpha = 0.05$ **over the entire period of 2007–2017.** The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker is the width of an edge (or the bigger is an arrow), the greater is the magnitude of the short-run error adjustment coefficient between the stock market pair. The directionality of each arrow indicates the direction in which one stock market adjusts the short-run disequilibrium towards a long-run equilibrium relationship with the other one.

Table A.1

The asymmetric adjacent matrix for the directed and weighted international stock market network during the sub-period of 2007–2009 at an FDR significance level of $\alpha = 0.05$.

	CAN	US	AUS	BEL	DEN	FIN	FRA	GER	IRE	ISR	ITA	NETH	NOR	POR	SPA	SWD	SWI	UK	AUST	HK	JAP	NZ	SIN	BRA	CHI	COL	MEX	PER	CR	EGY	GRE	HUN	POL	QAT	RUS	SA	TUR	UAE	IND	INDO	KOR	MAL	PAK	PHI	TW	THA	To
CAN	0	0.093	0.477	0.216	0.138	0.17	0.141	0.141	0.194	0.203	0.1	0.198	0	0.198	0.131	0.289	0.057	0.103	0.364	0.184	0.189	0.13	0.365	0.097	0.15	0.171	0.28	0.22	0.139	0.108	0.201	0.039	0.098	0	0.446	0.267	0.078	0	0.112	0.17	0.229	0.162	0.106	0	0.341	0.308	
US	0.02	0	0.174	0.268	0.032	0.341	0.22	0.058	0.372	0.025	0.238	0.164	0.016	0.207	0.099	0.244	0.062	0.247	0.134	0.111	0.238	0.305	0.194	0	0	0.07	0.059	0.147	0.073	0.045	0.274	0.048	0.24	0.004	0.122	0.106	0.053	0	0	0.064	0.173	0.091	0.135	0.083	0.155	0.124	
AUS	0	0	0	0.196	0	0.133	0	0	0.189	0	0	0.062	0	0	0.023	0.217	0	0	0.095	0	0.116	0.091	0.175	0.025	0	0.061	0.013	0	0	0.012	0.136	0	0	0	0.187	0.122	0	0	0	0	0.135	0	0.104	0	0.188	0.18	
BEL	0	0	0	0	0	0.233	0	0	0.377	0	0	0	0	0.222	0	0.116	0	0	0.002	0	0.093	0.16	0	0.003	0	0.013	0	0	0	0	0.119	0	0	0	0.062	0.041	0	0	0	0	0.109	0.076	0.12	0	0	0.12	
DEN	0.163	0.162	0.611	0.305	0	0.231	0.198	0.186	0.25	0.083	0.156	0.349	0.015	0.214	0.163	0.358	0.064	0.171	0.282	0.151	0.265	0.156	0.354	0.073	0	0.135	0.31	0.198	0.175	0.074	0.204	0.084	0.145	0.001	0.235	0.238	0.066	0.006	0	0.1	0.216	0	0.115	0	0.239	0.245	
FIN	0	0	0	0	0	0	0	0	0.293	0	0	0	0	0.188	0	0.079	0	0	0.003	0.067	0.083	0.139	0.088	0	0.04	0.018	0	0	0	0	0.16	0	0	0	0.058	0.019	0.006	0	0	0.017	0.129	0.077	0.129	0.07	0.102	0.064	
FRA	0	0.121	0.148	0.451	0	0.483	0	0	0.376	0.003	0.073	0.156	0.015	0.29	0.062	0.241	0	0.163	0.12	0.133	0.202	0.261	0.213	0	0	0.048	0.041	0	0.033	0.017	0.376	0	0.182	0	0.125	0.103	0.036	0.002	0	0.043	0.177	0.089	0.173	0.088	0.162	0.141	
GER	0.043	0.17	0.372	0.35	0.034	0.394	0.405	0	0.286	0.052	0.16	0.293	0.019	0.311	0.282	0.306	0.036	0.201	0.335	0.24	0.298	0.211	0.414	0	0	0.109	0.129	0.199	0.141	0.04	0.411	0.044	0.226	0	0.233	0.228	0.067	0.014	0.095	0.082	0.239	0.129	0.17	0.104	0.217	0.207	
IRE	0	0	0	0	0	0.034	0	0	0	0	0	0	0	0.174	0	0.031	0	0	0	0.037	0.013	0.045	0.021	0.006	0.032	0.008	0	0	0	0	0.027	0	0	0	0.03	0.018	0	0	0.04	0.015	0.071	0.064	0.103	0.052	0.083	0.044	
ISR	0.234	0.081	0.262	0.176	0.145	0.149	0.133	0.153	0.146	0	0.101	0.156	0	0.203	0.165	0.214	0.066	0.115	0.321	0.217	0.153	0.134	0.283	0.147	0.164	0.222	0.174	0.22	0.147	0.138	0.203	0.097	0.105	0	0.469	0.273	0.1	0	0.148	0.274	0.215	0.202	0.092	0.122	0.319	0.302	
ITA	0.001	0.165	0.121	0.271	0	0.497	0.204	0.027	0.401	0.027	0	0.072	0	0	0.083	0.195	0	0.122	0.111	0	0.166	0.309	0	0	0	0.045	0.058	0	0.068	0.032	0.264	0	0.195	0	0.109	0.089	0.05	0	0	0	0.156	0	0.165	0	0.133	0	
NETH	0	0.05	0.095	0.401	0	0.251	0.021	0	0.291	0	0.065	0	0	0	0.052	0.177	0	0.045	0.06	0	0.179	0.142	0	0	0	0.037	0.03	0	0	0.016	0.162	0	0.062	0	0.093	0.072	0	0	0	0	0.127	0	0.119	0	0.136	0	
NOR	0.128	0.123	0.131	0.125	0.129	0.123	0.124	0.124	0.124	0.123	0.123	0.127	0	0.125	0.124	0.125	0.123	0.124	0.127	0.124	0.123	0.123	0.126	0.138	0.129	0.132	0.125	0.128	0.125	0.127	0.12	0.124	0.121	0.129	0.126	0.123	0.122	0.138	0.122	0.123	0.12	0.126	0.119	0.121	0.127	0.124	
POR	0	0	0	0	0	0	0	0	0.021	0	0	0	0	0	0	0	0	0	0	0.042	0	0	0	0	0.039	0	0	0	0	0	0	0	0	0	0	0	0	0	0.007	0	0.042	0.016	0.089	0.069	0.074	0	
SPA	0.023	0.08	0.113	0.223	0	0.254	0.093	0	0.237	0.021	0.04	0.091	0	0.31	0	0.224	0	0.098	0.186	0.242	0.222	0.187	0.256	0.04	0.108	0.078	0.082	0.201	0.046	0.024	0.261	0.005	0.111	0	0.148	0.203	0.068	0	0.108	0.073	0.198	0.124	0.172	0.124	0.203	0.214	
SWD	0	0	0	0	0	0.047	0	0	0.156	0	0	0	0	0.155	0	0	0	0	0	0.048	0.098	0.018	0.079	0.012	0.089	0.016	0	0.215	0	0	0.075	0	0	0	0.087	0.007	0	0	0.033	0.007	0.195	0.067	0.103	0.051	0.231	0.1	
SWI	0.063	0.318	0.226	0.379	0.105	0.489	0.53	0.221	0.403	0.068	0.623	0.262	0.015	0.227	0.262	0.244	0	0.377	0.176	0.158	0.243	0.334	0.222	0	0	0.091	0.139	0.153	0.162	0.073	0.317	0.189	0.4	0.011	0.155	0.153	0.104	0.02	0.092	0.093	0.185	0.113	0.197	0.101	0.162	0.159	
UK	0	0.155	0.125	0.398	0	0.587	0.168	0.021	0.559	0.011	0.207	0.11	0.013	0.307	0.076	0.292	0	0	0.122	0.13	0.272	0.403	0.251	0	0	0.06	0.059	0.157	0.02	0.016	0.411	0	0.054	0	0.104	0.118	0.037	0	0.067	0.055	0.213	0.098	0.127	0.086	0.157	0.142	
AUST	0	0.018	0.071	0.159	0	0.136	0.013	0	0.205	0	0	0.047	0	0.251	0.008	0.312	0	0.012	0	0.191	0.145	0.1	0.378	0.021	0.103	0.061	0.01	0.183	0	0	0.268	0	0	0	0.198	0.252	0.019	0	0.088	0.034	0.266	0.122	0.102	0	0.243	0.205	
HK	0	0.028	0	0	0	0.065	0	0	0.115	0	0	0	0	0.168	0	0.161	0	0.012	0	0	0.114	0.061	0.16	0	0.123	0.025	0.006	0.215	0	0	0.122	0	0.007	0	0.081	0.102	0	0	0.001	0	0.209	0.035	0.09	0.063	0.184	0.074	
JAP	0	0.005	0.044	0.094	0	0.143	0	0	0.206	0.045	0	0	0	0.191	0.017	0.216	0	0	0.022	0.104	0	0.102	0.178	0.031	0.072	0.051	0.024	0.181	0.032	0.036	0.168	0	0.051	0	0.122	0.097	0.007	0	0.072	0.043	0.154	0.082	0.133	0.059	0.185	0.109	
NZ	0	0	0	0.041	0	0.238	0	0	0.299	0.002	0	0	0	0.228	0	0.119	0	0	0.017	0.115	0.078	0	0.093	0	0	0.024	0.01	0	0	0.001	0.185	0	0	0	0.06	0.082	0.038	0	0.067	0.034	0.155	0.078	0.098	0.091	0	0.067	
SIN	0	0	0	0	0	0.044	0	0	0.099	0	0	0	0	0.155	0	0.231	0	0	0	0.041	0.097	0.022	0	0.004	0.099	0.019	0	0.22	0	0	0.011	0	0	0	0.082	0.079	0	0	0.02	0	0.188	0	0	0.041	0.221	0.099	
BRA	0	0	0.052	0	0	0	0	0	0.075	0.005	0	0	0	0	0	0.078	0	0	0.049	0	0.075	0	0.101	0	0.161	0.05	0	0.135	0	0.003	0	0.003	0	0	0.134	0.093	0	0	0.08	0.08	0.098	0.124	0	0	0.215	0.133	
CHI	0	0	0	0	0	0	0	0	0	0.011	0	0	0	0	0	0.023	0	0	0	0.033	0.025	0	0.052	0.008	0	0	0	0.177	0	0	0.051	0	0	0	0.057	0.033	0.005	0	0.048	0.048	0.069	0.078	0	0.032	0.234	0.035	
COL	0.067	0.025	0.057	0.058	0.025	0.075	0.039	0.034	0.082	0.092	0.037	0.04	0	0.115	0.057	0.126	0.012	0.042	0.096	0.172	0.108	0	0.178	0.218	0.283	0	0.101	0.281	0.037	0.084	0.085	0	0.025	0.019	0.215	0.232	0.041	0	0.124	0.119	0.129	0.136	0	0.083	0.354	0.201	
MEX	0.046	0.049	0.232	0.148	0	0.141	0.077	0.028	0.172	0.093	0.056	0.104	0	0.149	0.055	0.195	0.003	0.065	0.159	0.119	0.149	0.099	0.197	0.087	0	0.119	0	0.224	0.174	0.109	0.152	0	0.101	0	0.305	0.138	0	0.045	0.088	0.095	0.132	0.126	0.145	0	0.287	0.211	
PER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.082	0	0	0	0	0	0	0	0	0	0	0	0	0	0.005	0	0	0.029	0	0	0.253	0	
CR	0.103	0.067	0.288	0.171	0.065	0.154	0.11	0.072	0.15	0.093	0.073	0.143	0	0	0.093	0.15	0.015	0.091	0.195	0	0.1	0.102	0	0.058	0	0.081	0.151	0.139	0	0.098	0	0	0.1	0	0.292	0	0	0.032	0	0	0	0	0.131	0	0.174	0.174	
EGY	0.051	0	0.082	0	0.044	0	0.066	0.066	0.083	0.086	0	0	0	0	0	0.091	0	0	0	0	0	0	0	0.086	0	0.045	0.069	0	0.041	0	0	0.026	0.038	0	0.175	0.105	0	0	0	0	0	0	0.097	0	0.149	0.155	
GRE	0	0.002	0	0.067	0	0.177	0	0	0.224	0	0	0	0	0.307	0	0.163	0	0	0.056	0.077	0.111	0.206	0.126	0.002	0.068	0.014	0	0.126	0	0	0	0	0	0	0.048	0.053	0	0	0	0.018	0.171	0.068	0.088	0.081	0.119	0.099	
HUN	0.219	0.183	0.386	0.23	0.235	0.239	0.223	0.26	0.201	0.126	0.193	0.2	0	0.176	0.153	0.256	0.093	0.201	0.282	0.17	0.218	0.157	0.335	0.083	0.107	0.133	0.259	0.187	0.261	0.098	0.257	0	0.268	0.013	0.268	0.189	0	0	0	0.117	0.169	0	0.112	0	0.19	0.177	
POL	0.122	0.225	0.292	0.276	0.114	0.288	0.239	0.144	0.25	0.071	0.192	0.191	0	0.166	0.113	0.211	0.131	0.243	0.238	0.106	0.148	0.207	0.163	0.051	0	0.054	0.115	0.138	0.136	0.068	0.218	0.025	0	0	0.169	0.117	0.05	0.028	0	0.065	0.115	0	0.14	0	0.132	0.139	
QAT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.144	0.084	0.102	0	0.091	0	0.178	0	0	0	0	0.11	0	0	0.185	0	0	0	0	0	0	0.096	0.1	
RUS	0	0.002	0	0.05	0	0.055	0.001	0	0.073	0	0.002	0.016	0	0.126	0.003	0.089	0	0.012	0.05	0.07	0.048	0.047	0.08	0.025	0.117	0.013	0	0.143	0	0	0.036	0	0	0	0	0.049	0	0	0	0.019	0.092	0.103	0	0	0.221	0.152	
SA	0	0.02	0.017	0.07	0	0.092	0	0	0.134	0	0	0.008	0	0.218	0	0.24	0	0	0	0.235	0.193	0.053	0.344	0	0.196	0.06	0.003	0.276	0	0	0.116	0	0	0	0.132	0	0	0	0.076	0.015	0.315	0.115	0.099	0.078	0.299	0.196	
TUR	0.053	0.084	0	0	0	0.142	0.075	0.07	0.12	0.039	0.068	0	0	0.169	0.059	0.189	0.035	0.082	0.133	0.265	0.166	0.125	0.2	0	0.114	0.081	0	0.165	0	0	0.159	0.027	0	0	0	0.174	0	0	0.106	0.085	0.267	0.092	0	0.125	0.129	0.09	
UAE	0	0	0.105	0.099	0.088	0	0	0	0	0.127	0	0	0	0.087	0	0	0	0	0.1	0	0	0	0.089	0	0	0	0.081	0	0.098	0.198	0	0	0.079	0	0.121	0	0	0	0	0.095	0.077	0.104	0	0	0.092	0.112	
IND	0	0	0	0	0	0	0	0	0	0	0	0	0	0.113	0.003	0.069	0	0	0.031	0.18	0.059	0.049	0.082	0.009	0.096	0.024	0	0.123	0	0	0	0	0	0	0	0.078	0.05	0	0	0.027	0.117	0.078	0	0.17	0.102	0.034	
INDO	0	0	0	0	0	0	0	0.026	0	0.014	0	0	0	0	0.029	0.109	0	0	0.064	0.171	0.077	0	0.126	0.072	0.138	0.094	0.046	0.172	0	0	0.07	0	0	0	0.141	0.192	0.067	0	0.165	0	0.157	0.164	0	0	0.175	0.09	
KOR	0	0.009	0.011	0.048	0	0.062	0	0	0.126	0	0	0.002	0	0.219	0	0.147	0	0	0	0.07	0.109	0.038	0.029	0.003	0.1	0.017	0	0.201	0	0	0.065	0	0	0	0.061	0.028	0	0	0.01	0	0	0.041	0.089	0.066	0.155	0.059	
MAL	0	0.022	0	0	0	0.04	0.015	0.005	0.057	0	0	0	0	0.139	0.023	0.058	0.003	0.011	0.007	0.101	0.047	0.044	0	0	0.053	0.008	0.003	0.081	0	0	0.051	0	0	0	0.028	0.057	0.033	0	0.114	0	0.105	0	0	0.104	0	0.01	
PAK	0.015	0.019	0.014	0.035	0.008	0.04	0.011	0.002	0.054	0.013	0.009	0.01	0	0.056	0	0.026	0.009	0.021	0.028	0.012	0.008	0.065	0	0.007	0.026	0.002	0	0	0	0	0.042	0	0	0	0.017	0.018	0.026	0	0	0	0.037	0.041	0	0.062	0	0	
PHI	0	0	0	0	0	0.051	0	0.021	0.05	0.001	0	0	0	0.086	0.011	0.068	0	0.023	0	0.094	0.059	0.037	0.054	0	0.052	0.015	0	0.066	0	0	0.065	0	0	0	0.035	0.067	0.088	0	0.079	0	0.113	0.031	0	0	0	0.008	
TW	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.079	0	0	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
THA	0	0	0	0	0	0.027	0	0	0.065	0	0	0	0	0.11	0	0.061	0	0	0	0.091	0.041	0.02	0.071	0.009	0.097	0	0	0.144	0	0	0.041	0	0	0	0.05	0.076	0.032	0	0.096	0.041	0.106	0.161	0	0	0.205	0	
From																																															

Note: The numerical values in the matrix represent the magnitudes of the statistically significant error correction coefficients (in absolute terms) at an FDR significance level of $\alpha = 0.05$ for the stock market pairs.

We define the nodes listed in the first column as source nodes, and those listed in the first row as destination nodes.

"From" refers to the outgoing linkages from source nodes to the corresponding destination nodes; "To" refers to the reverse direction.

Table A.2

The asymmetric adjacent matrix for the directed and weighted international stock market network during the sub-period of 2010–2012 at an FDR significance level of $\alpha = 0.05$.

	CAN	US	AUS	BEL	DEN	FIN	FRA	GER	IRE	ISR	ITA	NETH	NOR	POR	SPA	SWD	SWI	UK	AUST	HK	JAP	NZ
CAN	0	0.055	0.069	0.072	0.096	0.078	0.069	0.094	0	0.092	0.064	0.08	0.061	0.061	0.061	0.2	0.077	0.061	0.028	0.073	0.037	0.032
US	0.012	0	0.035	0.033	0.011	0.038	0.032	0	0	0.03	0.046	0.025	0.071	0.052	0.049	0.025	0.011	0.002	0.008	0.025	0.016	0
AUS	0	0	0	0.156	0	0.175	0.077	0.03	0	0.099	0.087	0.062	0.05	0.064	0	0	0	0	0.022	0.083	0.004	0
BEL	0.038	0.052	0.028	0	0.05	0.111	0	0.031	0	0.062	0.078	0.026	0.065	0.064	0	0.051	0.039	0	0.024	0.087	0.011	0.044
DEN	0.007	0.056	0.029	0.028	0	0.034	0.03	0	0.01	0.028	0.038	0.027	0.045	0.043	0.039	0.077	0	0.019	0.003	0.034	0.012	0.001
FIN	0.008	0.039	0	0	0.023	0	0	0.01	0	0	0.07	0	0.062	0.067	0.049	0	0.02	0.016	0.006	0.016	0	0.033
FRA	0.054	0.062	0.146	0.298	0.06	0.195	0	0.045	0	0.137	0.13	0.092	0.084	0.099	0.079	0.065	0.052	0.047	0.04	0.104	0.017	0.055
GER	0.077	0	0.036	0.044	0.198	0.055	0.034	0	0	0.051	0.044	0.042	0.052	0.046	0.045	0.295	0.097	0.076	0.045	0.069	0	0.041
IRE	0.096	0.134	0.084	0.088	0.126	0.096	0.083	0.109	0	0.091	0.082	0.095	0.093	0.091	0.09	0.115	0.126	0.116	0.104	0.095	0.08	0.106
ISR	0.031	0.043	0.125	0.127	0.045	0.179	0.095	0.034	0.03	0	0.095	0.089	0.068	0.092	0.08	0.051	0.037	0.034	0.024	0.081	0.014	0.038
ITA	0.028	0.048	0	0.002	0.032	0.074	0	0.024	0	0.031	0	0.004	0.087	0.059	0	0.031	0.03	0.029	0.025	0.036	0.016	0.043
NETH	0.067	0.071	0.101	0.133	0.074	0.141	0.076	0.051	0	0.15	0.101	0	0.086	0.095	0.082	0.088	0.063	0.052	0.042	0.124	0.029	0.063
NOR	0.017	0.033	0.018	0.017	0.018	0.03	0.014	0.018	0.018	0.016	0.017	0.018	0	0.025	0.004	0.018	0.02	0.02	0.018	0.021	0.015	0.027
POR	0.023	0.035	0.026	0.033	0	0.067	0.014	0	0	0.029	0.091	0.017	0.075	0	0.009	0	0	0	0.019	0.032	0.015	0
SPA	0.038	0.061	0.037	0.036	0.04	0.081	0.011	0.033	0.031	0.046	0.104	0.021	0.115	0.187	0	0.039	0.038	0.036	0.032	0.042	0.023	0.05
SWD	0	0.058	0.053	0.051	0.066	0.055	0.056	0	0	0.058	0.065	0.038	0.069	0.067	0.062	0	0.002	0	0	0.055	0.002	0.023
SWI	0.038	0.075	0.036	0.038	0.129	0.044	0.033	0.079	0	0.04	0.044	0.032	0.054	0.048	0.045	0.139	0	0.038	0	0.044	0	0.014
UK	0.08	0.116	0.068	0.067	0.169	0.074	0.063	0.115	0	0.075	0.074	0.058	0.086	0.077	0.075	0.29	0.199	0	0	0.073	0.029	0.069
AUST	0.186	0.105	0.093	0.103	0.179	0.098	0.096	0.259	0.049	0.122	0.089	0.118	0.089	0.089	0.089	0.395	0.29	0.264	0	0.106	0.026	0.078
HK	0.058	0	0.075	0.095	0.092	0.089	0.073	0.072	0.046	0.123	0.075	0.102	0.068	0.068	0.065	0.099	0.066	0.053	0.037	0	0.01	0.056
JAP	0.179	0.11	0.172	0.167	0.144	0.163	0.176	0.188	0.107	0.197	0.13	0.193	0.114	0.131	0.13	0.191	0.18	0.173	0.213	0.203	0	0.121
NZ	0.036	0.116	0.03	0.03	0.087	0.035	0.028	0.052	0.017	0.029	0.038	0.03	0.056	0.041	0.039	0.072	0.125	0.059	0.028	0.031	0.008	0
SIN	0.032	0	0.041	0.044	0.165	0.044	0.043	0.069	0	0.046	0.046	0.044	0	0.048	0	0.161	0.077	0.039	0.003	0.039	0.006	0.02
BRA	0.022	0.057	0.035	0.041	0.034	0.125	0.03	0.027	0.032	0.04	0.1	0.031	0.102	0.097	0.1	0.032	0.034	0.028	0.018	0.01	0.006	0.055
CHI	0.017	0	0.041	0.042	0.053	0.043	0.042	0.039	0	0.042	0.044	0.04	0.043	0.044	0.044	0.062	0.023	0.012	0	0.041	0.012	0.017
COL	0.031	0.039	0.044	0.042	0.053	0.044	0.044	0.032	0.039	0.043	0.049	0.041	0.053	0.053	0.049	0.05	0.038	0.024	0.022	0.043	0.03	0.02
MEX	0.012	0.113	0.044	0.045	0.123	0.049	0.043	0.04	0.023	0.044	0.054	0.039	0.069	0.058	0.057	0.085	0.066	0.025	0	0.036	0.018	0.021
PER	0.019	0.032	0	0	0	0	0	0.025	0	0	0	0	0	0	0	0.039	0.03	0.03	0.02	0	0.018	0.012
CR	0.028	0	0.204	0.153	0	0.183	0.107	0.029	0	0.09	0.139	0.07	0.065	0.105	0.074	0	0.029	0	0.023	0.06	0.015	0
EGY	0	0	0	0.026	0	0	0.024	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0	0
GRE	0	0	0.012	0.018	0	0.02	0.014	0	0	0.017	0.024	0.017	0.044	0	0	0	0	0	0	0.023	0.014	0
HUN	0.035	0.047	0.099	0.142	0.041	0.154	0.096	0.032	0.03	0.079	0.201	0.065	0.1	0.115	0.085	0.041	0.035	0.035	0.029	0.055	0.023	0.042
POL	0.031	0	0.061	0.13	0.055	0.077	0.078	0.037	0	0.09	0.059	0.098	0	0.049	0.046	0.065	0.04	0	0.01	0.091	0	0
QAT	0.024	0.033	0.024	0.022	0.027	0.019	0.023	0.025	0.022	0.022	0.026	0.022	0.041	0	0.025	0.03	0.03	0.03	0.026	0.023	0.022	0.019
RUS	0.157	0.051	0.111	0.107	0.067	0.116	0.119	0.101	0	0.138	0.087	0.15	0.064	0.08	0.084	0.121	0.074	0.068	0.076	0.092	0.072	0.043
SA	0.06	0.078	0.062	0.063	0.14	0.064	0.061	0.097	0.041	0.071	0.065	0.06	0.072	0.067	0.065	0.277	0.124	0.054	0.011	0.065	0.012	0.042
TUR	0	0	0	0.008	0.031	0	0.004	0	0	0	0	0	0	0	0	0	0	0	0	0.007	0	0
UAE	0.081	0.075	0.142	0.181	0.086	0.133	0.156	0.087	0.085	0.115	0.129	0.134	0.099	0.113	0.109	0.088	0.088	0.083	0.091	0.132	0.075	0.074
IND	0.028	0.049	0.066	0.086	0.036	0.09	0.059	0.03	0.037	0.046	0.094	0.045	0.084	0.088	0.078	0.035	0.034	0.031	0.022	0.025	0.013	0.041
INDO	0.037	0.044	0.032	0.03	0	0.029	0.03	0.044	0.033	0.031	0.026	0.032	0.026	0	0.027	0.051	0.049	0.043	0.036	0.032	0.028	0.018
KOR	0.125	0.087	0.057	0.061	0.146	0.057	0.06	0.166	0.047	0.063	0.057	0.068	0.061	0.058	0.057	0.271	0.191	0.148	0.096	0.058	0.022	0.052
MAL	0.016	0.051	0.031	0.029	0.041	0.03	0.03	0.029	0.026	0.027	0.032	0.028	0.038	0.036	0.033	0.04	0.035	0.024	0.014	0.024	0.019	0
PAK	0.009	0.095	0	0	0.024	0	0	0.013	0.012	0	0	0.01	0	0	0	0.021	0.029	0.024	0.014	0.011	0.008	0.04
PHI	0.003	0.002	0.016	0.013	0.004	0.016	0.013	0.005	0.006	0.01	0.017	0.01	0.025	0.025	0.015	0.005	0.004	0	0	0.009	0.006	0
TW	0.167	0	0.075	0.083	0.092	0.079	0.076	0.119	0	0.121	0.056	0.104	0.047	0.054	0.053	0.197	0.077	0.075	0.088	0.117	0.004	0
THA	0.007	0.025	0	0	0.021	0	0	0.015	0	0	0	0	0	0	0	0.017	0.011	0.009	0.006	0.013	0.009	0
From																						

	SIN	BRA	CHI	COL	MEX	PER	CR	EGY	GRE	HUN	POL	QAT	RUS	SA	TUR	UAE	IND	INDO	KOR	MAL	PAK	PHI	TW	THA	To
CAN	0.074	0.061	0.098	0.076	0.071	0.06	0.067	0.061	0.063	0.062	0.096	0.062	0.057	0.072	0.086	0.062	0.065	0.053	0.027	0.072	0.056	0.06	0.068	0.063	
US	0.011	0.043	0.032	0.048	0	0.075	0.042	0.049	0.069	0.043	0.026	0.127	0.02	0.017	0.029	0.034	0.041	0.046	0.002	0.079	0.091	0.1	0.019	0.083	
AUS	0.035	0	0	0	0	0	0	0	0.071	0.044	0.065	0	0.003	0	0.078	0.039	0.092	0	0	0	0	0	0.019	0	
BEL	0.047	0	0.046	0.049	0.045	0.047	0.021	0.061	0.086	0.031	0.049	0.055	0.02	0.04	0.107	0.043	0.088	0.05	0.039	0.05	0.052	0.054	0.029	0.049	
DEN	0.001	0.035	0.043	0.06	0.081	0.046	0.03	0.039	0.047	0.03	0.018	0.047	0.007	0.019	0.054	0.034	0.033	0	0	0.056	0.051	0.05	0	0.052	
FIN	0.022	0.013	0.024	0.028	0.026	0.031	0	0.041	0.073	0	0	0.042	0	0.018	0.049	0.018	0.061	0.037	0.018	0.034	0	0.042	0	0	
FRA	0.06	0.077	0.057	0.061	0.056	0.057	0.095	0.072	0.103	0.082	0.117	0.066	0.036	0.052	0.112	0.071	0.109	0.061	0.051	0.062	0.064	0.067	0.051	0.061	
GER	0.119	0.049	0.087	0.09	0.103	0.061	0.038	0.053	0.054	0.039	0.052	0.066	0.016	0.097	0.092	0.049	0.052	0.059	0.067	0.087	0.074	0.065	0.041	0.072	
IRE	0.098	0.094	0.094	0.099	0.123	0.104	0.088	0.094	0.093	0.082	0.09	0.104	0.089	0.103	0.097	0.095	0.093	0.095	0.099	0.105	0.127	0.102	0.09	0.1	
ISR	0.038	0.08	0.048	0.046	0.037	0.041	0.081	0.06	0.074	0.062	0.107	0.048	0.028	0.036	0.093	0.059	0.105	0.043	0.027	0.043	0.045	0.049	0.032	0.044	
ITA	0.033	0.034	0.029	0.036	0.036	0.042	0	0.051	0.125	0	0.02	0.053	0.014	0.032	0.052	0.033	0.062	0.047	0.033	0.043	0	0.058	0.023	0	
NETH	0.072	0.075	0.07	0.074	0.068	0.067	0.087	0.079	0.099	0.071	0.137	0.074	0.032	0.062	0.131	0.082	0.105	0.07	0.058	0.074	0.074	0.075	0.059	0.071	
NOR	0.018	0.029	0.017	0.02	0.021	0.03	0.015	0.035	0.09	0.009	0.016	0.049	0.015	0.019	0.023	0.017	0.033	0.032	0.02	0.026	0	0.058	0.017	0	
POR	0	0.028	0	0	0	0	0.03	0	0.093	0.028	0.029	0	0.015	0	0.04	0.028	0.063	0	0	0	0	0	0.019	0	
SPA	0.041	0.05	0.037	0.044	0.044	0.049	0.051	0.051	0.112	0.037	0.04	0.061	0.03	0.039	0.052	0.042	0.073	0.051	0.04	0.049	0.057	0.067	0.033	0.051	
SWD	0.024	0.056	0.091	0.09	0.051	0.062	0.058	0.069	0.075	0.055	0.041	0.071	0	0	0.088	0.058	0.061	0.058	0	0.084	0.067	0.072	0	0.078	
SWI	0.078	0.045	0.083	0.081	0.101	0.065	0.038	0.056	0.055	0.039	0.036	0.075	0.018	0.06	0.063	0.042	0.045	0.064	0.041	0.097	0.077	0.075	0.023	0.095	
UK	0.137	0.074	0.138	0.14	0.158	0.127	0.072	0.088	0.088	0.07	0.072	0.118	0.053	0.162	0.093	0.074	0.075	0.111	0.126	0.155	0.115	0.113	0.067	0.135	
AUST	0.159	0.084	0.156	0.131	0.154	0.11	0.088	0.09	0.09	0.085	0.133	0.108	0.098	0.201	0.12	0.087	0.092	0.101	0.136	0.13	0.102	0.104	0.108	0.119	
HK	0.065	0	0.079	0.075	0.065	0.062	0.062	0.073	0.074	0.065	0.099	0.059	0.032	0.056	0.213	0.066	0.092	0	0	0.065	0.058	0.062	0.013	0.061	
JAP	0.165	0.144	0.159	0.129	0.148	0.124	0.148	0.114	0.12	0.135	0.199	0.112	0.197	0.183	0.155	0.157	0.147	0.115	0.158	0.123	0.113	0.12	0.259	0.119	
NZ	0.07	0.042	0.054	0.073	0.11	0.078	0.031	0.044	0.047	0.033	0.031	0.103	0.03	0.06	0.038	0.029	0.033	0.092	0.062	0.135	0.119	0.12	0.03	0.139	
SIN	0	0	0.114	0.117	0.106	0	0.04	0	0	0.043	0.044	0.058	0	0.066	0.077	0.043	0.043	0	0	0.096	0.056	0	0.011	0.081	
BRA	0.031	0	0.031	0.037	0.04	0.045	0.04	0.044	0.083	0.034	0.026	0.06	0.001	0.027	0.044	0.027	0.057	0.048	0.028	0.049	0.066	0.067	0.003	0.054	
CHI	0.017	0.043	0	0.096	0	0.021	0.043	0.045	0.045	0.043	0	0.044	0.02	0	0	0.043	0	0.033	0	0.046	0.031	0.044	0.001	0.046	
COL	0.024	0.046	0.06	0	0.04	0.034	0.047	0.05	0.053	0.047	0.036	0.044	0.034	0.017	0.045	0.051	0.046	0.045	0.021	0.07	0.031	0.062	0.024	0.075	
MEX	0.036	0.053	0.065	0.098	0	0.098	0.048	0.056	0.068	0.049	0.041	0.091	0.021	0.027	0.056	0.049	0.048	0.068	0.002	0.132	0.104	0.108	0.018	0.126	
PER	0	0	0.05	0.062	0.031	0	0	0.032	0	0.026	0	0.098	0.018	0.038	0	0	0.022	0.091	0.034	0.111	0	0	0.02	0.101	
CR	0.029	0.067	0	0	0	0	0	0	0.087	0.108	0.061	0	0.008	0	0	0.041	0.097	0	0.024	0	0	0	0.025	0	
EGY	0	0	0	0	0	0	0	0	0.038	0	0	0.059	0	0	0.028	0.01	0	0.047	0	0	0	0	0	0	
GRE	0	0.015	0	0	0	0	0.008	0.041	0	0.006	0.019	0	0	0	0.029	0.02	0.028	0	0	0	0	0	0	0	
HUN	0.034	0.082	0.037	0.04	0.039	0.046	0.065	0.065	0.136	0	0.046	0.056	0.026	0.035	0.059	0.037	0.088	0.048	0.033	0.044	0.049	0.06	0.029	0.05	
POL	0.037	0	0	0	0	0	0.015	0	0.055	0.032	0	0	0	0	0.112	0.041	0.068	0	0	0	0	0	0	0	
QAT	0.027	0.017	0.033	0.05	0.033	0.074	0.023	0.026	0.035	0.023	0.022	0	0.023	0.037	0.021	0.025	0.017	0.088	0.028	0.071	0.023	0.1	0.022	0.101	
RUS	0.055	0.092	0.074	0	0.057	0.052	0.092	0.053	0.065	0.075	0.136	0.051	0	0.072	0	0.06	0.08	0.046	0.044	0.051	0.052	0.054	0.169	0.051	
SA	0.121	0.061	0.193	0.155	0.116	0.102	0.061	0.074	0.072	0.061	0.067	0.09	0.032	0	0.079	0.063	0.064	0.102	0.043	0.146	0.075	0.095	0.023	0.121	
TUR	0.023	0	0	0	0	0	0	0.047	0.041	0	0	0	0	0	0	0.015	0.026	0	0	0	0	0	0	0	
UAE	0.085	0.106	0.079	0.073	0.076	0.076	0.122	0.154	0.127	0.172	0.143	0.084	0.085	0.077	0.136	0	0.138	0.077	0.075	0.072	0.082	0.074	0.086	0.073	
IND	0.026	0.055	0.029	0.036	0.035	0.046	0.067	0.064	0.094	0.086	0.041	0.054	0.016	0.028	0.076	0.038	0	0.039	0.027	0.04	0	0.051	0.01	0.041	
INDO	0	0.03	0.045	0.051	0	0.018	0.03	0.046	0.031	0.029	0.033	0.044	0.032	0.04	0.031	0.035	0.031	0	0.034	0.099	0	0	0.03	0.078	
KOR	0.098	0.055	0.136	0.115	0.133	0.094	0.055	0.064	0.062	0.055	0.068	0.094	0.053	0.284	0.072	0.058	0.056	0.095	0	0.14	0.077	0.084	0.053	0.106	
MAL	0.007	0.031	0.026	0.047	0.03	0.022	0.032	0.036	0	0.032	0.026	0.066	0.019	0.015	0.027	0.034	0.029	0.011	0	0	0.033	0.067	0.016	0.124	
PAK	0.021	0.007	0.016	0.034	0.051	0	0	0	0	0	0.01	0.056	0.008	0.022	0.011	0	0	0	0.009	0.047	0	0.085	0.008	0.074	
PHI	0	0.016	0	0.003	0	0	0.016	0	0	0.016	0.009	0.005	0.007	0	0.007	0.015	0.013	0	0	0	0	0	0.004	0.007	
TW	0.082	0	0.117	0.074	0.067	0.048	0.06	0	0.05	0.057	0.127	0.048	0.072	0.126	0.098	0.051	0.069	0	0.051	0.056	0	0	0	0.053	
THA	0.006	0.015	0.009	0.019	0.013	0	0	0	0	0	0.014	0.005	0.01	0.002	0.014	0	0	0	0	0.061	0.012	0.093	0.007	0	
From																									

Note: The numerical values in the matrix represent the magnitudes of the statistically significant error correction coefficients (in absolute terms) at an FDR significance level of $\alpha = 0.05$ for the stock market pairs.

We define the nodes listed in the first column as source nodes, and those listed in the first row as destination nodes.

"From" refers to the outgoing linkages from source nodes to the corresponding destination nodes; "To" refers to the reverse direction.

Table A.3

The asymmetric adjacent matrix for the directed and weighted international stock market network during the full sample period of 2007–2017 at an FDR significance level of $\alpha = 0.05$.

	CAN	US	AUS	BEL	DEN	FIN	FRA	GER	IRE	ISR	ITA	NETH	NOR	POR	SPA	SWD	SWI	UK	AUST	HK	JAP	NZ	SIN	BRA	CHI	COL	MEX	PER	CR	EGY	GRE	HUN	POL	QAT	RUS	SA	TUR	UAE	IND	INDO	KOR	MAL	PAK	PHI	TW	THA	To
CAN	0	0.021	0.024	0.024	0.021	0.023	0.021	0.021	0.023	0.025	0.021	0.023	0.022	0.024	0.021	0.044	0.02	0.023	0.115	0.029	0.023	0.027	0.087	0.026	0.041	0.036	0.043	0.06	0.023	0.02	0.022	0.024	0.033	0.021	0.041	0.071	0.043	0.02	0.027	0.031	0.055	0.042	0.023	0.024	0.061	0.026	
US	0	0	0.002	0	0	0	0	0	0	0	0.003	0	0.012	0	0.003	0.003	0	0	0	0	0	0	0.001	0.004	0.002	0.002	0	0.001	0	0	0	0	0	0.005	0.001	0.001	0.001	0	0	0	0	0	0.033	0	0.007	0.013	
AUS	0	0	0	0.015	0	0.015	0.007	0	0.016	0	0	0.011	0	0.017	0.003	0	0	0	0	0.013	0	0	0	0	0	0	0	0	0	0.008	0.017	0.011	0.007	0	0	0	0	0	0	0	0	0	0	0	0	0	
BEL	0	0	0.005	0	0	0.003	0	0	0.048	0	0	0	0	0	0	0	0	0	0	0.017	0.021	0.022	0	0	0	0	0	0	0	0.008	0	0	0.009	0	0	0	0	0.015	0.014	0	0.017	0	0.019	0	0	0	
DEN	0.001	0.055	0	0.001	0	0.002	0.001	0.002	0.003	0.006	0	0	0.011	0	0.005	0.012	0.013	0.001	0	0.004	0.023	0.004	0	0.006	0	0.004	0	0	0	0	0	0	0.002	0.008	0.003	0	0	0	0.003	0	0.006	0	0.038	0	0.014	0	
FIN	0	0	0.012	0.049	0	0	0.015	0	0.031	0	0.01	0.021	0	0	0	0	0	0	0	0	0	0.017	0	0	0	0	0	0	0	0.006	0	0.007	0.013	0	0	0	0	0.011	0	0	0	0	0.014	0	0	0	
FRA	0	0.019	0.027	0.08	0.019	0.059	0	0.019	0.044	0.019	0.018	0.04	0.018	0.02	0.012	0	0.02	0	0	0.022	0.023	0.025	0.022	0.018	0.02	0.02	0	0.02	0.015	0.017	0.021	0.015	0.029	0.021	0	0	0	0.021	0.019	0.019	0.021	0.019	0.023	0.02	0.024	0.019	
GER	0.007	0.055	0.01	0.008	0.04	0.008	0.005	0	0.012	0.019	0.011	0.006	0.021	0.014	0.011	0.044	0.059	0.007	0.011	0.016	0.051	0.045	0.018	0.014	0.015	0.013	0	0.014	0.013	0.01	0.015	0.009	0.008	0.019	0.01	0	0.011	0.012	0.012	0.018	0.022	0.017	0.06	0.035	0.043	0.03	
IRE	0.007	0	0	0	0	0	0	0.013	0	0.01	0	0	0	0.005	0.002	0	0	0	0.007	0.01	0.019	0.019	0	0	0	0	0	0	0.005	0.002	0	0.001	0.002	0	0	0	0	0.008	0.009	0	0.011	0	0.018	0	0	0	
ISR	0.008	0.023	0.012	0.013	0.025	0.012	0.011	0.023	0.014	0	0.013	0.012	0.019	0.013	0.012	0.042	0.028	0.011	0.014	0.03	0.028	0.02	0.023	0.013	0.016	0.013	0.013	0.014	0.013	0.012	0.015	0.011	0.011	0.016	0.012	0.023	0.013	0.011	0.026	0.025	0.028	0.021	0.023	0.032	0.075	0.034	
ITA	0	0	0.022	0.012	0	0.013	0.009	0	0.015	0	0	0.01	0	0.023	0.002	0	0	0	0	0.011	0	0.012	0	0	0.012	0	0	0	0.01	0.014	0.029	0	0.012	0	0	0	0	0.011	0.011	0.014	0	0.012	0	0.013	0	0.013	
NETH	0	0.019	0.011	0.078	0.018	0.018	0	0	0.051	0.017	0.01	0	0	0	0	0	0	0	0	0.021	0.026	0.032	0	0	0	0	0	0	0.01	0.011	0.014	0.01	0.017	0	0	0	0	0.018	0.018	0	0.022	0	0.025	0	0.026	0	
NOR	0.005	0.008	0	0.005	0.008	0.006	0.006	0.006	0.005	0.007	0.007	0.005	0	0.012	0.007	0.005	0.007	0.005	0.005	0.004	0.006	0.005	0.005	0.006	0.005	0.005	0.005	0.005	0.009	0.008	0.024	0.005	0.005	0.01	0	0.005	0.005	0	0.006	0.011	0.006	0.007	0	0.017	0.006	0.014	
POR	0	0	0.002	0.003	0	0.002	0.001	0.007	0.006	0.008	0	0.003	0.013	0	0	0.006	0.008	0.003	0.003	0.005	0	0	0.005	0	0.006	0	0.005	0	0	0	0.029	0	0.002	0.017	0.003	0.005	0.004	0	0.006	0.009	0.006	0.006	0	0	0	0	
SPA	0.012	0.015	0.03	0.016	0.016	0.019	0.014	0.014	0.017	0.015	0.048	0.013	0.023	0.047	0	0.014	0.015	0.012	0.013	0.014	0.014	0.015	0.014	0	0.015	0.015	0.014	0.015	0.017	0.019	0.05	0.011	0.015	0.021	0.016	0.014	0.013	0.014	0.013	0.018	0.014	0.015	0.014	0.018	0.014	0.017	
SWD	0	0.019	0.01	0	0.008	0.007	0	0	0.008	0.011	0.012	0	0.021	0.014	0.011	0	0	0	0	0.002	0.015	0.009	0.019	0.014	0.019	0.016	0.006	0.017	0.014	0.011	0.018	0.009	0	0.017	0.011	0.012	0.011	0.009	0.01	0.025	0.002	0.028	0.023	0.03	0.046	0.033	
SWI	0.004	0.027	0.006	0.002	0.017	0.004	0.002	0.003	0.003	0.013	0.008	0	0.016	0.009	0.007	0.033	0	0	0.006	0.011	0.012	0.012	0.013	0.007	0.009	0.007	0.01	0.008	0.008	0.006	0.011	0.006	0.003	0.016	0.006	0.012	0.007	0.001	0.008	0.016	0.014	0.015	0.027	0.035	0.028	0.031	
UK	0.018	0.018	0.014	0.016	0.018	0	0	0.018	0.021	0.019	0.012	0	0.017	0.016	0.012	0.039	0.021	0	0.032	0.023	0.022	0.029	0.039	0.017	0.02	0.02	0.026	0.025	0.014	0.01	0.016	0	0.023	0.018	0.02	0.028	0.022	0.014	0.018	0.02	0.033	0.024	0.022	0.02	0.032	0.021	
AUST	0	0.02	0.019	0.02	0.018	0.018	0	0.015	0.021	0.02	0.018	0.016	0.02	0.02	0.018	0.036	0.017	0.014	0	0.018	0.019	0.022	0.072	0.02	0.031	0.028	0.024	0.046	0.018	0.015	0.02	0	0.012	0.02	0.03	0.041	0.03	0.017	0.02	0.025	0.039	0.03	0.021	0.021	0.044	0.023	
HK	0.023	0.034	0.023	0.027	0.032	0.024	0.022	0.035	0.03	0.036	0.023	0.026	0.027	0.023	0.022	0.052	0.033	0.025	0.028	0	0.034	0.04	0.043	0.022	0.028	0.024	0.027	0.03	0.022	0.021	0.025	0.021	0.023	0.025	0.022	0.036	0.024	0.024	0.041	0.03	0.053	0.029	0.037	0.033	0.087	0.034	
JAP	0.003	0.059	0.007	0.001	0.033	0.003	0.002	0.015	0.005	0.015	0.008	0	0.018	0.012	0.008	0.015	0.028	0	0.004	0.006	0	0.027	0.008	0.012	0.008	0.008	0.007	0.008	0.011	0.007	0.014	0.005	0.003	0.016	0.008	0.008	0.007	0.008	0.009	0.012	0.008	0.01	0.071	0.027	0.022	0.02	
NZ	0	0.023	0.003	0	0.019	0	0	0.009	0.003	0.009	0	0	0	0	0	0.021	0.015	0	0	0.001	0.017	0	0	0	0	0	0	0	0	0	0	0.003	0	0	0	0.007	0.005	0	0.006	0	0.011	0	0.027	0	0.017	0	
SIN	0	0	0	0	0	0	0	0	0	0.009	0	0	0	0	0	0.028	0.008	0	0	0	0	0	0	0	0.025	0	0.005	0.027	0	0	0	0	0.001	0	0.012	0.029	0.009	0	0	0.02	0.009	0.026	0	0	0.035	0.018	
BRA	0	0.02	0.01	0.01	0.019	0.009	0.009	0.014	0.011	0.011	0.01	0.009	0.015	0.017	0.01	0.01	0.015	0.008	0.004	0.007	0.016	0.012	0.006	0	0.005	0.007	0.004	0.011	0.011	0.009	0.015	0.009	0.005	0.02	0.01	0.005	0	0.018	0.008	0.008	0.008	0.008	0.017	0.015	0.009	0.012	
CHI	0	0	0	0	0	0	0	0	0.016	0	0.014	0	0	0	0	0	0	0	0	0	0	0	0.001	0	0	0.015	0	0.011	0	0	0	0	0	0	0.01	0	0.001	0.02	0	0.005	0	0.004	0	0	0.007	0.006	
COL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.009	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
MEX	0.015	0.019	0.018	0.017	0.016	0.018	0.016	0.014	0.019	0.024	0.019	0.015	0.022	0.02	0.018	0.042	0.016	0.013	0.033	0.018	0.018	0.019	0.103	0.022	0.044	0.035	0	0.047	0.019	0.018	0.021	0.017	0.017	0.018	0.023	0.078	0.029	0.017	0.021	0.042	0.034	0.082	0.022	0.027	0.047	0.034	
PER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.006	0	0	0	0	0	0	0	0	0.024	0.018	0	0	0	0	0	0	0	0	0.011	0	0	0	0	0.006	0.003	0.007	0	0	0.007	0	
CR	0.007	0.012	0.027	0.011	0.013	0.012	0.009	0.011	0.011	0.011	0.019	0.009	0.017	0.048	0.016	0.01	0.012	0.008	0.009	0.01	0.011	0.011	0.01	0.015	0.011	0	0.009	0.013	0	0.012	0.029	0.009	0.006	0.018	0.023	0.009	0.009	0.011	0.01	0.011	0.01	0.01	0	0.014	0.01	0.012	
EGY	0.012	0.011	0.024	0.02	0.011	0.025	0.024	0.011	0.015	0.012	0.033	0.018	0.018	0.029	0.038	0.011	0.011	0.017	0.014	0.012	0.011	0.011	0.011	0	0.012	0.012	0.011	0.011	0.019	0	0.028	0.012	0.018	0.015	0	0.011	0.013	0.012	0.011	0.013	0.011	0.011	0.011	0.012	0.01	0.013	
GRE	0	0	0.005	0.004	0	0.003	0.003	0	0.005	0	0.001	0.004	0.004	0.006	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.003	0	0	0	0	0	0	0	0	0	0	0	0	0	
HUN	0	0	0.022	0	0	0.025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0	0	0	0	0	0	0	
POL	0.029	0.016	0.033	0.036	0.017	0.029	0.032	0.017	0.025	0.018	0.019	0.039	0	0.019	0.017	0.028	0.018	0.044	0.047	0.025	0.02	0.024	0.031	0	0	0	0.019	0.025	0.015	0.015	0.017	0.02	0	0	0.03	0.024	0.021	0.017	0.019	0	0.025	0	0.017	0	0.028	0.017	
QAT	0.009	0.017	0	0	0.019	0	0	0.016	0	0.019	0	0	0.017	0	0.007	0.017	0.017	0.008	0.009	0.012	0.013	0	0.012	0.005	0	0	0.011	0	0	0	0	0.007	0	0	0	0.012	0	0	0	0.017	0.014	0.015	0	0.036	0.018	0.032	
RUS	0.001	0	0	0	0	0	0	0	0	0.012	0	0	0	0	0	0.011	0	0.006	0.008	0.01	0	0.011	0.011	0.023	0.018	0.017	0.006	0.027	0.008	0	0	0	0	0	0	0.01	0.011	0	0.011	0.012	0.011	0.012	0	0	0.013	0	
SA	0	0.022	0.02	0.019	0.017	0.019	0.017	0.012	0.021	0.02	0.021	0.016	0.024	0.021	0.02	0.038	0.017	0.009	0.014	0.01	0.02	0.02	0.103	0.022	0.046	0.033	0.018	0.046	0.02	0.019	0.023	0.018	0.012	0.02	0.022	0	0.022	0.02	0.019	0.043	0.025	0.063	0.024	0.027	0.058	0.035	
TUR	0.022	0.02	0.021	0.019	0.019	0.019	0.018	0.016	0.02	0.017	0.02	0.018	0.021	0.023	0.02	0.022	0.017	0.018	0.031	0.017	0.019	0.019	0.039	0.029	0.043	0.046	0.026	0.053	0.023	0.019	0.022	0.019	0.02	0.021	0.032	0.03	0	0.024	0.018	0.023	0.022	0.028	0.022	0.02	0.025	0.021	
UAE	0	0	0	0.013	0.022	0.009	0.009	0.025	0.018	0	0	0.014	0	0	0	0	0.021	0	0	0	0.023	0.025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.025	0	0	0	
IND	0.012	0.023	0.015	0.017	0.023	0.016	0.015	0.02	0.018	0.026	0.016	0.015	0.019	0.016	0.015	0.025	0.02	0.014	0.015	0.027	0.023	0.023	0	0.015	0	0.015	0	0.017	0.015	0.014	0.016	0.014	0.014	0	0.014	0.019	0.013	0.016	0	0	0.026	0	0.025	0	0.045	0	
INDO	0.002	0	0	0	0	0	0	0	0	0.005	0	0	0.011	0	0	0.01	0	0	0.005	0	0	0	0.007	0	0.018	0.008	0.003	0.011	0	0	0	0	0	0	0	0.01	0.006	0	0	0	0.008	0.009	0	0	0.015	0.007	
KOR	0.004	0.027	0.016	0.017	0.022	0.015	0.014	0.02	0.021	0.029	0.017	0.014	0.023	0.017	0.016	0.076	0.026	0.012	0.014	0.007	0.026	0.029	0.042	0.016	0.026	0.018	0.019	0.025	0.016	0.015	0.02	0.014	0.011	0.018	0.015	0.041	0.014	0.016	0.017	0.03	0	0.028	0.028	0.03	0.089	0.032	
MAL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.008	0	0	0.005	0	0	0	0.005	0	0	0.015	0	0	0	0	0	0	0	0	0	0.006	0.01	0	0	0.011	0	0	0	0	0	0.005	
PAK	0	0.037	0	0	0.014	0	0	0.002	0	0.004	0	0	0	0	0	0.005	0.008	0	0	0	0.012	0.012	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001	0	0.003	0	0	0	0.004	0	
PHI	0.001	0	0	0	0	0	0	0	0	0	0	0	0.01	0	0.007	0.003	0	0.002	0.002	0	0	0	0.003	0	0	0	0.002	0	0	0	0	0	0	0	0	0.003	0.003	0	0	0	0.001	0.005	0	0	0	0.01	
TW	0	0.016	0.009	0.008	0.011	0.008	0.006	0.002	0.011	0.002	0.012	0.003	0.017	0	0.01	0.018	0.007	0	0	0	0.009	0.012	0	0.01	0.015	0.01	0	0.011	0.011	0.009	0	0.006	0	0.01	0.007	0	0.006	0.007	0.003	0.017	0	0	0.019	0.021	0	0.023	
THA	0.002	0	0	0	0	0	0	0	0	0	0	0	0.012	0	0	0.006	0	0.003	0.003	0.002	0	0	0.005	0	0.008	0	0.003	0.006	0	0	0	0	0	0	0	0.005	0.004	0	0	0.018	0.005	0.01	0	0.033	0.008	0	
From																																															

Note: The numerical values in the matrix represent the magnitudes of the statistically significant error correction coefficients (in absolute terms) at an FDR significance level of $\alpha = 0.05$ for the stock market pairs.

We define the nodes listed in the first column as source nodes, and those listed in the first row as destination nodes.

"From" refers to the outgoing linkages from source nodes to the corresponding destination nodes; "To" refers to the reverse direction.

B Degree and strength distributions of three international stock market networks at FDR significance levels of $\alpha = 0.01$ and $\alpha = 0.05$

We also briefly characterize the topological structures of global stock market networks during various periods by using the statistical properties of degree and strength distributions at FDR significance levels of $\alpha = 0.01$ and $\alpha = 0.05$, respectively. Figures B.1 and B.2 clearly show that, compared to the degree and strength distributions at the FDR significance level of $\alpha = 0.05$, those for $\alpha = 0.01$ exhibit longer tails, especially during the crisis periods relative to the entire period of 2007–2017. This result indicates that there is a higher probability of many stock markets having a small degree and strength, but a few stock markets tend to exhibit a very large degree and strength. Besides this, the heavy tails reflect evidence that, if a key stock market (e.g., the US or another developed stock market) is subject to financial stress, the negative effects are more likely to spread through the network. In contrast, as shown in Figure B.2, at an FDR significance level of $\alpha = 0.05$, the degree and strength distributions exhibit a strong rightward shift and are distributed very similarly to Poisson distributions. This not only shows the homogeneous behaviours across the global stock markets but also further verifies the structural characteristics of the networks shown in Figures A.2 and A.3 of random graphs at an FDR significance level of $\alpha = 0.05$. Note also that the degree and strength distributions only capture the basic structural characteristics of the derived networks.

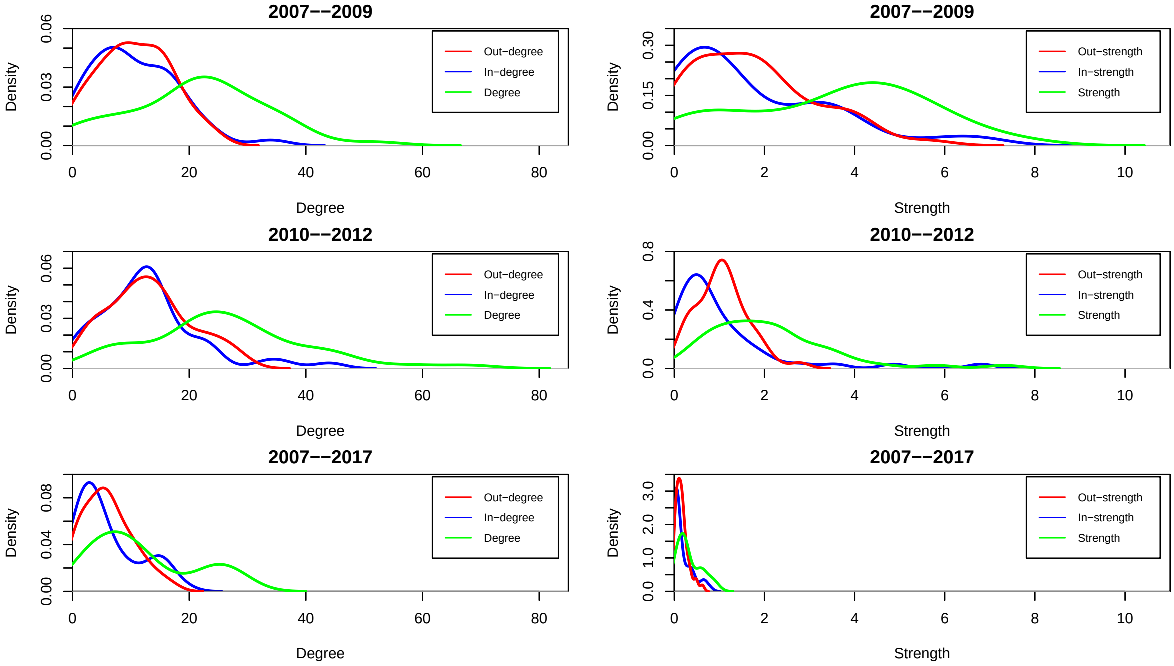


Figure B.1. The degree and strength distributions of the international stock market networks at an FDR significance level of $\alpha = 0.01$ over the 2007–2009, 20102012, and 2007–2017 periods. The figure reflects the probability density of a randomly chosen node in the network having degree k or strength s.

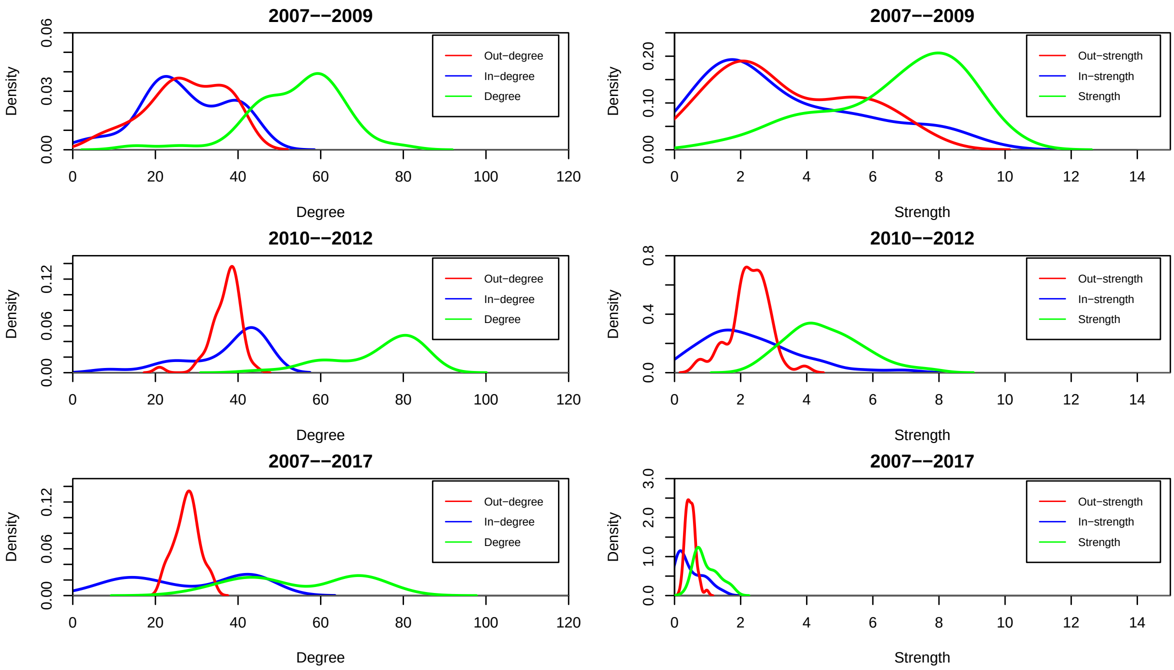


Figure B.2. The degree and strength distributions of the international stock market networks at an FDR significance level of $\alpha = 0.05$ over the 2007–2009, 20102012, and 2007–2017 periods. The figure reflects the probability density of a randomly chosen node in the network having degree k or strength s.