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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 directional interconnectedness of the short-run disequilibrium adjustment towards long-run equilibrium affecting the international stock market 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 2007–2009 Global Financial Crisis, 2010–2012 European Sovereign Debt Crisis, and the entire period of 2007–2017. The main results indicate that changes in directional interconnectedness within stock markets worldwide did occur under the impact of the recent financial crises. The extent of the short-run disequilibrium adjustment towards long-run equilibrium for individual stock markets is not homogeneous over different time scales. 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 mitigating 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 directional interconnectedness within the world's developed and emerging stock markets alters during periods of crisis. 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 equilibrium adjustment towards long-run equilibrium that affects the global stock markets over time. We expect that the proposed analytical framework, and thus our better understanding of the interconnectedness, may play a more 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, over the last two decades, correlation-based measures have been broadly utilized to characterize financial markets as complex networks ever since the seminal work of Mantegna (1999).[1] Within this setting, 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. 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.,

[1] See, for instance, 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) among many others.

2012; Diebold and Yilmaz, 2014, 2015; Anufriev and Panchenko, 2015; Wang et al., 2017; Stavroglou et al., 2017; Geraci and Gnabo, 2018; Hamill et al., 2019). Yet, it should be noted that calculating price returns as first-differences form of log prices can produce a stationary process, while, by using only return data, the long-run information might be lost. In this regard, a solid framework can be utilized for modelling the long-run interdependency across non-stationary variables in financial markets, that is, the cointegration.

Engle and Granger (1987) and Granger et al. (2000) claim that cointegration stipulates the long-run equilibrium relationship, or equivalently the existence of a common stochastic trend, between two or more 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., Kasa, 1992; Arshanapalli and Doukas, 1993; Alexander, 1999; Masih and Masih, 2001; Alexander, 2001; Chen et al., 2002; Yu et al., 2010; Narayan et al., 2011).

In the current paper, we attempt to utilize the error correction model (ECM) (Engle and Granger, 1987) as it captures such a self-regulating disequilibrium mechanism that could automatically calibrate the short-run departures from long-run equilibrium across the non-stationary financial variables. Nevertheless, as mentioned above, in the context of the complex system of financial markets, by using the econometric techniques of cointegration (or the ECM model only) it is relatively hard to provide a comprehensive picture of long-run interdependency structures and short-run disequilibrium correction dynamics, across non-stationary financial variables over time. 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 degree of long-run interconnectedness and the extent of short-run disequilibrium adjustments towards long-run equilibrium 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 latest 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). 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 stock markets across the world.

Our main contribution is developing a network-based analytical framework to identify and monitor the changes in the directional interconnectedness structure, concerning the short-run equilibrium adjustment towards long-run equilibrium that affects global stock markets over time. Our data sample ranges from January 2007 to June 2017, which covers the rising number of financial crises, e.g., the August 2007–June 2009 Global Financial Crisis (GFC) and the January 2010–December 2012 European Sovereign Debt Crisis (ESDC), that have occurred in recent times around the globe. Thus, it enables us to investigate how the recent financial crises have affected the patterns of pairwise directional network interconnectedness across the world's stock markets from a more systematic perspective. 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

[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.

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 interconnected markets. By contrast, the high degree of segmentation across stock markets provides supportive evidence of the existence of possible benefits from an international portfolio diversification.

The key findings can be summarized as follows. First, the overall results show that changes in directional interconnectedness within global stock markets indeed occurred over the recent periods of financial crisis. Our sub-period network analysis confirms that the extent of short-run disequilibrium adjustment towards long-run equilibrium shows quite dramatic differences across individual stock markets during the 2007–2009 GFC, 2010–2012 ESDC and the longer horizon period of 2007–2017. To be specific, over the period of the GFC, stock markets in the world's advanced economies and particularly most of the European ones, tended to be densely interconnected as a component in the network associated with faster adjustments of short-run disequilibrium towards the long-run equilibrium, relative to the ESDC and 2007–2017 period. Particularly, the level of directional interconnectedness within the stock markets of the US, Italy, Finland, the UK, Germany, France, Ireland, Switzerland and Belgium rose markedly, associated with the highest short-run disequilibrium corrections back to long-run equilibrium. 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. In contrast, most emerging stock markets, especially from the Asia-Pacific and MENA[3], were likely to be more globally segmented during the GFC, which provides evidence in support of international diversification opportunities (e.g. Christoffersen et al., 2012; Ghysels et al., 2016). However, the reverse results are found within the emerging stock markets from Latin America over the period of the GFC.

Remarkably, our results also demonstrate that the interconnectedness patterns in

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

European stock markets during the two financial crises are divergent. In particular, most 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. 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 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. Our results further show that European stock markets are clustered into different sub-groups, i.e., "PIIGS"[4] stock markets and most EMU[5] stock markets (e.g., Austria, Netherlands, Belgium, Finland, Ireland, France, Poland, the UK and the Czech Republic), which decreases the rewards from diversification. 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 US stock market, see when comparing the results during the GFC, ESDC and 2007–2017 period. Initially, 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, it becomes relatively segmented from most stock markets in the Eurozone during the onset of the ESDC, and has become more globally segmented from most world's other stock markets between 2007 and 2017 compared to the periods of the GFC and the ESDC. Therefore, over the longer horizon of 2007–2017, the US stock

[4]This refers to Portugal, Italy, Ireland, Greece, and Spain.

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

market can be regarded as a safer haven than the world's other stock markets, especially those in Europe.

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

2 Data and Descriptive Statistics

2.1 Data Description

Our empirical data consist of weekly[6] closing prices 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:

(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 nominated in US dollars to mitigate the impacts of local inflation and national currency fluctuation on each stock market index (Bekaert and Harvey, 1995). 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, they must be rescaled so as to be comparable. The first step is to calculate the percentage change in each stock market

[6]Therefore, the adverse effects of belonging to different time zones and having different operating days are minimized.

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 series to be $R_i(1) = 1$, 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.[7]

2.2 Descriptive Statistics

In order 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 2007–2009 GFC, 2010–2012 ESDC, and the whole sample period of 2007–2017 in Tables 2–4, respectively.

As Table 2 shows, each individual stock market posted a negative mean return associated with high volatility level during the 2007–2009 GFC, as expected. In particular, among the developed stock markets, Ireland presented the minimum value of −1.151%. In contrast, Norway (−0.020%) followed by Israel (−0.165%), Hong Kong (−0.184%), and Japan (−0.329%), experienced relatively smaller losses than the other developed markets. Concerning the emerging stock markets, only Qatar was largely insulated from the 2007–2009 GFC, with a positive average return of 0.048%. Pakistan (−0.961%), followed by Poland (−0.871%), Greece (−0.792%), and Hungary (−0.693%), appear to have been seriously negatively affected by the GFC. By contrast, Brazil (−0.057%), Chile (−0.079%), and India (−0.189%) exhibit relatively smaller average returns. Note that,

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

the skewness coefficients are negative for all stock markets except Norway, Russia, and South Africa. The kurtosis coefficients are greater than three for all stock markets (with the exception of Taiwan), suggesting that they are skewed and leptokurtic during the GFC period. Furthermore, the Jarque-Bera normality test rejects the normality hypothesis for all the stock market indices, excluding Australia, India, Malaysia, and Taiwan, at the 1% significance level.

With respect to the 2010–2012 ESDC, Table 3 confirms there were substantial differences relative to the period of the GFC. As expected, all Eurozone stock markets clearly appear to have negative average returns during the onset of the ESDC. Among the developed stock markets, most saw positive returns, with highest mean value coming from Denmark (0.194%), followed by Sweden (0.155%), and the US (0.147%), and the lowest from Portugal (−0.310%), Spain (−0.299%), and Italy (−0.281%). It is interesting to see that, most emerging stock markets, the exceptions being Brazil (0.178%), the Czech Republic (0.067%), Egypt (0.168%), Greece (0.623%), Hungary (0.200%), the United Arab Emirates (0.035%), and India (0.035%), exhibit higher positive average returns than the developed stock markets. The negative skewness (with the exception of Peru, Poland and India) and high kurtosis values (more than three) indicate that all stock market indices (with the exception of India) are skewed to the left and leptokurtic. Besides this, based on the Jarque-Bera normality test results, we reject the assumption of normality at the 1% significance level for all stock markets excluding the US, Norway, Spain, the United Arab Emirates, India, and Thailand.

Turning now to the entire period of 2007–2017, Table 4 shows that the developed stock markets of Denmark (0.123%), the US (0.099%), and Germany (0.091%) posted the highest positive average returns, while the lowest are found in Portugal (-0.167%), Italy (-0.152%), and Norway (-0.133%), but the differences between the highest and lowest are less dramatic. Among the emerging markets, the highest mean return is exhibited by the stock market of Pakistan (0.180%), followed by those of Thailand (0.179%), Qatar (0.173%), and Philippines (0.170%), while the stock market of Greece (-0.337%) exhibits the lowest average return. As expected, the emerging markets seem to exhibit higher volatilities, which is affirmed by larger standard deviation values, except in the case of Malaysia (0.024). In particular, Greece (0.053), Egypt (0.053), and Brazil (0.053) both have the highest volatilities among all the stock markets included in this study. In regard to developed markets, the smallest volatility is shown by the stock market of Norway (0.020), followed by the US (0.026), Japan (0.027), Switzerland (0.028), and New Zealand (0.029), respectively. Conversely, the highest volatilities can be seen in the cases of Austria (0.043), Italy (0.042), and Spain (0.041), indicating that investment in these developed markets may be riskier than in the other ones. Moreover, all the 46 stock markets, with negative skewness coefficients and high kurtosis values (greater than three), which indicates that the probability distributions of them are skewed and leptokurtic. Meanwhile, according to the Jarque-Bera values, the null hypothesis of normality can be rejected as its p-value is less than 0.001 for all stock markets.

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

3 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.

3.1 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

$I(1)$[8] 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.[9] We assume that the two non-stationary $I(1)$ series $\{X_t, t = 1, ..., n\}$ and $\{Y_t, t = 1, ..., n\}$ are respectively the log-levels of stock market indices (after being rescaled), 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

[8] The variables are non-stationary at the log-level, while stationary at the first-difference through the unit root test.

[9] 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.

model[10] can be presented by

$$\Delta Y_t = \alpha_0 + \delta ECT_{t-1} + \sum_{i=1}^{\tilde{p}} \theta_i \Delta Y_{t-i} + \sum_{i=1}^{\tilde{q}} \gamma_i \Delta X_{t-i} + \eta_t, \tag{5}$$

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 index Y_t (i.e. ΔY_t) is a function of the lagged equilibrium error term δECT_{t-1} (i.e., $\hat{\varepsilon}_{t-1}$, the degree to which two stock indices Y_t and X_t are outside of their equilibrium in the previous time period $t-1$), the lagged changes in Y_t (i.e., $\sum_{i=1}^{\tilde{p}} \theta_i \Delta Y_{t-i}$), X_t (i.e., $\sum_{i=1}^{\tilde{q}} \gamma_i \Delta X_{t-i}$), the drift α_0, and the white noise series η_t. The statistical significance of the negative term δECT_{t-1} demonstrates that the stock indices X_t and Y_t also have a long-run equilibrium relationship in the previous period $t-1$, where the increase (or decrease) in stock index X_t causing them to diverge from their equilibrium state. As a result, stock index Y_t will tend to change and correct the disequilibrium so as to converge to the equilibrium state with X_t. However, the change in stock index Y_t may not happen instantaneously in the short term, rather occurring over future time periods at a speed dictated by the negative adjustment parameter δ, through the t-test (Keele and De Boef, 2004). Therefore, if the error correction term carries a statistically significant and negative coefficient δ, this will provide further evidence of the long-run cointegration between the two stock market indices. With regard to the terms $\sum_{i=1}^{\tilde{p}} \theta_i \Delta Y_{t-i}$ and $\sum_{i=1}^{\tilde{q}} \gamma_i \Delta X_{t-i}$, for example, if we assume the coefficient of γ_i in the latter term is statistically significant through F-tests, once the stock index X_t sees change in the period $t-1$, then the stock index Y_t will response immediately to the lagged change in X_t (i.e., measured by $\sum_i^q \gamma_i \Delta X_{t-i}$). This is consistent with the standard Granger causality test (Granger, 1988). 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 index X_t experiences changes to correct the disequilibrium and converge to the

[10] The error correction term has to be included with lag 1 (i.e., p=1) since the deviation from the long-run equilibrium in the period $t-1$ starts the adjustment process in period t.

long-run equilibrium with Y_t.

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

3.2 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 mitigating 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.[11]

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.

3.3 Interconnectedness Network Construction

As mentioned earlier, in the ECM setting, 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), we construct an $N \times N$ asymmetric adjacent matrix $A = [w_{ij}]$ to represent the ECM-based network of the N stock market indices. Notice that it is a directional measure considering that, if a stock market i adjusts the short-run disequilibrium towards a long-run equilibrium relationship with stock market j associated with corresponding magnitude w_{ij} (the corresponding δ), then a directed edge would be drawn from i to j, and vice versa. Meanwhile, $w_{ij} = 0$ indicates the absence of a statistically significant and reverse short-run disequilibrium correction from i towards j to restore the long-run equilibrium, and therefore no directed linkage. In this directed and weighted network, long-run equilibrium relationships and directions of short-run disequilibrium adjustments between stock market pairs can be intuitively

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

explored.[12]

4 Network Analysis of International Stock Markets

As explained in Section 3.1, prior to the cointegration test, the ADF and PP unit root tests were conducted on the 46 stock market indices to estimate the order of integration. Tables 5–7 summarize the outcomes of the ADF and PP tests on each individual stock market index for the two sub-sample periods 2007–2009 and 2010–2012, as well as the full-sample period 2007–2017, respectively. The derived results indicate that all the stock market indices are non-stationary (i.e., have stochastic trends) in log-form, while their first-differences are stationary, thus indicating that each stock index follows an $I(1)$ process. Given the fact that the stock market indices are not stationary and are integrated with 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. The detailed results of the stationarity tests for the estimated residuals from the cointegration equations are not presented here but are available upon request. Once the variables included are found to be cointegrated, we proceed to conduct the ECM model for all pairs of cointegrated stock market indices.

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

We then characterize the directed and weighted networks of the 46 stock markets based on the statistically significant and negative results for the error correction terms in

[12]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.

the ECM models, where the detailed results are displayed as the corresponding adjacent asymmetric matrices in Tables 8–10. Figures 1–3 visualize the international networks of stock markets directional interconnectedness over the three time periods, 2007–2009 GFC, 2010–2012 ESDC, and 2007–2017, respectively. The nodes which present the 46 stock markets worldwide 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 magnitude of the short-run error adjustment coefficient (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, 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 stock markets that share similar characteristics in terms of their short-run disequilibrium adjustment towards the 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.

4.1 The 2007-2009 GFC Period

As is shown in Figure 1, several interesting observations emerge during the GFC. 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). This highly interconnected component of the network highlights the presence of faster short-run disequilibrium adjustments toward long-run equilibrium and co-movements amongst these world's advanced economies and most of the European ones during the GFC. In fact, in line with the observations made by Lehkonen (2015) and Bekaert et al. (2014), 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 most 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. Another important finding observed in Figure 1 is that the US stock market and several developed European stock markets, including Italy, Finland, the UK, Germany, France, Ireland, Switzerland and Belgium, tend to be more directionally interconnected and appear as a hairball within this component. Their greater exposure to the US stock market is accompanied by the fastest 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, the Middle-East, and Africa, during the time of the GFC. As Figure 1 illustrated, the directional interconnectedness of these emerging stock markets with other stock markets across the globe is loosely visible compared with that between the advanced stock markets and most of the European ones. It is evident that several emerging Asia-Pacific stock markets, namely the Philippines, India, Malaysia, and Indonesia, appear to be separated from the central component of the network.

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 lower globally interconnectivity 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. 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., Bekaert et al., 2014). At the same time, Figure 1 also suggests that emerging markets in the Middle-East and North Africa (i.e., 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. 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, good economic fundamentals, appropriate policy responses, and sizeable currency reserves helped them to relatively mitigate the impact of the GFC (Bekaert et al., 2014).

As is shown in Figure 1, the remaining emerging stock markets in the region of Asia-Pacific, namely South Korea, Taiwan, Thailand, and Pakistan, are mostly grouped closer to the central component of the network. 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. The results concur with the stylized fact that these relatively higher exposure 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 world market. Note also that, among the emerging Latin America stock markets, we find that Chile, Peru, Columbia, Brazil, and Mexico appear to be tightly interconnected with the central component of the network. As displayed in Figure 1, 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 America stock markets was more significant than that on emerging stock markets in Asia-Pacific and MENA. 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 America and US stock markets more closely than those from Asia-Pacific and MENA. It is also noteworthy that the adverse impact of the US-originated GFC was not the same across all emerging Latin America stock markets. As it is shown, Mexico, Columbia, and Peru, with their low levels of export diversification, were particularly affected and exhibit more directional interconnectedness with the world's other stock markets during the GFC.

[Figure 1 about here.]

4.2 The 2010–2012 ESDC Period

We next consider the time 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 2, captures some interesting signs. It appears that the directional interconnectedness within the European stock markets is substantially different from how it was during the GFC period. The most visible difference is that most European stock markets form distinct structural components within the network, which are characterized by highly directional interconnectedness inside and are significantly linked externally.

To be specific, the first structural component contains ten stock markets from the Eurozone countries (i.e., Spain, Greece, Italy, Portugal, Finland, Belgium, France, Austria, and Netherlands) and four non-Eurozone stock markets of Norway, Poland, the Czech Republic, and Hungary. This tightly intensified and interconnected group highlights the presence of faster adjustments of the short-run disequilibrium toward long-run equilibrium within most of the Eurozone stock markets. The evidence supports the view that the risk of the ESDC mainly concentrated in the Eurozone countries. As the greater synchronization of monetary and fiscal policies, closer trade links, and financial integration within the Eurozone area, it is more likely for those economies to be exposed to common shocks, which led the Eurozone stock markets to be the most responsive and to be the most severely hit by the shocks that occurred during the ESDC. Another interesting finding in Figure 2 is that the emerging stock markets of India, the United Arab Emirates, Turkey, Egypt, and Brazil are particularly close to most of the Eurozone stock markets, with high degree of interconnectedness accompanied by sizeable short-run disequilibrium correction coefficients. In particular, the stock market in India is seen to be closely grouped within this component of the network.

Figure 2 also shows that Germany and most of the non-Eurozone economies (i.e., the UK, Denmark, Switzerland, and Sweden) are grouped together with high level of interconnectedness, and are externally interconnected to the stock market of Israel and a set of Asia-Pacific stock markets (i.e., Australian, Japan, Hong Kong, and Korean). 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 MENA were relatively segmented globally. While they are less segmented and 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 during the period 2010–2012, resulted in greater co-movements between the emerging and the rest of world's stock markets.

It should also be noted that, in Figure 2, the US stock market appears to be segmented from the group of the Eurozone stock markets in the network. Our finding supports the fact that the US stock market has experienced a strong recovery path compared with other markets in the aftermath of the GFC, especially compared to the Eurozone stock markets whose performance lagged behind that of the US during the onset of the ESDC. Besides this, different monetary policy responses might be another reason for the reduction in co-movements between the US and most Eurozone stock markets. For instance, the very prompt adoption the policy of the quantitative easing (QE) by the US Federal Reserve over the 2010–2012 period, in contrast to fiscal tightening and very limited monetary easing in the Eurozone, have led to divergent growth experiences in the two regions (Caporale et al., 2016; Chen et al., 2018).

[Figure 2 about here.]

4.3 The Full-sample Period of 2007–2017

Finally, we repeat the analysis for the entire sample period, from January 2007 to June 2017. At first glance, the directed and weighted network in Figure 3 differs markedly from those of the GFC and ESDC sub-periods. 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, inconsistent with the results at the times of the GFC and ESDC, 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 during this period. It can be interpreted as evidence that, over the period of 2007–2017, 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. According to Froot and Ramadorai (2008) and Bekaert et al. (2011), capital flows from advanced countries were a potential determinant of the greater synchronization of stock markets in emerging economies. Like during the 2007–2009 GFC and 2010–2012 ESDC sub-periods, the prominent Asia-Pacific stock markets of Hong Kong, Australia, New Zealand, and Korea, as expected, appear to be strongly internally interconnected and significantly interconnected to other Asia-Pacific stock markets and the rest of the world's advanced markets over the 2007–2017 period.

[Figure 3 about here.]

As displayed in Figure 3, 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 "PIIGS" 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 towards long-run equilibrium. 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 US stock market has been decoupled from most of the rest of the world's stock markets, with the exception of Japan, Germany, Denmark, and Pakistan. In Figure 3, it is apparent that there are lower degree of directional interconnectedness between the US stock market and the world's other stock markets, relative to the 2007–2009 GFC and 2010–2012 ESDC periods. 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. In other words, our finding characterizes the US stock market as being the one that is the most decoupled from most other markets worldwide between 2007 and 2017. The observed segmentation of the US stock market 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.

4.4 Potential Implications for Policy-makers and Investors

The entropy of each complex economical system ineluctably can lead the policy-makers and investors in general to the breakdown of any empirical observation of any generality. Clearly this is an important challenge, even more if someone considers that the turbulence of the past few decades could be a very powerful data point in his favour about the underrated power of understanding the hidden structure of international stock markets, an observation that undoubtedly have made by others (Stavroglou et al., 2019).

Our results clearly reflect changes in the pairwise directional interconnectedness within the world's stock markets, in particular during the recent financial crises. It seems that the extent of the short-run disequilibrium adjustment towards long-run equilibrium for individual stock markets is heterogeneous during the 2007–2009 GFC, 2010–2012 ESDC and the entire period of 2007–2017. Our network analysis is meaningful since the visualization of directional interconnectedness among stock markets around the globe highlights which specific stock markets form interconnected groups or components, when exhibiting similar behaviours in their short-run disequilibrium adjustment towards long-run equilibrium. More specifically, the presence of network clusters composed of large numbers of highly interconnected stock markets provides supportive evidence of the potential limitation of diversification within these co-moving stock markets. By contrast, the high degree of segmentation of stock markets allows for possible gains from international portfolio diversification.

Consistent with the observations made by Christoffersen et al. (2012) and 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., Italy, Finland, the UK, Germany, France, Ireland, Switzerland, Belgium, etc.) further provides supportive evidence of the extremely small diversification opportunities when investing in these markets. In striking contrast, emerging stock markets in Asia-Pacific and 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.

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. At the same time, the benefits of international diversification are decreasing for the US, the core European stock markets, and a set of emerging stock markets worldwide (i.e., Asia-Pacific, Latin-Americas, South Africa, and Qatar), as the degree of interconnectedness increased throughout the period of the ESDC.

Note also that, based on a 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 "PIIGS" stock markets, indicates the absence of potential diversification benefits. Conversely, the observed low level of long-run interconnectedness (1) among the US and the majority non-US developed and emerging stock markets; (2) between Norway, Russia, Sweden, Switzerland, Germany, Denmark, and the several local European stock markets; (3) between the "PIIGS" stock markets and most emerging stock markets, etc., thereby offer potential arbitrage from diversification for the entire sample period of 2007–2017.

Finally, most importantly, what our analysis implies for financial economists in particular is that the sub-periods analysis, which includes two major international shocks, the GFC and ESDC, of our findings is much different than we realise. Comparing with the whole 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.

5 Conclusions and Perspectives

In this paper, we investigate the short-run error 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. In particular, we conduct a comparative analysis of the 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 that changes in the pairwise directional interconnectedness within the world's stock markets did occur under the impact of the recent financial crises. We find substantial differences in the extent of short-run disequilibrium adjustment towards long-run equilibrium for individual stock markets, throughout the periods of the GFC, ESDC and the entire period of 2007–2017. 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 fixed periods, 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, 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.

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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 Stated (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	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 period August 2007 to June 2009.

	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 3
The descriptive statistics of the weekly returns of the global stock market indices over the period January 2010 to December 2012.

	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

Table 4
The descriptive statistics of the weekly returns of the global stock market indices over the period January 2007 to June 2017.

	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 5
The results of ADF and PP unit root tests on 46 stock market indices over the sub-period of 2007–2009.

	Log Level				**First 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 6
The results of ADF and PP unit root tests on 46 stock market indices over the sub-period of 2010–2012.

	Log Level				First 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%).

Table 7
The results of ADF and PP unit root tests on the 46 stock market indices over the full period 2007–2017.

	Log Level				First 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%).

Figures

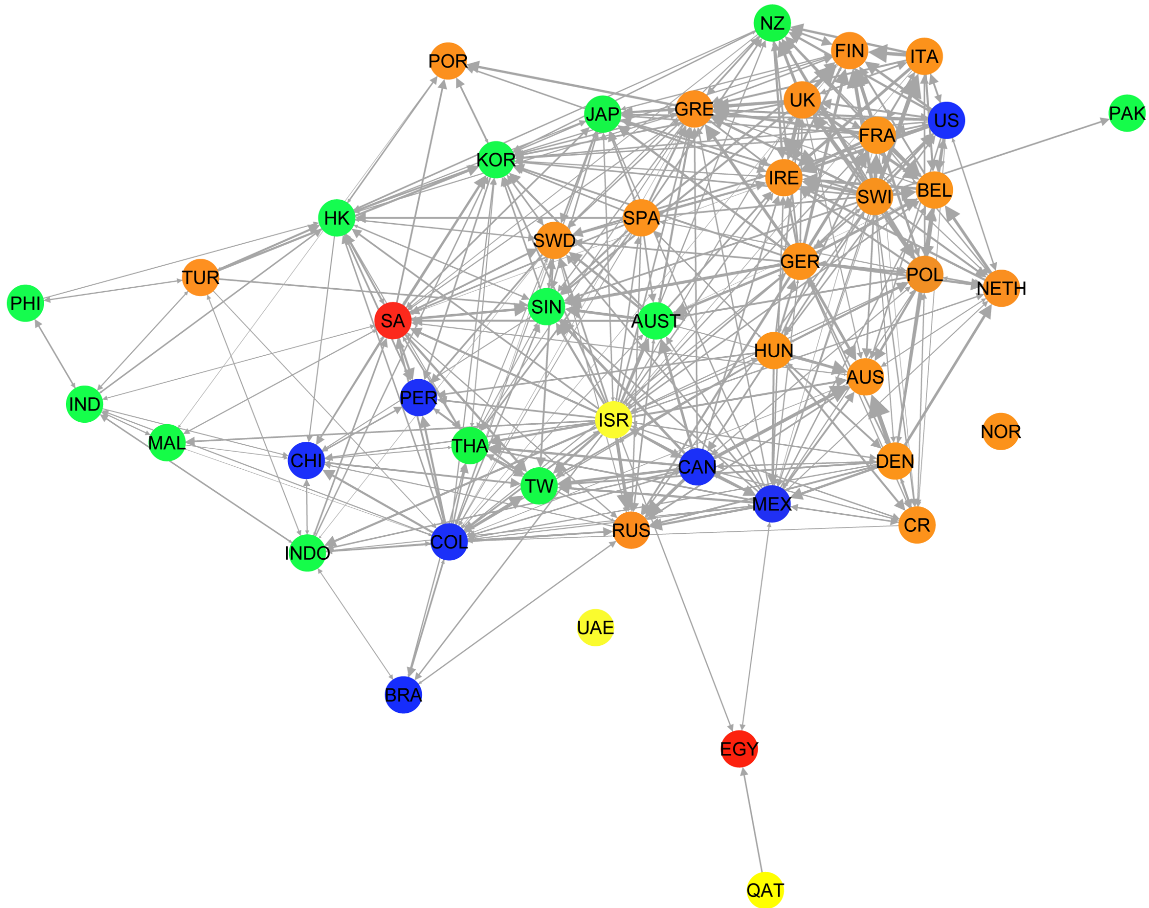

Figure 1. The international network of the 46 stock markets over the sub-period of 2007–2009. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker 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.

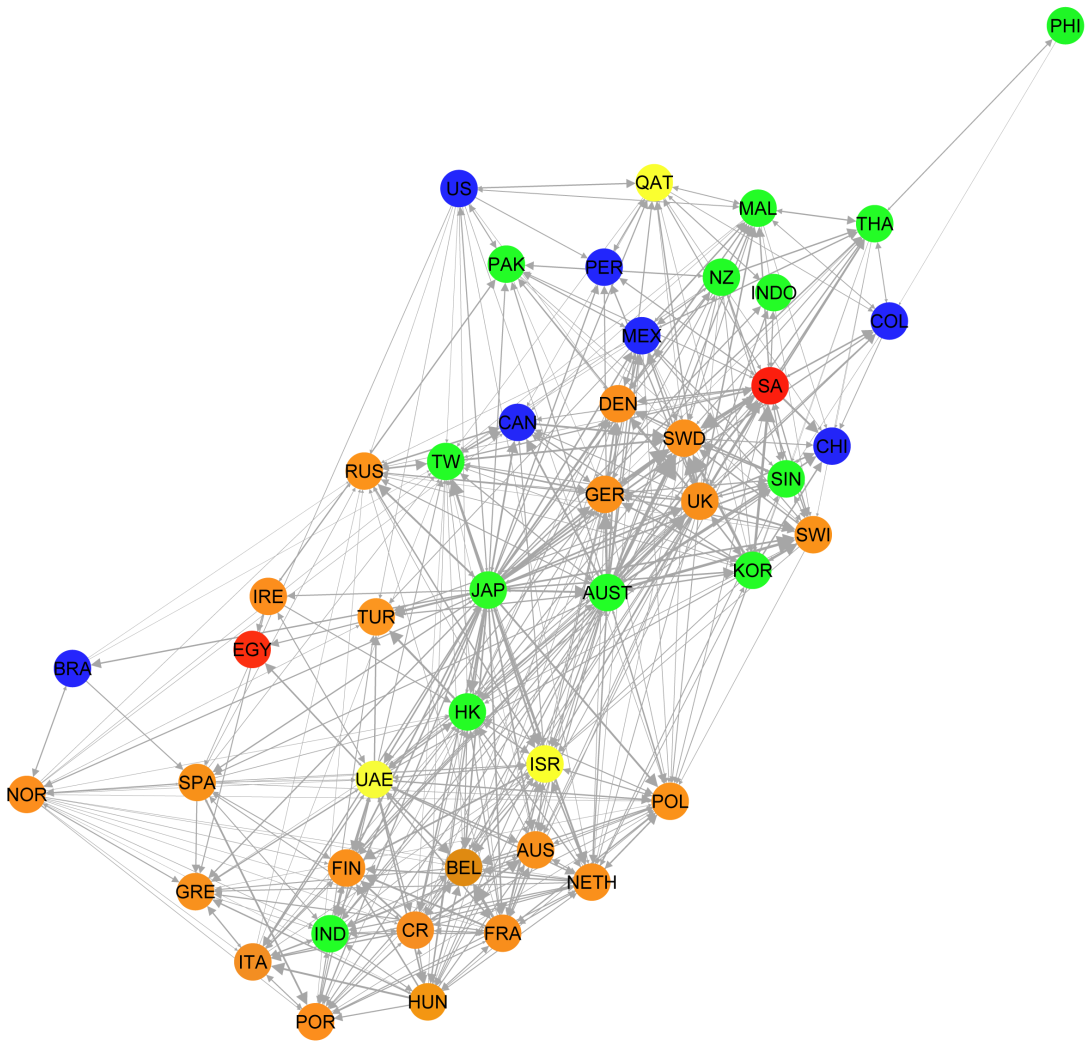

Figure 2. The international network of the 46 stock markets over the sub-period of 2010–2012. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker 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.

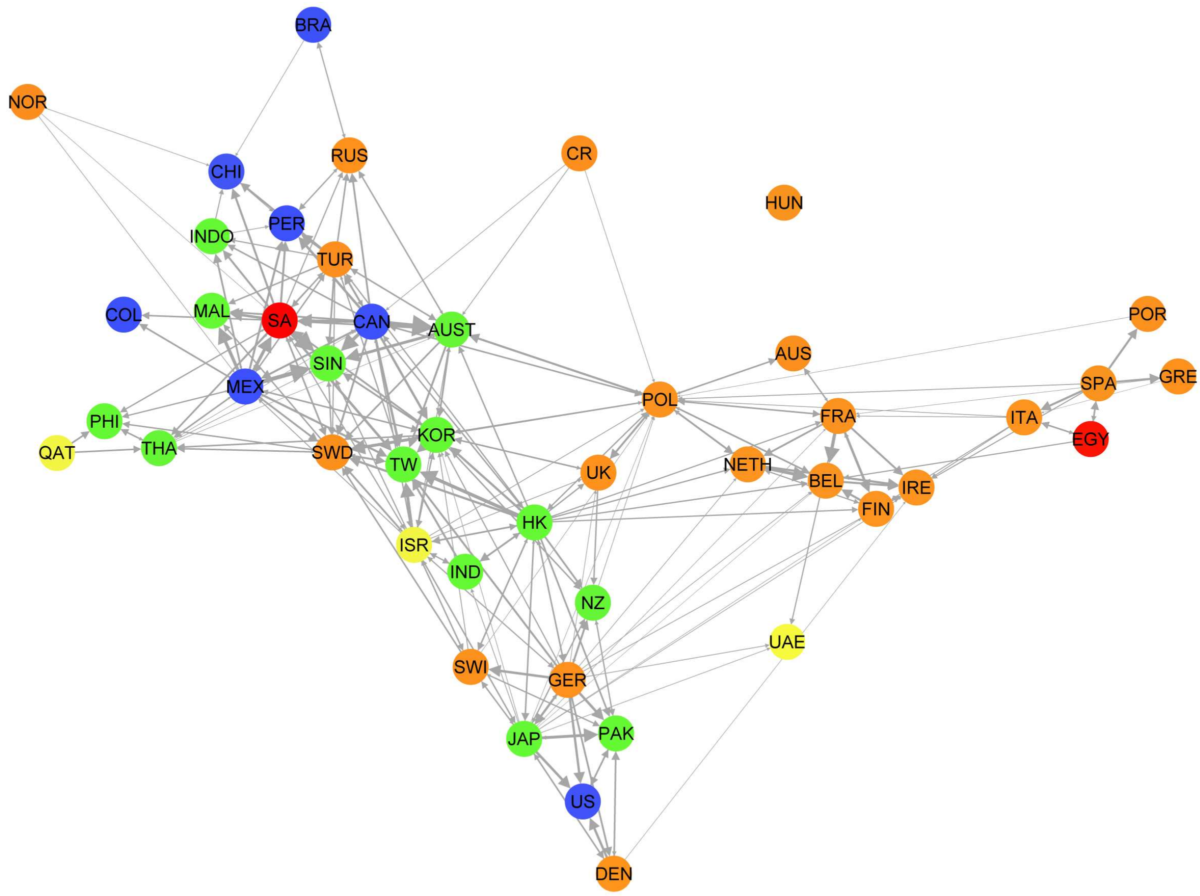

Figure 3. The international network of the 46 stock markets over the full period 2007–2017. The individual stock markets are colour-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. The thicker 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.

Table 8

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 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 9
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 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 10

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 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.