Physica A 490 (2018) 1555–1574

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Networks of volatility spillovers among stock markets

Eduard Baumöhl [a], Evžen Kočenda [b,c,d,e], Štefan Lyócsa [a,*], Tomáš Výrost [a]

[a] University of Economics in Bratislava, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia
[b] Charles University in Prague, Faculty of Social Sciences, Institute of Economic Studies, Opletalova 26, 110 01 Prague, Czech Republic
[c] Institute of Information Theory and Automation, Czech Academy of Sciences, Prague, Czech Republic
[d] CES Munich, Germany
[e] IOS Regensburg, Germany

HIGHLIGHTS

- We analyze volatility spillovers and its determinants among 40 stock markets.
- Networks of volatility spillovers are highly persistent.
- The significance of a temporal proximity effect is confirmed.
- Spatial dependence among markets is high.
- The most relevant determinants are market size, liquidity and economic openness.

ARTICLE INFO

Article history:
Received 28 November 2016
Received in revised form 29 May 2017
Available online 21 September 2017

JEL classification:
C31
C58
F01
G01
G15

Keywords:
Volatility spillovers
Stock markets
Shock transmission
Granger causality network
Spatial regression
Financial crisis

ABSTRACT

In our network analysis of 40 developed, emerging and frontier stock markets during the 2006–2014 period, we describe and model volatility spillovers during both the global financial crisis and tranquil periods. The resulting market interconnectedness is depicted by fitting a spatial model incorporating several exogenous characteristics. We document the presence of significant temporal proximity effects between markets and somewhat weaker temporal effects with regard to the US equity market — volatility spillovers decrease when markets are characterized by greater temporal proximity. Volatility spillovers also present a high degree of interconnectedness, which is measured by high spatial autocorrelation. This finding is confirmed by spatial regression models showing that indirect effects are much stronger than direct effects; i.e., market-related changes in 'neighboring' markets (within a network) affect volatility spillovers more than changes in the given market alone, suggesting that spatial effects simply cannot be ignored when modeling stock market relationships. Our results also link spillovers of escalating magnitude with increasing market size, market liquidity and economic openness.

1. Introduction: Motivation, related literature and contribution

Recent econophysics literature has analyzed the most important phenomena of the last decade: the global financial crisis (GFC) of 2008 and spillover effects on financial markets. Number of empirical analyses document severe effects of the GFC on world financial markets that materialized via far reaching contagions [1–4]. It was also documented that excessive

* Corresponding author.
E-mail address: stefan.lyocsa@euba.sk (Š. Lyócsa).

http://dx.doi.org/10.1016/j.physa.2017.08.123
0378-4371/

co-movements between stocks and stock market indices were associated with contagion [5,6]. The stock and commodity markets were in particular peril as they exhibit a long-range dependence [7]. However, the impact of the GFC was not limited only to stock markets of large economies as the Eurozone [8], the U.S. [3], or China [3,9] but it also spread to relatively smaller, yet important, economies in Asia [10–15], Africa [16] and Latin America [17].

Spillover effects, often associated with the GFC, have been recently analyzed in the econophysics literature predominantly from the type-of-the-market or type-of-the-asset perspective. Attention has been paid by the researchers to the equity and stock markets [17–21] as well as to commodity markets [22,23]. Additional evidence has been put forward for spillovers between spot and futures markets [24,25] or spot and derivative markets [26]. Among the assets, a special attention was received by crude oil [21,27] due to its general economic importance. Finally, it was shown that stock market linkages and their structure vary with crisis periods [6,28–30].

The two strands of the econophysics literature briefly reviewed above motivate our research. We aim to bring additional insights into the underlying phenomena behind the elusive dynamics of volatility spillovers on stock markets, namely crashes, distress and contagion that were all part of the GFC [7,31,32]. Crashes in financial markets are (by definition) unexpected and they represent a major concern for policy makers, investors, and the general public as market downturns or crashes are connected with crucial periods of high volatility [33]. The above motivation is firmly grounded in the fact that volatility has long ago become a standard measure of risk in finance. Hence, the issue of how the volatility spillovers propagate across stock markets over space and time has become central to investors (i) in managing their portfolio diversification strategies [34,35], (ii) in determining the cost of capital along with evaluating various asset allocation decisions [36] and (iii) to policy makers in fostering financial stability [37].

In our approach we differentiate from the spillover literature in that we focus on *volatility spillovers*. Our analysis is based on the network approach that has gained currency in the econophysics literature (see for example [1,6,12,14,16,19,30]). Specifically, we build on the approach of the bi-directional Granger causality networks between daily returns of developed stock markets around a world [19] where return spillovers were observed to be more probable when markets trade (in terms of trading hours) more closely to each other. Similarly, stronger return spillovers were identified also between markets which, in a given time zone, trade at similar trading hours [38]. Despite the above evidence of a temporal proximity effect between equity market *returns*, the temporal proximity links between *volatilities* on specific markets have not yet been sufficiently explored.

Volatility propagates across markets via spillovers that exert greater impact when markets are more connected [39,40]. Hence, we employ a network approach and analyze volatility spillovers across 40 stock markets over the 2006–2014 period. In our analysis we contribute to the econophysics literature in that we show how topology of stock market linkages change with respect to market distress associated with market volatility – we describe and model volatility spillovers during both the GFC and tranquil periods. We document the presence of significant temporal proximity effects between markets and somewhat weaker temporal effects with regard to the US equity market volatility spillovers decrease when markets are characterized by greater temporal proximity. Our results also link spillovers of escalating magnitude with increasing market size, market liquidity and economic openness.

The remainder of this paper is organized as follows. In Sections 2 and 3, we describe our data and methodology. In Section 4, we present and discuss our results. Section 5 briefly concludes and offers some implications.

2. Data description and return alignment procedure

Our sample covers the daily data on the key stock market indices from 40 markets across five continents from January 2, 2006, until December 31, 2014. According to the Dow Jones Classification System, 21 markets may be regarded as developed, 14 as emerging, and 5 as frontier. The list of countries is available in Table 1. Further we employ the following data: market capitalization of listed companies (% of GDP and in current US$), net trade in goods and services (% of GDP), turnover ratio (%), foreign direct investment — net inflows and net outflows (% of GDP); the data were obtained from the World Development Indicators database of the World Bank and definitions of variables correspond to the that of the source. Data on equity prices and exchange rates are collected from the Thomson Reuters Datastream. Detailed description of the data can be found in a working paper version of this manuscript, in Appendix A–C [41]. We chose our sample of markets based on the availability of the following data: (i) closing values, (ii) closing hours, and (iii) changes in closing hours. Our analysis of equity volatility spillovers is based on local currency, as we did not want to obscure the extent of market co-movements with forex market fluctuations [42].

Because we cover markets in different time zones, we carefully address the issue of non-synchronous trading to avoid distorted results. Especially with respect to performing the Granger causality test, caution must be exercised because information sets must be precisely aligned with respect to time. Our return alignment procedure follows [19], which we briefly summarize below:

(1) Closing prices for two stock markets are pairwise synchronized; i.e., when there is a missing observation (non-trading day) on one market, observations corresponding to this day on the other market are deleted.
(2) Consecutive returns are computed, which means that returns over non-trading days during the week are excluded.
(3) Returns are aligned to address the different closing hours on the respective national stock exchanges. By this step, we also take into account historical changes in trading hours (collected directly from the national stock exchanges), daylight saving time, and the type of closing auctions.

3. Applied methodology

3.1. Granger causality networks

First, we outline our approach to assess links between volatilities of market pairs. In testing for volatility spillovers, we formally set the '*causality in variance hypothesis*' in the following form that follows [43]:

$$H_0 : E\{(Y_{1t} - E[Y_{1t}|I_{t-1}])^2|I_{1t-1}\} = E\{(Y_{1t} - E[Y_{1t}|I_{t-1}])^2|I_{t-1}\}$$
$$H_1 : E\{(Y_{1t} - E[Y_{1t}|I_{t-1}])^2|I_{1t-1}\} \neq E\{(Y_{1t} - E[Y_{1t}|I_{t-1}])^2|I_{t-1}\}.$$

$I_t = (I_{1t}, I_{2t})$ is the information set, which consists of information subsets I_{it}, $i = 1, 2$ of a given time series Y_{it}, and t is the usual time index. The definition of the hypothesis above filters out causality in-mean (if it is present) using information set I_{t-1} in $E[Y_{1t}|I_{t-1}]$. Hence, the hypothesis compares the differences in conditional variance with respect to a common mean that is conditioned on full information. We say that time series Y_{2t} causes Y_{1t} in variance with respect to information set I_{t-1} if H_0 is rejected in favor of H_1. Evidence of causality in variance from series Y_{2t} to Y_{1t} is understood as evidence of volatility spillovers for a given time period.

We use Granger causality tests to create a network, which is graph $G_t = (V, E_t)$ at time t, where elements of the vertex set $V \subset \mathbb{N}$ correspond to individual markets. The elements of the set of edges $E_t \subset V \times V$ contains all edges (i, j) between markets $i, j \in V$, for which volatility spillovers were found using the appropriate Granger causality test and significance level; i.e., a directed edge from market i to market j is constructed if series Y_{it} Granger causes the variance in series Y_{jt}.

Some of the procedures are performed on the entire sample period, such as the filtration procedure. The tests are performed on rolling subsamples of 12 months: we begin with a subsample from January 2006 to December 2006 and end with a subsample from January 2014 to December 2014.

3.2. Filtration procedure

The causality in variance test aims to assess the significance of the cross-lagged correlation coefficient of squared standardized conditional returns from a suitable ARFIMAX-GARCH model [43]. As standardized residuals are defined as error terms divided by conditional volatility, in this manner, we remove the effects of spurious causality in variance that might be caused by the conditional heteroskedasticity of the underlying return series. In this section, we describe the filtration procedure used to derive the squared standardized conditional returns.

When modeling volatility spillovers between equity markets, our main quantity of interest is continuous returns, r_t:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t is the value of a corresponding equity market index at time t. First, each series of continuous returns r_t is filtered via an ARFIMAX-GARCH model. The mean equation is defined as:

$$\begin{aligned} & r_t = \alpha_0 + \alpha_1 FX_{t-1} + \alpha_2 STX_{t-1} + \alpha_3 GOLD_{t-1} + \alpha_4 OIL_{t-1} + \alpha_5 VIX_{t-1} + z_t \\ & \left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d z_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_t \end{aligned} \tag{2}$$

$$\varepsilon_t = \sigma_t \eta_t, \quad \eta_t \sim i.i.d\,(0,\ 1)$$

where η_t follows the Johnson-SU distribution [44,45] with the probability density function:

$$f(x) = (2\pi)^{-1/2} J e^{-\frac{z^2}{2}} \tag{3}$$

where $z = \varsigma^{-1}(sinh^{-1}(x) - \lambda)$ and $J = \varsigma^{-1}(x^2+1)^{-1/2}$. Here, λ and ς are parameters that determine the skewness and kurtosis of the distribution. To account for the short-term shocks that might be responsible for volatility spillovers, we include the following variables in the mean equations: (i) FX_t, the continuous return on the foreign exchange rate of the local currency to USD; (ii) STX_t, the daily continuous returns of the STOXX Global 1800 index; (iii) OIL_t, continuous daily returns from the Europe Brent Spot Price; (iv) continuous daily returns of the Gold spot price (at PM fix); and (v) continuous daily returns of VIX_t to account for the overall appetite for risk of international investors. The returns of STX_t, OIL_t, and $GOLD_t$ are denominated in US dollars.

The variance equation was chosen from the following GARCH-type specifications. Apart from the standard GARCH model:

$$\sigma_t^2 = \omega + \sum_{k=1}^{r} \alpha_i \varepsilon_{t-k}^2 + \sum_{l=1}^{s} \beta_l \sigma_{t-l}^2 \tag{4}$$

we also consider the following models established in the literature: AVGARCH, NGARCH, EGARCH, GJR-GARCH, APARCH, NAGARCH, TGARCH, FGARCH, and CSGARCH. The preferred model is chosen based on the following steps:

(1) For each specification, we consider all combinations of lag orders $p, q, r, s = 1, 2$ with the differencing parameter set to $d = 0$.
(2) A specification is removed if the resulting standardized residuals show signs of autocorrelation and conditional heteroskedasticity (up to 20 lags) based on the Peña and Rodríguez test [46] with Monte Carlo critical values (see [47]). If no suitable model is found, we proceed to step 4.
(3) Appealing to the parsimonious principle, we retain only specifications with the lowest number of parameters $p + q + r + s$.
(4) The selection of the preferred specification is then made as follows:

   a. If the remaining set of specifications includes more than one model, the final specification is selected based on the Bayesian information criterion (BIC; [48]).
   b. If no suitable specification is found using $d = 0$, steps 1–4 are repeated with $d \neq 0$.
   c. If no suitable specification is found after (4b), the final specification is selected directly from all models based on the BIC.

Our econometric analysis was performed in the R software using the rugarch [49] package.

3.3. The Granger causality test

After the filtration procedure described above, we proceed to test the Granger (non-)causality among markets in our sample. Formally, we test the null hypothesis of Granger non-causality from market j to market i (denoted by $j \neq> i$) using standardized conditional demeaned variances $s_{it}^2 = (\varepsilon_{it}/\sigma_{it})^2 - \left(\sum_{k=1}^{T} (\varepsilon_{ik}/\sigma_{ik})^2\right)/T$ from the preferred ARFIMAX-GARCH specifications estimated in the previous section. We calculate the cross-lagged correlations:

$$\hat{\rho}(k) = \frac{\hat{C}_{ij}(k)}{\sqrt{\hat{C}_{ii}(0)\,\hat{C}_{jj}(0)}} \tag{5}$$

where

$$\hat{C}_{ij}(k) = \frac{1}{T}\sum_{t=k+1}^{T} s_{it}^2 s_{jt-k}^2,\ k \geq 0 \tag{6}$$

It should be noted that prior to the calculation of cross-lagged correlations, standardized conditional mean returns were aligned as specified in Section 2. Note however, that k may sometimes (in addition to cases described by Eq. (9)) be equal to 0 and remain valid for testing the hypothesis $j \neq> i$. The minimum value of k depends on the alignment of the standardized conditional mean returns.

Next, the null hypothesis of Granger non-causality ($j \neq> i$) is tested using the proposed test statistic [43]:

$$Q(M) = \frac{T\sum_{k=1}^{T-1} w^2(k/M)\,\hat{\rho}^2(k) - \sum_{k=1}^{T-1}(1-k/T)\,w^2(k/M)}{\sqrt{2\sum_{k=1}^{T-1}(1-k/T)(1-(k+1)/T)\,w^4(k/M)}} \tag{7}$$

where we use the Bartlett weighting scheme:

$$w\left(z = \frac{j}{M}\right) = \begin{cases} 1 - |z|, & |z| < 1 \\ 0, & |z| \geq 1 \end{cases} \tag{8}$$

Using a non-uniform kernel weighting scheme, the choice of the M in the kernel-weighting scheme should not affect the size of the test in a meaningful manner [43], whereas power is affected only slightly. The asymptotic distribution of $Q(M)$ under the null hypothesis follows the standardized normal distribution.

In our empirical application, the choice of M is 5, as it corresponds to one trading week, which also has implications for the properties of the dependent variable used in the spatial regression models described in Section 3.5. Thus, this variable becomes:

$$\bar{\hat{\rho}}(M) = \frac{1}{M}\sum_{k=1}^{M}\hat{\rho}(k) \tag{9}$$

A simple extension allows for instantaneous volatility spillovers from market j to market i, by allowing $k = 0$ in calculating cross-lagged correlations [50], i.e.:

$$Q_u(M) = \frac{T\sum_{k=0}^{T-2} w^2(k/M)\,\hat{\rho}^2(k) - \sum_{k=1}^{T-1}(1-k/T)\,w^2(k/M)}{\sqrt{2\sum_{k=1}^{T-1}(1-k/T)(1-(k+1)/T)\,w^4(k/M)}} \tag{10}$$

This extension is used for markets with the same closing hours (otherwise k starts from 1). Among the 40 markets, there are 1560 possibilities for Granger causality in variances, which may lead to an excessive overall type I error in the tests. We decided to err on the safe side and therefore employ a rather conservative Bonferroni adjustment using the significance level $0.01/(N(N-1))$, where N is the number of stock markets.

3.4. Measures of connectedness

A Granger causality network defined above is a representation of a structure of relationships between volatilities of the world stock market indices. Within such a complex system of relationships investors and policy makers must possess measures helping them (i) to identify the most important markets and (ii) to know when the markets are most interconnected. With daily data, a highly interconnected market suggests that from a short-term perspective, an investor faces a higher chance of (negative) volatility spillovers, which translates into higher risk. There are two general approaches for measuring the interconnectedness of vertices within a network: local and global measures of connectedness.

3.4.1. Vertex-wise connectedness measures

Local measures of vertices' connectedness consider only possible links with other vertices in the network through one edge; i.e., for each vertex, we consider only its neighbors. A vertex's degree is the simplest measure; within a directed network, we must discriminate between the in-degree, $\deg^{\text{in}}(i)$ defined as:

$$\deg^{\text{in}}(i) = |\{(j,i) \in E_t; j \in V\}| \tag{11}$$

and out-degree $\deg^{\text{out}}(i)$, defined as:

$$\deg^{\text{out}}(i) = |\{(i,j) \in E_t; j \in V\}| \tag{12}$$

Here, the $|.|$ corresponds to the cardinality of the given set. Markets with a higher in-degree are more likely to be influenced in terms of volatility by other markets in the system, whereas markets with a higher out-degree are likely to create or propagate volatility spillovers within the system.

Global measures of connectedness attempt to measure the relative importance of a market within a network with respect to other vertices in the network. The most frequently used measures are closeness and betweenness centrality, and both use the concept of the shortest path. Let us define $d(i,j)$ to be the shortest path from vertex i to vertex j. However, neither of the two measures considers graphs that are not strongly connected; i.e., at least one vertex is not reachable from at least one other vertex in the network. If there is no path between two vertices, we can set the shortest path to $d(i,j) = \infty$ and define conveniently that $1/d(i,j) = 0$. The harmonic centrality of market i is defined [51] as:

$$H(i) = \sum_{d(i,j)<\infty, i\neq j} \frac{1}{d(i,j)} \tag{13}$$

More connected markets within the network should have higher harmonic centrality than less connected markets; i.e., such markets are more important.

3.4.2. Network-wise connectedness measures

Conceptually, the centrality of an entire network (i.e., centralization) can be understood in two different ways: (i) as a network's compactness and (ii) as a concentration of vertices within a network [52]. We use two network-wise measures that follow the intuition of the former approach to a network's centrality.

The standardized average out-degree is defined as:

$$\frac{1}{(|V|-1)\,|V|} \sum_{i\in V} \deg^{out}(i) \tag{14}$$

The standardized average in-degree is defined in the same manner. The average harmonic centrality is defined as:

$$\frac{1}{|V|} \sum_{i\in V} H(i) \tag{15}$$

Two related measures from the latter group of centralization approaches are also used in this study, the out-degree and in-degree centralization:

$$\frac{\sum_{i\in V}\left(\max_j \deg^{out}(j) - \deg^{out}(i)\right)}{(n-2)(n-1)} \tag{16}$$

$$\frac{\sum_{i\in V}\left(\max_j \deg^{in}(j) - \deg^{in}(i)\right)}{(n-2)(n-1)} \tag{17}$$

Both are based on the notion that the network is considered more centralized if the dispersion (Euclidean distance) of out-degrees (in-degrees) of all vertices to the most centralized vertex in a given network – the one with the highest out-degree (in-degree) – is also larger. It is essentially a measure of network concentration, similar to measures used to assess industry concentration.

We expect that during turbulent periods, we will observe networks that are more interconnected, i.e., more compact (Eqs. (14)– (15)). Similarly, if volatilities in the equity markets are dominated by a single event in one market, we might observe an increase in concentration measures (Eqs. (16)– (17)).

3.4.3. Stability of networks

Granger causality networks are constructed for 97 overlapping subsamples of 12 months in length. Because the subsamples are overlapping, it might naturally be expected that the consecutive networks will look similar. However, it might be interesting to know how these relationships change over time – particularly after 12 steps when two subsamples are no longer overlapping. For this assessment, we use survival ratios [53]. Let us define E_t as a set of edges of the Granger causality volatility spillover network at time t. One-step survival ratio at time t is defined as:

$$SR\left(s=1,t\right)=\frac{\left|E_t\cap E_{t-s}\right|}{\left|E_{t-s}\right|} \tag{18}$$

Multi-step survival ratio at time t is then:

$$SR\left(s,t\right)=\frac{\left|E_t\cap E_{t-1}\ldots\cap E_{t-s}\right|}{\left|E_{t-s}\right|} \tag{19}$$

where s is the number of steps. Observing one- and multi-step survival ratios let us assess the stability of volatility spillovers around the world. A more stable system of relationships suggests better predictability of the entire system of volatility spillovers.

3.5. Spatial regression

3.5.1. Models and estimation

To model the (non)existence of a volatility spillover and its size, we must address several methodological concerns. First, the dependent variable is defined as:

$$s_{ijt}=\begin{cases}\bar{\hat{\rho}}_{ij}\left(M\right), & i=>j\\ 0 & , i\neq> j\vee\bar{\hat{\rho}}_{ij}\left(M\right)<0\end{cases} \tag{20}$$

Such a definition might suggest a tobit-type censored specification. However, the dependent variable (the estimated size of the volatility spillover) is actually observable, and there is no fixed truncation point; i.e., sometimes an estimate of the average correlation at 0.06 might be retained if the corresponding Granger causality test of a volatility spillover turns out to be statistically significant, whereas for another pair (or direction) of markets, it might be set to 0.

Second, volatility spillovers between markets may be clearly related. For example, a volatility spillover from the US to the Japanese market and spillover from the US to the South Korean market might be related because they both originate from the same market (vertex). The size (and the existence) of a volatility spillover from the US to Japan might therefore be related to the volatility spillover from the US to South Korea. Such dependencies raise endogeneity issues. Spatial regression models allow us to link related volatility spillovers through the spatial weighting matrix. Consider the spatial autoregressive lag model of the form:

$$\mathbf{y}=\rho\mathbf{W}\mathbf{y}+X\boldsymbol{\beta}+\boldsymbol{\varepsilon},\quad \boldsymbol{\varepsilon}\sim\mathbf{N}\left(\mathbf{0},\sigma_{\varepsilon}^2\mathbf{I}_{N(N-1)}\right) \tag{21}$$

In our setting, the variable of interest ($\mathbf{y}$) corresponds to Eq. (20). We set $s_{ijt}\in\mathbf{S}_t$. The matrix $\mathbf{S}_t$ is our volatility spillover matrix. To obtain our dependent variable, we first vectorize the matrix $\mathbf{S}$ (by calculating *vec* ($\mathbf{S}$)), and then exclude the elements corresponding to the diagonal of $\mathbf{S}$, as we are not interested in modeling loops, as they have no economic meaning in our Granger analysis. We thus obtain a vector $\mathbf{y}$ of length $N(N-1)$. Exogenous variables are in $\mathbf{X}$. The model parameters include vector $\boldsymbol{\beta}$ and a scalar ρ, which is related to spatial autocorrelation.

Next, we define the matrix of spatial weights to indicate neighboring observations, allowing for the modeling of spatial dependence. In our case, we must define the spatial weight matrix $\mathbf{W}$ for all potential edges in $\mathbf{y}$; thus, $\mathbf{W}$ is a matrix of order $N(N-1)\times N(N-1)$. In general, for any two distinct possible edges $(i,\ j)\in V\times V$ and $(k,\ l)\in V\times V$, we set the corresponding element of $\mathbf{W}$ to 1 if the possible edges share the outgoing or incoming vertex (either $i=k$ or $j=l$) and 0 otherwise. For the purposes of estimation, we have used the row-standardized version of $\mathbf{W}$, where the sum of elements in each row is equal to 1.

Perhaps a more intuitive explanation is that a given value at position (i,j) in matrix $\mathbf{W}$ corresponds to a *possible* volatility spillover from market i to market j. The elements of $\mathbf{W}$ define the neighbors of each edge; if two edges share an outgoing vertex, they model the information flow from the same market, and it is thus conceivable that their presence in the network might be related. Similarly, we consider the edges to be neighbors when they share the incoming vertex. For any row (column) p in $\mathbf{W}$, the nonzero values designate the neighbors for edge p. Now, it should be clear why the definition of the dependent variable in Eq. (20) was chosen in the particular way it was. If we set insignificant volatility spillovers to 0, the $\rho\mathbf{W}\mathbf{y}$ on the right-hand side always yields zero elements whenever the two volatility spillovers (edges) are unrelated. We can therefore specify $\mathbf{W}$ exogenously and simultaneously take into account the structure of the Granger causality volatility spillover network.

The interpretation of the spatial lag model effects is different than the interpretation of the usual regression coefficients because the incorporation of the spatial dependence has the effect that a unit change in a predictor k does not simply correspond to a change of β_k of the dependent variable [54]. The spatial dependence between neighboring observations means that a change of a predictor in one spatial unit (in our case, a spillover between two markets, or equivalently, an edge) may induce changes in the values of the dependent variable of its neighbors, which in turn may induce changes back into the initial spatial unit. Thus, the effect of the predictor is both direct within a given spatial unit and indirect through a feedback loop of its neighbors.

More formally, for a predictor k, we may calculate a matrix $S_k(\mathbf{W}) = (I - \rho\mathbf{W})^{-1}\beta_k$, which describes the overall effect of a unit change in predictor k. A so-called *average direct effect* describes the isolated effect of a changing predictor on the dependent variable of its corresponding spatial unit, taking into account the effects of neighbors (averaged over all units). An *average indirect effect* contains information regarding how much the dependent variable in a spatial unit would change on average as a result of a unit change in the corresponding variable in all other spatial units (except for the initial one). The *average total effect* is the sum of the average direct and indirect effects.

As for the matrix $S_k(\mathbf{W})$, its diagonal elements are related to the direct effects and off-diagonal elements to the indirect effects. The proportion of direct and indirect effects in the total effects may vary depending on several factors, notably by the interconnectedness defined by $\mathbf{W}$ and the strength of the spatial dependence given by ρ.

3.5.2. Model specification

The extent of volatility spillovers is explained via variables related to the importance, development and liquidity of the equity market. We have considered variables that are readily available and that are used in the previous literature (e.g., [55–57]). As our dependent variable corresponds to the extent of volatility spillovers from market i to market j, each country/market variable corresponds either to the out-vertex market ('i') or in-vertex market ('j'). We have considered the same set of explanatory variables for in- and out-vertex markets at first, but the four stocks and foreign exchange variables were not important for the in-vertex market; additionally, we made a pragmatic choice to report only the results from the models, where four (stock and foreign exchange) market variables were not used for the in-vertex market.

Two additional notes are important to the description of our data. Our subsamples were rolled one month ahead, and the estimation window has a length of 12 months. However, except for the market variables, we have data with an annual sampling frequency; these observations correspond to a given year. Therefore, if we have a subsample beginning in say May 2009 and ending in April 2010, for example, we have two observations for a given variable, i.e., one for 2009 and one for 2010. We used a simple linear weighting scheme in which the weight was distributed between two annual observations based on the ratio of months in a given year. As market volatilities might be of considerable difference between markets, we standardized each of the return series over the entire period prior to the calculation of market volatilities. The realized volatility was then calculated for a given subsample from standardized returns, which allows the market volatilities across different markets to be compared within one model. Next, for each model, all variables were standardized to have a zero mean and unit variance; spatial temporal variables are an exception. In this manner, we can observe the relative importance of market and country variables on the propagation of volatility shocks.

We report the results from the Moran I test and Geary test to support our choice of the spatial model specification. For purposes of comparison, we also report Nagelkerke's pseudo R^2 and the *AIC*. The analysis was performed in R using the spdep package [58].

4. Empirical results and discussion

4.1. Connectedness of markets: A network approach to return spillovers

Fig. 1a depicts the visual structure of complex volatility relationships, which corresponds to a subsample period of the highly volatile year of 2008, a subsample with the highest harmonic centralization. Obviously, the plot cannot be interpreted for its complexity. However, Fig. 1b corresponds to a much calmer period beginning in September 2013 and ending in August 2014. However, although the resulting network corresponds to a period with the lowest harmonic centralization and the relationships appear to be less chaotic, the figure remains difficult to visually interpret. To describe such complex systems, we might resort to network variables either on the network or vertex level.

In Fig. 2, we plot four time-varying measures of connectedness based on the 97 subsamples. The top left panel captures the evolution of out-degree centralization, where several peaks of the out-degree centralization are visible. Such peaks correspond to periods when one or more markets exert a significant influence (in the Granger sense) on the volatilities of other markets in the network. For example, when out-degree centralization peaked, the US stock market had an out-degree of 23 (Hong Kong had the highest of 26), which is a considerable outlier with only 5.8 being the mean. Peaks indicate the presence of a few markets that are subject to an extremely large number of volatility spillovers. Peaks are frequent in the out-degree centralization, but such events do not appear to occur in the in-degree centralization.

Both out/in-degree centrality and mean harmonic weighted centrality measure the density or compactness of the Granger causality network, i.e., the interconnectedness of volatility spillovers around the world. Their evolution is similar, with two periods of a high number of volatility spillovers and a declining pattern throughout the end of the examined period. The two periods of the high number of volatility spillovers correspond to the financial crisis (2008) and the European debt-crisis (2011).

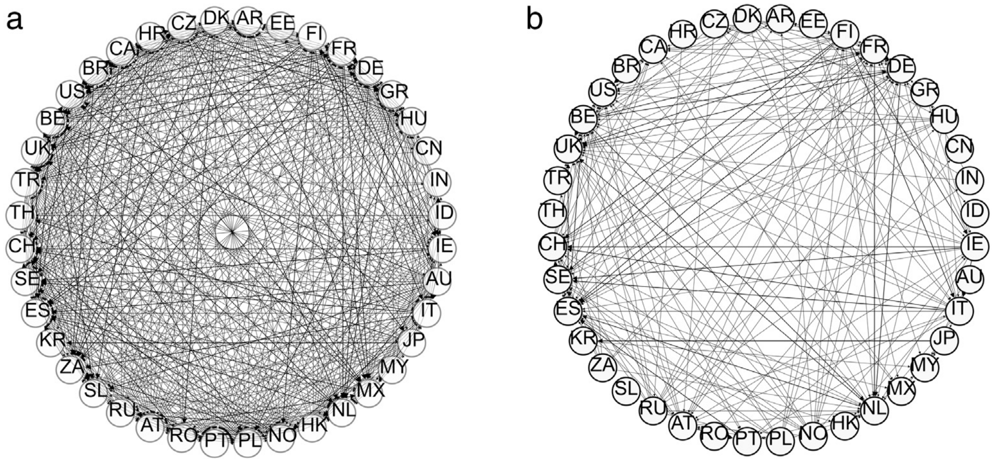

Fig. 1. Granger causality networks. *Note: a corresponds to a subsample beginning in January 2008 and ending in December 2008, and 1 corresponds to a subsample beginning in September 2013 and ending in August 2014.*

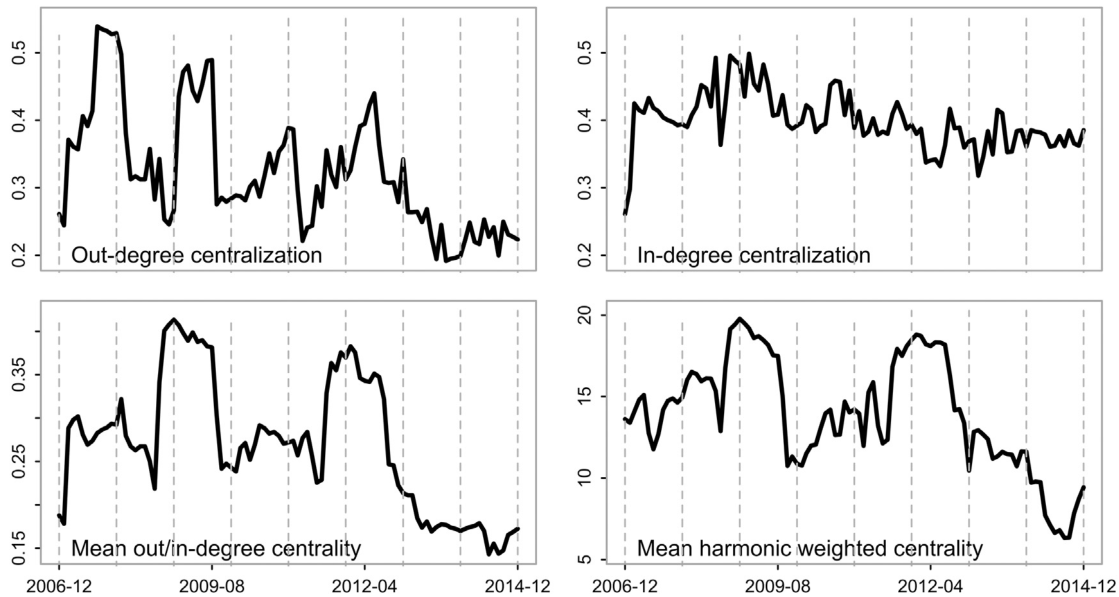

Fig. 2. Time-varying spillovers: network centralization.

Table 1 provides some basic statistics of out-/in-degree and harmonic centralities. To emphasize the heterogeneity of our sample, we divided markets into frontier, emerging and developed. However, we refrain from comparing out/in-degrees and harmonic centrality across these groups for the following reasons. For example, the position of the US market might appear to be surprising with an average of 5.8 out-degrees. However, this observation actually resonates well with the motivation of our paper: when sampling with daily data frequency, the trading hours of national exchanges matter significantly regarding volatility spillovers. The explanation for this particular out-degree is that even if we agree that the US stock market might be the most influential in the world, as national exchanges begin trading, additional information interferes with news from the US market, leading to the insignificance of volatility spillovers in a direct bivariate test between the US and other markets in our sample – particularly in those markets in which trading begins later the next business day. However, higher out/in-degrees and weighted harmonic centrality is observed for markets that operate in the same time zones. Naturally, as trading closes at the same time, it is more likely that there will be more linkages within this group of markets. We find this pattern among the European markets.

The left panel of Fig. 3 suggests that there are markets that tend to influence – and others that are more likely to be influenced by – other markets. A positive correlation between in/out-degrees can be interpreted as a market situation in

Table 1
Connectedness of markets: vertex centrality.

	Out-degree					In-degree					Weighted harmonic centrality				
	Mean	SD	Max	Trend	R^2	Mean	SD	Max	Trend	R^2	Mean	SD	Max	Trend	R^2
Frontier markets															
AR	4.6	3.5	13	−4.7	14.5%	17.8	10.5	32	−25.1 [c]	45.0%	9.5	5.7	18.66	−10.4	25.9%
HR	8.2	8.6	28	−7.7	6.4%	3.8	4.1	15	−7.0 [b]	23.2%	11.4	7.9	25.02	−4.4	2.5%
EE	2.7	3.3	18	0.5	0.2%	1.4	2.2	9	−0.2	0.1%	8.1	6.3	20.03	−5.2	5.4%
RO	5.9	4.5	18	−4.8	9.1%	4.3	3.3	16	−5.2 [c]	19.6%	12.4	5.2	20.81	−8.5	21.5%
SL	4.1	5.4	22	−4.9	6.3%	4.5	5.8	21	0.2	0.0%	9.3	7.2	22.44	−5.3	4.4%
Emerging markets															
BR	4.8	3.2	15	−3.2	7.5%	17.4	10.1	31	−21.4	35.7%	10.3	4.9	19.30	−6.4 [b]	13.7%
CZ	18.0	6.1	26	−14.4 [c]	44.0%	6.0	5.3	17	−13.5 [c]	50.6%	18.2	4.0	23.82	−9.7 [c]	47.2%
HU	10.7	6.5	21	−2.4	1.0%	4.7	3.4	15	−3.2	7.1%	14.4	4.2	21.95	−2.8	3.4%
CN	6.0	7.7	26	−17.5 [b]	41.1%	0.8	1.0	4	0.8	4.7%	12.3	5.8	23.24	−13.1 [c]	40.3%
IN	7.0	5.3	21	5.9	9.9%	3.6	2.9	14	−6.0 [c]	34.2%	13.1	4.8	20.80	2.6	2.3%
ID	8.6	7.2	26	−1.3	0.3%	3.9	2.6	16	−1.8	3.7%	14.3	5.7	23.62	−7.3	13.0%
MY	9.2	9.3	31	−23.2 [c]	49.2%	4.6	4.7	19	2.9	3.0%	13.8	6.6	25.33	−15.9 [c]	45.7%
MX	5.8	5.2	18	−3.3	3.2%	16.7	6.9	28	−9.2	14.2%	10.4	6.0	20.03	−3.2	2.2%
PL	17.7	5.5	28	−7.5 [a]	14.7%	8.6	5.4	20	−4.9	6.5%	17.7	3.8	24.64	−6.6 [b]	24.5%
RU	15.5	7.6	27	4.1	2.3%	4.7	2.5	12	−2.0	5.1%	16.9	4.1	23.77	−0.6	0.1%
ZA	16.1	5.9	28	−5.8	7.6%	6.4	4.6	23	−8.2 [b]	25.2%	17.0	4.0	24.00	−5.0	12.7%
KR	7.4	4.6	19	−6.2	14.7%	2.4	2.1	11	−1.6	4.5%	14.0	4.9	21.15	−6.4	13.7%
TH	5.4	5.7	22	−3.2	2.4%	2.9	3.1	14	−1.2	1.1%	11.2	6.5	22.51	−6.2	7.0%
TR	15.9	8.6	30	−18.6 [a]	36.8%	4.8	3.6	14	−6.2 [b]	23.6%	16.6	6.4	25.14	−13.5 [b]	35.1%
Developed markets															
AU	8.5	6.9	25	−9.7	15.6%	2.6	2.5	13	−2.3	6.5%	14.5	5.0	23.33	−9.3 [a]	27.4%
AT	10.9	1.8	14	−2.7 [a]	18.1%	15.6	3.8	26	−7.3 [b]	29.9%	13.9	2.8	18.06	−5.1 [b]	26.2%
BE	10.6	1.7	15	−3.1 [c]	26.2%	21.1	4.3	32	−5.1	11.3%	14.1	3.0	19.71	−5.3 [b]	24.6%
CA	4.3	2.0	9	−0.4	0.3%	19.5	7.7	30	−9.8	12.8%	10.1	4.5	16.94	−0.5	0.1%
DK	16.9	2.8	22	−3.7 [a]	14.1%	7.3	2.7	13	−5.3 [c]	30.3%	17.1	2.7	21.21	−4.3	19.3%
FI	16.6	2.5	20	−2.8	10.0%	14.0	2.8	21	−5.8 [c]	32.7%	16.9	2.8	21.14	−4.6	21.4%
FR	10.6	1.2	13	−2.2 [a]	26.6%	21.5	3.0	29	−2.7	6.4%	13.8	2.7	18.82	−4.6	22.6%
DE	10.9	1.7	16	−4.6 [c]	56.6%	22.1	3.4	31	−2.7	5.0%	14.1	3.1	19.78	−6.3 [b]	34.2%
GR	13.3	8.6	26	−25.6 [b]	70.5%	4.2	5.0	17	−11.2 [b]	39.0%	15.5	5.5	22.65	−15.6 [c]	64.7%
IE	16.0	3.3	24	−2.4	4.3%	11.5	3.4	19	−4.5 [a]	13.5%	16.5	3.0	22.14	−4.3	16.1%
IT	17.0	2.3	22	−4.7 [c]	34.9%	13.8	5.6	28	−9.6 [b]	23.5%	17.2	2.8	21.76	−5.8 [a]	33.8%
JP	7.2	6.7	25	−3.2	1.9%	3.1	2.9	13	−4.8 [b]	22.1%	13.2	5.8	23.93	−3.8	3.4%
NL	11.2	2.5	17	−2.0	5.3%	21.6	3.2	30	−3.3	8.5%	14.2	3.4	19.85	−4.6	14.9%
HK	11.4	8.7	33	−10.9	12.3%	5.7	5.4	21	4.8	6.3%	15.7	6.0	26.57	−11.5	29.1%
NO	17.1	3.7	24	−3.7	8.1%	10.2	4.8	20	−8.6	25.1%	17.3	3.2	22.81	−5.2 [a]	21.0%
PT	3.8	2.0	10	−2.6 [a]	13.0%	19.6	7.6	34	−12.6 [b]	21.9%	10.1	3.5	15.05	−4.5 [c]	13.4%
ES	10.3	1.5	14	−3.0 [c]	32.6%	21.0	4.4	32	−6.0 [a]	14.7%	13.7	2.7	19.80	−5.4 [c]	31.5%

(*continued on next page*)

Table 1 (*continued*)

	Out-degree					In-degree					Weighted harmonic centrality				
	Mean	SD	Max	Trend	R^2	Mean	SD	Max	Trend	R^2	Mean	SD	Max	Trend	R^2
SE	16.9	3.0	25	−0.9	0.7%	13.1	2.7	19	−0.3	0.1%	17.1	3.0	23.17	−3.3	9.9%
CH	16.7	3.2	23	−4.6	16.3%	13.9	3.9	23	−3.3	5.7%	17.1	3.3	22.31	−5.8	24.3%
UK	10.8	2.7	18	−1.6	2.8%	21.1	3.2	28	−2.6	5.3%	14.0	3.2	20.66	−4.1	12.7%
US	5.8	5.3	24	−4.5	5.7%	18.3	5.3	26	−1.6	0.7%	10.6	5.6	23.26	−2.7	1.8%
MG				−0.054 [c]					−0.054 [c]					−0.061 [c]	

Note: The countries in the table are as follows: Argentina, Croatia, Estonia, Romania, Slovenia, Brazil, Czech Republic, Hungary, China, India, Malaysia, Mexico, Poland, Russia, South Africa, South Korea, Thailand, Turkey, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Japan, Netherland, Hong Kong, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Trend denotes the estimated trend coefficient of a simple linear time trend regression, in which the dependent variable is out-degree (in-degree or harmonic centrality) of a corresponding market. We have used the HAC Newey–West standard errors estimated with automatic bandwidth selection and a quadratic spectral weighting scheme [59]. *MG corresponds to the pooled mean group estimator.*

[a] Denote statistical significance at the 10% level.

[b] Denote statistical significance at the 5% level.

[c] Denote statistical significance at the 1% level.

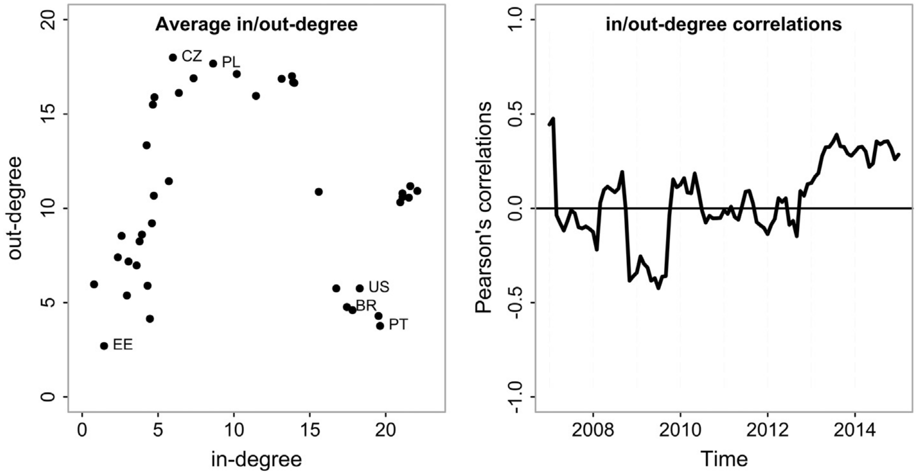

Fig. 3. In-/out-degree relationship. *Note: The left panel is a scatterplot of average in- and out-degrees. The right panel is a time series of in-/out-degree correlations calculated for each of the 97 subsamples.*

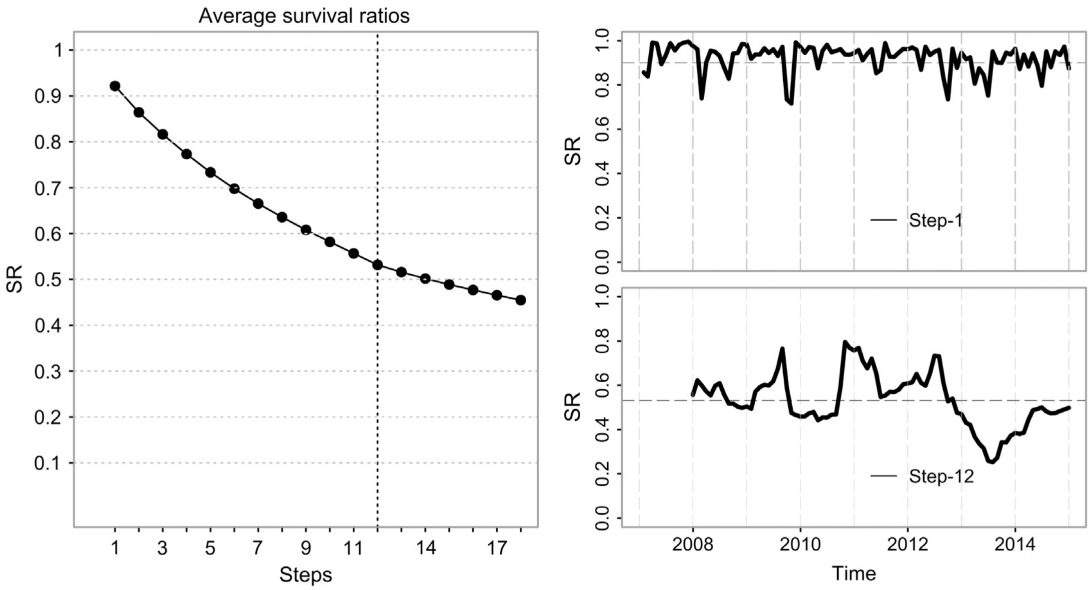

Fig. 4. In-/out-degree relationship. *Note: The left panel denotes the average ratio of surviving return spillovers after x number of months. The right panel denotes the time variation of a ratio of surviving return spillovers after one month (upper right figure) and 12 months (lower right figure).*

which volatility is propagated across markets because markets with a higher out-degree are also those with a higher in-degree. A negative correlation then indicates a market situation in which volatility is propagated from a few markets to many others; i.e., spillovers originate from a few markets and spill over to other markets, whereas these 'infected' markets do not propagate shocks back to the markets of origin. Such a drop in correlation between in/out-degree centrality is visible at the beginning of our sample period until 2009. During this period, there were apparently markets with increasing influence; to put it more simply, only a few markets were propagating volatility shocks to other markets around the world.

Although we use rolling subsamples, the structure of the volatility spillover network appears to be stable over time (see Fig. 4): more than half of the surviving spillovers remain even after a year, which indicates that the structure of the network changes only moderately.

The next two figures depict the most and least influential and influenced markets (Figs. 5 and 6, respectively). Both figures lead to a number of interesting observations.

The most influential markets in our sample are frequently those in which the trading session closes before the closing times of the European markets (e.g., Turkey at the beginning of our sample before the extension of trading hours). This is the consequence of our sample selection. It also shows that when modeling volatility spillovers between markets, we should not

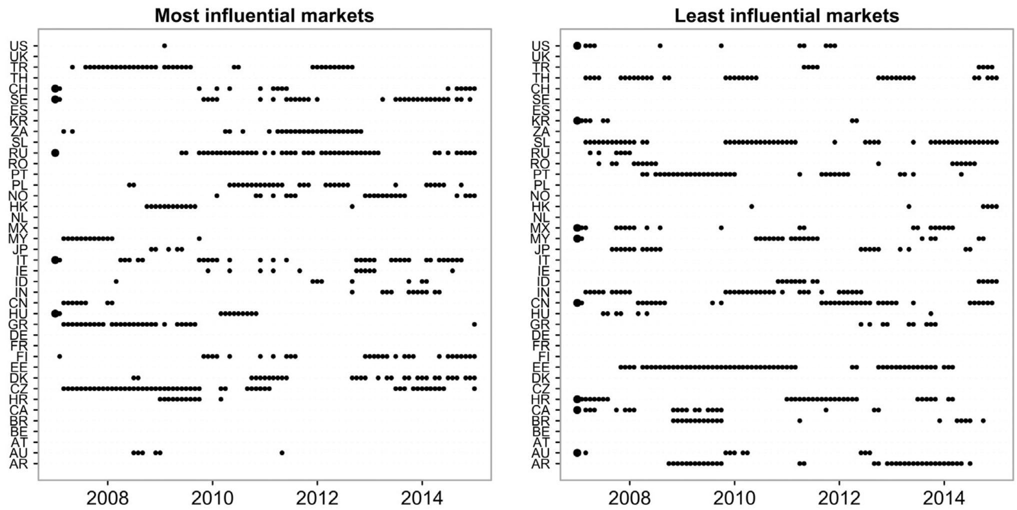

Fig. 5. Top 3 markets with the highest out-degree $\deg^{out}(i)$ over all subsamples. *Note: A point is drawn at time t for three markets with the highest (left panel) or lowest (right panel) out-degree.*

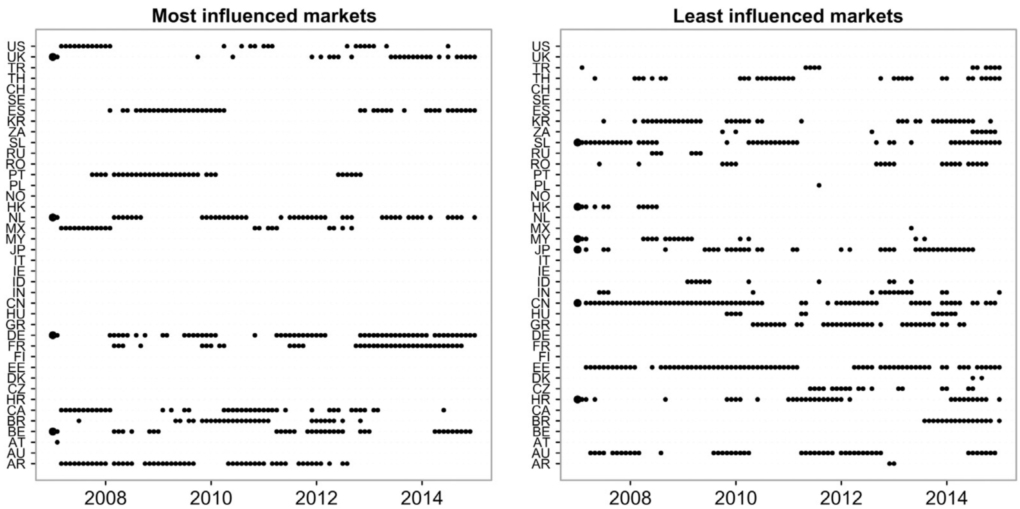

Fig. 6. Top 3 markets with the highest in-degree $\deg^{in}(i)$ over all subsamples. *Note: A point is drawn at the time t for three markets with the highest (left panel) or lowest (right panel) in-degree.*

ignore how closely they are trading, i.e., the temporal proximity effect. The most influenced markets (see Fig. 6) are those that are in business after the European markets close, namely the Argentinian, Canadian or US markets. It is intriguing to see the Argentinian market in one group with Canada and the US because they are quite different with respect to size and liquidity. However, our findings show that time proximity and trading hours matter.

An interesting observation can be made with respect to the Chinese stock market. It is quite a large stock market but was only occasionally highly influential. To the contrary, the market is frequently the least influential and is also the least influenced by other markets in the world, which suggests that during our sample period, the Chinese market was segmented with regard to volatility spillovers.

4.2. Determinants of volatility spillovers

Our baseline results that are based on specifications described in Section 3.5 are presented in Table 2, which summarizes model coefficients. The dynamics of the effects is presented as a complementary representation in graphical form in Figs. 7–11.

The key observation in Table 2 is the significant and negative coefficient of the temporal proximity between markets (see also Fig. 7). As expected, the further apart the closing hours between stock markets, the smaller the magnitude of the

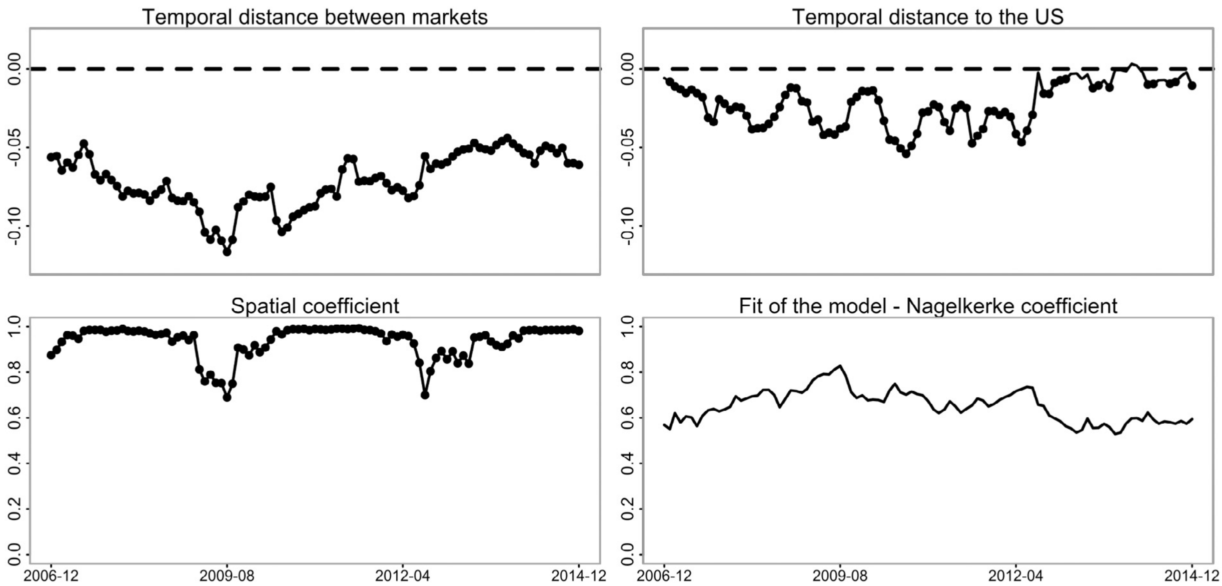

Fig. 7. Average direct effects of temporal coefficients, spatial and Nagelkerke coefficients. *Note: Bullets denote statistically significant coefficients at the 5% significance level.*

volatility spillover between markets. The temporal proximity to the US market has a similar impact on volatility spillovers, as corresponding coefficients are almost always negative and significant across subsamples. However, the effect of the temporal distance to the US market is smaller than the effect between two markets. Moreover, we can also observe a sudden decrease in the role of the US market for volatility spillovers during the annual sample ending in May 2012 (an increase of the coefficient towards 0 visible in Fig. 7). We therefore conclude that the US market is important for the propagation of volatility spillovers among markets, although its role seems to be declining.

The second observation of interest is that the spatial coefficient ρ is always positive and significant, and its value is mostly above 0.90. This result leads us to conclude that the spatial regression framework has merit because volatility spillovers are highly dependent; the size of a volatility spillover depends on the size of volatility spillovers already present in the out- and in-vertex markets. The result has some implications with regard to direct and indirect effects. First, average indirect effects are much larger, although they are highly correlated with direct effects across all subsamples; this dependence is not explicitly reported but is available upon request. The explanation for such sizeable discrepancies is that the markets are highly interconnected, as a number of markets exhibit more than 10 linkages in average (see Table 1). Therefore, a unit increase in a given variable is propagated across the entire network, as witnessed by a large spatial coefficient ρ. The implication of this result is that indirect relationships matter in highly interconnected markets. Sometimes, the indirect impact is more than 20 times higher than the direct impact. However, it must be noted that the signs of direct and indirect effects are equal and direct and that indirect effects are highly correlated. Hence, in the remainder of our discussion, we focus on results related to average direct impacts.

4.2.1. Effects of the out-vertex market

We observe a particularly consistent impact of the size of the market: the market capitalization coefficient is positive and significant in most cases (Table 2 and Fig. 8) and implies that larger markets propagate volatility shocks of greater size. Markets that are more important within a given economy (measured by a higher market capitalization to GDP) are associated with lower volatility spillovers. However, because we work with standardized variables, the effect of market capitalization to GDP is much lower than the market size itself.

Further, our results confirm our prior hypothesis that market liquidity matters for volatility spillovers. From Fig. 8 we observe that markets with a higher turnover ratio propagate larger volatility spillovers in the network.

How are volatility spillovers in a specific country related to the country's external economic factors? If equity markets mimic the underlying economies, then more export-oriented countries should also have a higher tendency to propagate volatility spillovers. This proposition is partially confirmed in our results as coefficients of the net trade to GDP are mostly positive and often significant. However, for some subsamples, particularly those corresponding to the period of the financial crisis, the respective coefficient is negative and significant, which might have resulted because the number of spillovers from the US market was increasing, while the US market had a negative net trade. A similar idea is behind using FDI net outflows in our specifications, where the effects were positive and significant most of the time. Compared to market capitalization,

Table 2
Estimates of the average direct and indirect effects of the spatial lag model for selected subperiods corresponding to given years.

(x1000)	31.12.2006		31.12.2007		31.12.2008		31.12.2009		31.12.2010	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
Intercept	46.49 [d]		71.95 [d]		68.11 [d]		72.21 [d]		81.57 [d]	
Temporal distance variables										
Temporal proximity	−0.056 [d]	−0.376 [b]	−0.074 [d]	−1.640 [d]	−0.084 [d]	−1.371 [d]	−0.080 [d]	−0.531 [b]	−0.087 [d]	−2.086 [d]
Temporal proximity to US	−0.006 [a]	−0.039	−0.026 [d]	−0.576 [d]	−0.012 [d]	−0.198 [b]	−0.014 [d]	−0.093 [a]	−0.027 [d]	−0.647 [d]
Out-vertex market variables										
Equity market returns	−5.443 [d]	−36.421 [b]	−9.330 [d]	−205.385 [d]	4.221 [d]	68.835 [c]	−2.238 [b]	−14.852	−2.169 [a]	−51.814 [a]
Equity realized volatility	−1.302	−8.714	−1.300	−28.619	0.095	1.552	1.356 [a]	9.001	3.010 [c]	71.885 [b]
Forex return	−1.657 [a]	−11.086	−1.918 [b]	−42.220 [b]	−0.536	−8.743	−0.604	−4.005	6.529 [d]	155.950 [d]
Forex realized volatility	1.858 [b]	12.429	2.712 [c]	59.705 [c]	1.343	21.894	−4.149 [d]	−27.533 [b]	−0.394	−9.419
Market capitalization	11.620 [d]	77.749 [b]	10.166 [d]	223.788 [d]	5.324 [d]	86.813 [b]	7.286 [d]	48.348 [b]	14.499 [d]	346.292 [d]
Market capitalization to GDP	−5.570 [d]	−37.270 [a]	−5.449 [d]	−119.954 [d]	−5.802 [d]	−94.604 [c]	−5.761 [d]	−38.226 [b]	−8.503 [d]	−203.081 [d]
Turnover ratio	−0.159	−1.061	−1.271	−27.985	4.909 [d]	80.042 [c]	2.449 [b]	16.250 [a]	4.377 [c]	104.540 [c]
Net trade to GDP	3.602 [d]	24.102 [a]	2.406 [b]	52.974 [b]	−1.643 [a]	−26.794 [a]	−0.985	−6.539	0.430	10.263
FDI net outflows	2.763 [d]	18.485 [a]	1.956 [b]	43.057 [b]	4.262 [d]	69.497 [c]	2.749 [c]	18.242 [a]	2.231 [a]	53.276 [a]
In-vertex market variables										
Market capitalization	−3.611 [c]	−24.165	−0.801	−17.623	−9.014 [d]	−146.979 [c]	−3.204 [b]	−21.261	0.073	1.734
Market capitalization to GDP	0.901	6.029	0.764	16.819	3.146 [b]	51.297 [b]	0.037	0.244	1.236	29.510
Turnover ratio	1.896 [a]	12.688	−2.729 [b]	−60.080 [b]	2.433 [b]	39.668 [a]	−0.200	−1.329	−0.947	−22.609
Net trade to GDP	−0.942	−6.300	−0.139	−3.068	−2.996 [d]	−48.847 [b]	−1.329	−8.820	0.458	10.941
FDI net inflows	−0.337	−2.255	0.178	3.908	−0.759	−12.377	−1.078	−7.150	0.420	10.041
Spatial coefficient (ρ)	0.875 [d]		0.983 [d]		0.961 [d]		0.874 [d]		0.989 [d]	
Spatial error model — fit statistics										
pseudo R^2 (Nagelkerke)	0.568		0.648		0.718		0.699		0.673	
AIC	−6613.9		−6459.7		−6464.6		−6506.8		−5846.1	
SD residual	0.028		0.030		0.030		0.029		0.036	
Correlation fitted vs. observed	0.758		0.810		0.850		0.839		0.826	
Dependent variable										
Mean and standard dev.	0.031	0.044	0.044	0.051	0.053	0.057	0.050	0.054	0.062	0.064
Lower and upper quartile	0.000	0.031	0.000	0.044	0.000	0.053	0.000	0.050	0.000	0.062
Spatial tests										
Moran I	0.109 [d]		0.205 [d]		0.176 [d]		0.162 [d]		0.224 [d]	
Geary Test	0.854 [d]		0.852 [d]		0.817 [d]		0.838 [d]		0.811 [d]	

(x1000)	31.12.2011		31.12.2012		31.12.2013		31.12.2014	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
Intercept	69.23 [d]		51.30 [d]		34.18 [d]		50.39 [d]	
Temporal distance variables								
Temporal proximity	−0.068 [d]	−1.251 [d]	−0.059 [d]	−0.346 [b]	−0.048 [d]	−0.779 [d]	−0.061 [d]	−1.307 [d]
Temporal proximity to US	−0.027 [d]	−0.494 [d]	−0.007 [b]	−0.042	−0.001	−0.022	−0.011 [c]	−0.228 [c]
Out-vertex market variables								
Equity market returns	−1.490	−27.392	−1.827 [b]	−10.644	5.507 [d]	90.170 [c]	−17.199 [d]	−368.432 [d]
Equity realized volatility	7.849 [d]	144.275 [d]	3.191 [d]	18.593 [a]	0.513	8.397	14.724 [d]	315.397 [d]

(*continued on next page*)

Table 2 (*continued*)

(x1000)	31.12.2011		31.12.2012		31.12.2013		31.12.2014	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
Forex return	3.605 [d]	66.268 [c]	−3.692 [d]	−21.513 [a]	−1.455	−23.825	2.262 [b]	48.457 [b]
Forex realized volatility	2.159 [c]	39.675 [b]	0.630	3.672	0.682	11.164	−6.246 [d]	−133.794 [d]
Market capitalization	12.348 [d]	226.968 [d]	10.281 [d]	59.902 [a]	1.840	30.132	5.837 [d]	125.044 [c]
Market capitalization to GDP	−2.972 [b]	−54.628 [a]	−6.352 [d]	−37.012 [a]	−0.063	−1.035	2.522	54.022
Turnover ratio	−4.989 [d]	−91.698 [c]	−0.718	−4.181	5.417 [d]	88.688 [b]	−1.034	−22.140
Net trade to GDP	5.060 [d]	93.016 [d]	−0.950	−5.534	−0.417	−6.830	4.325 [d]	92.646 [d]
FDI net outflows	2.686 [c]	49.375 [b]	3.579 [d]	20.853 [a]	1.757 [b]	28.761 [a]	−3.198 [c]	−68.505 [c]
In-vertex market variables								
Market capitalization	−4.277 [c]	−78.611 [b]	−5.362 [d]	−31.242 [a]	−2.638 [b]	−43.193 [a]	−8.957 [d]	−191.868 [d]
Market capitalization to GDP	2.597 [b]	47.743 [a]	2.601 [b]	15.158	1.998 [a]	32.716	2.941 [b]	63.007 [a]
Turnover ratio	−1.419	−26.077	2.781 [b]	16.205	2.321 [b]	38.002 [a]	5.146 [d]	110.238 [c]
Net trade to GDP	0.041	0.763	0.510	2.969	0.311	5.086	−0.121	−2.592
FDI net inflows	−0.150	−2.756	−0.443	−2.579	0.779	12.747	−2.164 [b]	−46.351 [b]
Spatial coefficient (*ρ*)	0.970 [d]		0.857 [d]		0.961 [d]		0.981 [d]	
Spatial error model — fit statistics								
pseudo R^2 (Nagelkerke)	0.661		0.585		0.575		0.594	
AIC	−6687.340		−6632.105		−6729.290		−6238.747	
SD residual	0.028		0.028		0.027		0.032	
Correlation fitted vs. observed	0.817		0.769		0.764		0.777	
Dependent variable								
Mean and standard dev.	0.042	0.048	0.036	0.044	0.029	0.042	0.034	0.051
lower and upper quartile	0.000	0.042	0.000	0.036	0.000	0.029	0.000	0.034
Spatial tests								
Moran I	0.170 [d]		0.119 [d]		0.128 [d]		0.172 [d]	
Geary Test	0.830 [d]		0.859 [d]		0.807 [d]		0.816 [d]	

[a] Significance at 10%.

[b] Significance at 5%.

[c] Significance at 1%.

[d] Significance at 0.1%.

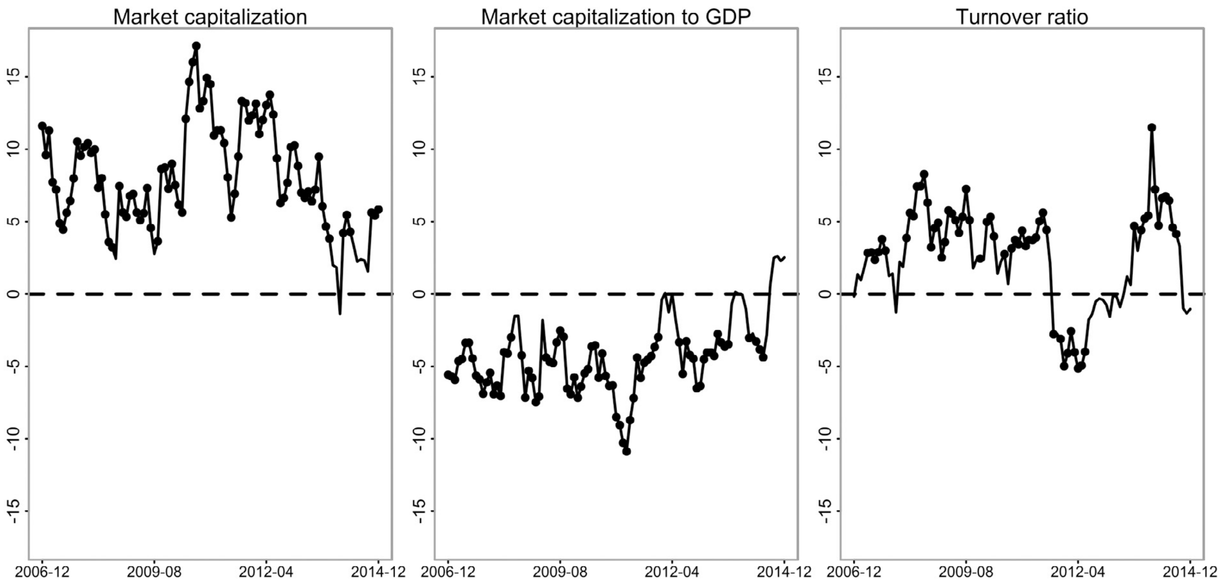

Fig. 8. Average direct effects of market capitalization and market liquidity (out-vertex). *Note: Bullets denote statistically significant coefficients at the 5% significance level.*

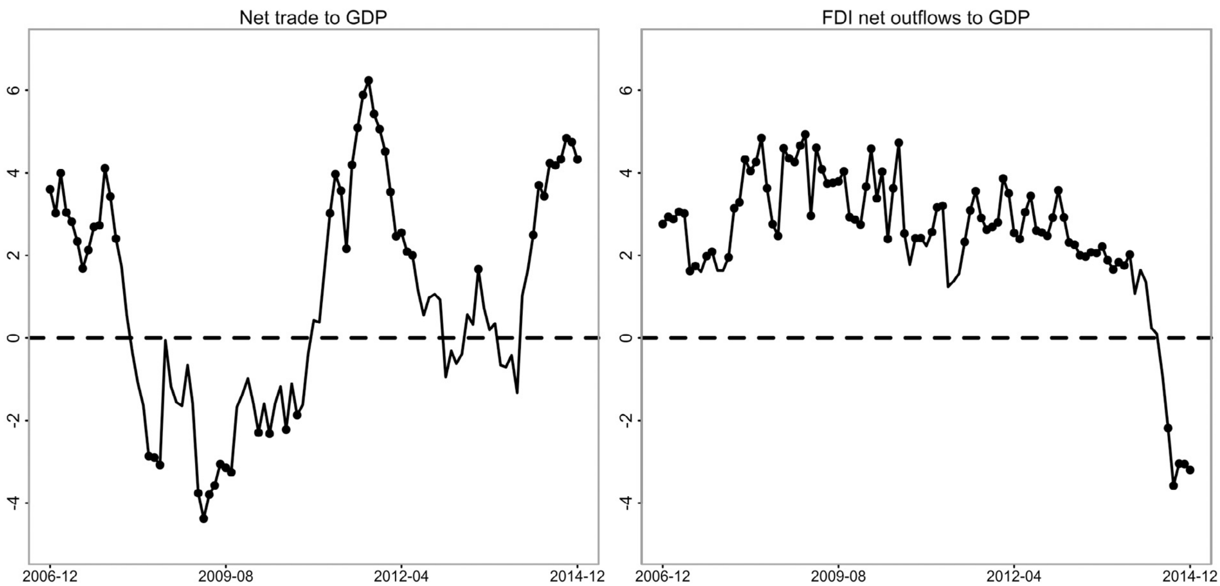

Fig. 9. Net trade to GDP and FDI outflows to GDP (out-vertex). *Note: Bullets denote statistically significant coefficients at the 5% significance level.*

both net trade to GDP and FDI net outflows to GDP have a rather small effect on the propagation of equity market volatility (Fig. 9).

We have also studied the effects of the equity and foreign exchange market conditions of the out-vertex market on volatility spillovers (Fig. 10). Generally, the estimated coefficients across different subsamples changed signs, which suggests that volatility spillovers are difficult to predict because they might materialize in the same manner under either bullish or bearish market conditions. However, we admit that the results might also reflect a general increasing or decreasing trend on the world stock markets during the observed period. For example, during 2008, when the markets were declining, we observed a higher number of significant volatility spillovers, which corresponds to the positive coefficient for the given subsamples. Similarly, mixed results are also observed for forex returns, where appreciation of the local currency is, for some periods, associated with larger volatility spillovers, while smaller spillovers prevail in other periods.

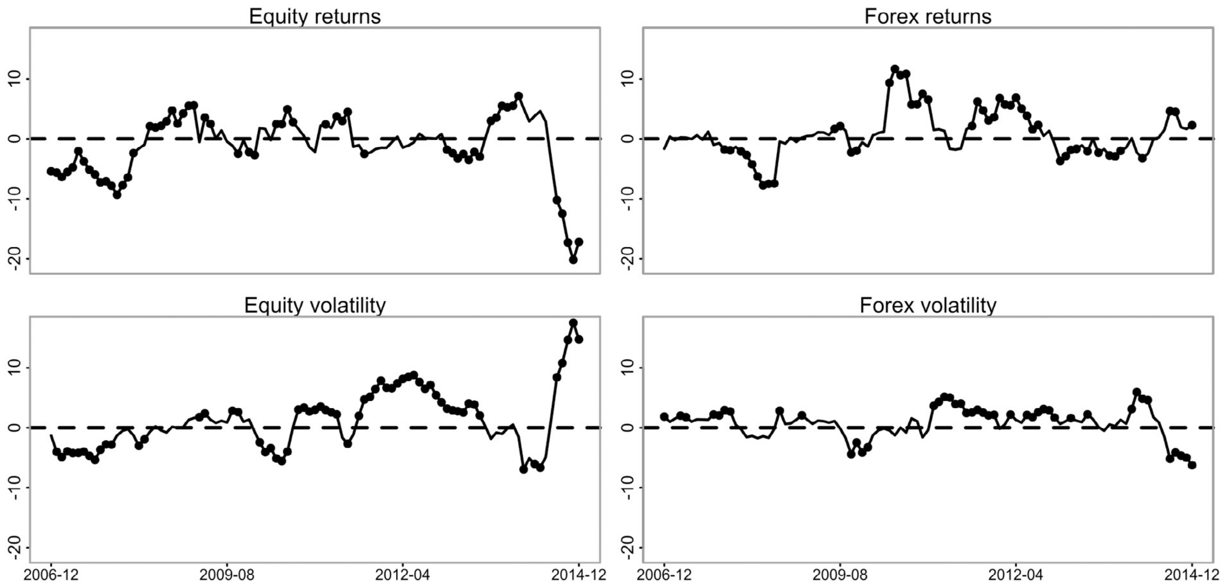

Fig. 10. Equity and forex market returns and volatility direct effects (out-vertex). *Note: Bullets denote statistically significant coefficients at the 5% significance level.*

Finally, we assess the volatility spillovers on the equity and forex markets. It appears that the size of the local market's volatility does not necessarily lead to larger volatility spillovers (Table 2), although such tendencies are more likely to be observed at the end of our sample period (Fig. 10). Periods with negative coefficients can be explained by conditions in which volatility in a given market is local in nature and does not spread across markets.

An increase in the volatility in the foreign exchange market increases investors' risks (Table 2). As local and international investors transfer investments to other (less risky) markets, the volatility in both markets increases and might be propagated. Such tendencies are observed in our results, as most of the coefficients on the foreign exchange volatility variable are positive and also significant in many instances (Fig. 10).

4.2.2. Effects of the in-vertex market

The key evidence from the effects of the in-vertex market is that the impact of variables related to the in-vertex market is frequently much less significant than the impact of out-vertex markets. The characteristics and market conditions of the markets from which volatility shocks are propagated therefore appear to be more important than the characteristics of the markets to which volatility shocks are transmitted. However, there are two variables that appear to systematically influence the extent of the received volatility spillovers: market capitalization and market liquidity (see Table 2 and Fig. 11). The larger the market, the less severe the volatility spillovers to that market. This finding suggests that market size protects a market from spillovers from other markets. Although this finding has certain implications for international equity portfolio diversification management, the effect of the market size is rather small compared to other variables.

Finally, trading activity increases the vulnerability of a country to receiving volatility shocks from other markets, which is evidenced by the effects of positive turnover ratios.

5. Conclusion

We study volatility spillovers among 40 equity markets over the period spanning from January 2, 2006, to December 31, 2014. We use daily closing-hours data across a number of time zones; therefore, we employ a careful data alignment strategy to study volatility spillovers using a Granger causality framework. Using information from Granger causality tests estimated for 97 overlapping subsamples, we construct Granger causality networks and study the structure of these networks along with the determinants of volatility spillovers. We employ spatial regressions that account for the endogenous interconnectedness of markets around the world.

Our specific findings can be summarized as follows:

(i) The interconnectedness of markets peaked during the financial crisis of 2008: 40% of the total of 1560 volatility spillovers among the 40 markets were identified and found to be statistically significant (see Fig. 2).
(ii) The interconnectedness of markets seems to be slightly declining, which might be sample-specific, as during recent years, we note an unprecedented level of connectivity of market volatilities, which declined recently (see Table 1).

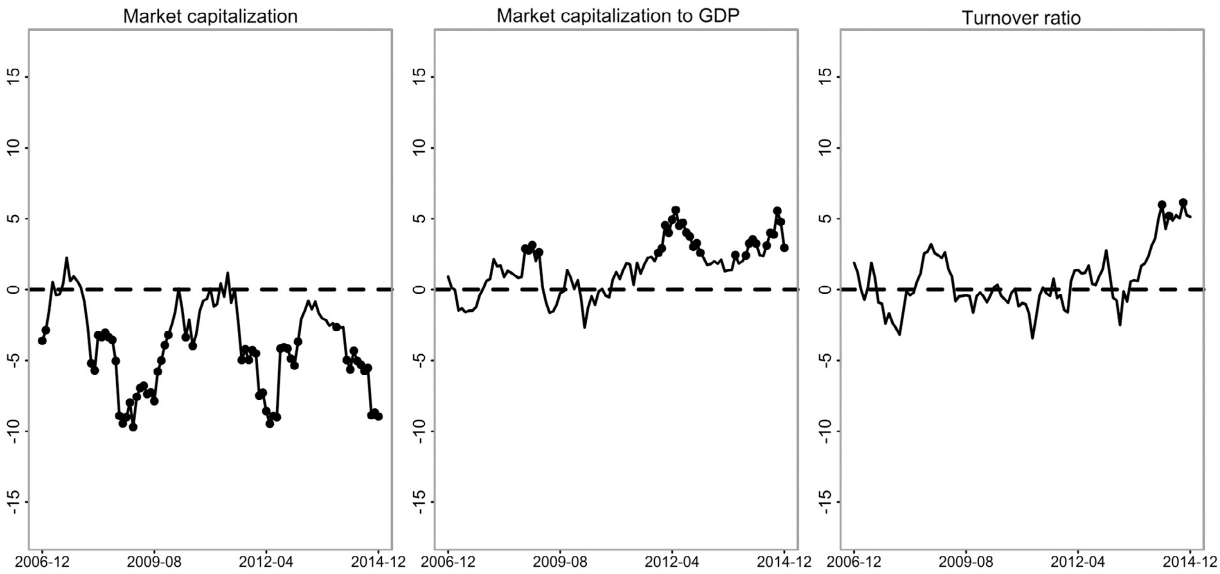

Fig. 11. Average direct effects of market capitalization and market liquidity (in-vertex). *Note: Bullets denote statistically significant coefficients at the 5% significance level.*

(iii) Volatility spillovers appear to be stable, as even after 12 months (non-overlapping subsample), over 50% of the relationships survive (see Fig. 4).

(iv) We find strong evidence of a temporal proximity effect for volatility spillovers. The further apart that closing hours are between stock markets, the lower the size of the volatility spillover between markets (see Fig. 7 and the results shown in Table 2). This finding implies that international diversification could be also determined via temporal proximity of stock markets.

(v) Temporal proximity effect is smaller but still statistically significant when the temporal distance to the US market is considered. This finding implies that the larger the temporal distance to the US market from a given market, the less likely such market is to propagate volatility spillovers to other markets in the world (see Fig. 7 and Table 2).

(vi) Markets are highly interconnected, as the statistically significant spatial coefficient is almost always over 0.90. This finding suggests that spatial effects cannot be ignored when modeling the interrelatedness of markets. More generally, a unit change in a variable of a vertex influences the creation (extent) of a node which is not connected to that vertex (indirect effect) or influences the creation (extent) of a node which is connected to that vertex (direct effect). In our data, indirect effects are much larger and thus cannot be ignored (see Fig. 7 for the spatial coefficient and Table 2 for direct and indirect effects). This result calls for new methods to build portfolios, which will take into account indirect (not only bi-variate) relationships between assets.

(vii) The larger the market (in terms of market capitalization), the larger the volatility spillover from that market. Simultaneously, the larger the market, the smaller the volatility shocks propagated to that market (see Table 2).

(viii) When markets are more liquid (in terms of turnover ratio), they propagate larger volatility shocks, but they are also subject to larger volatility shocks themselves (see Table 2).

(ix) More export-oriented countries are more likely to propagate larger volatility shocks (see Table 2).

To summarize, we show that networks of volatility spillovers capture the financial crisis and can be used to describe the interconnectedness of individual stock markets. We contribute to the econophysics literature in three ways. First, we use a spatial regression model to rigorously study how the structure of the network depends on properties of given vertices, i.e. markets. This approach can be further used to study different types of networks. Second, in a general way we enlarge the literature on return and volatility spillovers (e.g. [17–19,38]). Third, in a specific way we enrich the literature on financial crisis and market distress (e.g. [6,28–30]).

Acknowledgments

We benefited from helpful comments we received from two anonymous referees and participants at several presentations. This work was supported by the Slovak Research and Development Agency under the contracts Nos. APVV-0666-11 and APVV-14-0357. The authors also appreciate the support provided from the Slovak Grant Agency for Science (VEGA project No. 1/0406/17). Kočenda acknowledges research support from the GAČR Grant No. P402/12/G097 (DYME). The usual disclaimer applies.

References

[1] M.A.L. Caetano, T. Yoneyama, Boolean network representation of contagion dynamics during a financial crisis, Physica A 417 (2015) 1–6.
[2] M.F. da Silva, É.J.D.A.L. Pereira, A.M. da Silva Filho, A.P.N. de Castro, J.G.V. Miranda, G.F. Zebende, Quantifying the contagion effect of the 2008 financial crisis between the G7 countries (by GDP nominal), Physica A 453 (2016) 1–8.
[3] W. Chen, Y. Wei, B. Zhang, J. Yu, Quantitative measurement of the contagion effect between US and Chinese stock market during the financial crisis, Physica A 410 (2014) 550–560.
[4] E.C.M. Hui, K.K.K. Chan, The global financial crisis: Is there any contagion between real estate and equity markets? Physica A 405 (2014) 216–225.
[5] G. Dewandaru, R. Masih, A.M.M. Masih, Why is no financial crisis a dress rehearsal for the next? Exploring contagious heterogeneities across major Asian stock markets, Physica A 419 (2015) 241–259.
[6] . Š. Lyócsa, T. Výrost, E. Baumöhl, Stock market networks: The dynamic conditional correlation approach, Physica A 391 (2012) 4147–4158.
[7] S. Lahmiri, Long memory in international financial markets trends and short movements during 2008 financial crisis based on variational mode decomposition and detrended fluctuation analysis, Physica A 437 (2015) 130–138.
[8] P. Anagnostidis, C. Varsakelis, C.J. Emmanouilides, Has the 2008 financial crisis affected stock market efficiency? The case of Eurozone, Physica A 447 (2016) 116–128.
[9] R. Yang, X. Li, T. Zhang, Analysis of linkage effects among industry sectors in China's stock market before and after the financial crisis, Physica A 411 (2014) 12–20.
[10] K. Yim, G. Oh, S. Kim, An analysis of the financial crisis in the KOSPI market using Hurst exponents, Physica A 410 (2014) 327–334.
[11] E. Kantar, M. Keskin, B. Deviren, Analysis of the effects of the global financial crisis on the Turkish economy using hierarchical methods, Physica A 391 (2012) 2342–2352.
[12] A. Nobi, S.E. Maeng, G.G. Ha, J.W. Lee, Effects of global financial crisis on network structure in a local stock market, Physica A 407 (2014) 135–143.
[13] E.C.M. Hui, J. Chen, Investigating the change of causality in emerging property markets during the financial tsunami, Physica A 391 (2012) 3951–3962.
[14] T.U. Kuzubaş, I. Ömercikoğlu, B. Saltoğlu, Network centrality measures and systemic risk: An application to the Turkish financial crisis, Physica A 405 (2014) 203–215.
[15] K. Kanjamapornkul, R. Pinčák, E. Bartoš, The study of Thai stock market across the 2008 financial crisis, Physica A 462 (2016) 117–133.
[16] M. Majapa, S.J. Gossel, Topology of the South African stock market network across the 2008 financial crisis, Physica A 445 (2016) 35–47.
[17] B. Güloğlu, P. Kaya, R. Aydemir, Volatility transmission among Latin American stock markets under structural breaks, Physica A 462 (2016) 330–340.
[18] H. Boubaker, S. Ali Raza, On the dynamic dependence and asymmetric co-movement between the US and Central and Eastern European transition markets, Physica A 459 (2016) 9–23.
[19] T. Výrost, . Š. Lyócsa, E. Baumöhl, Granger causality stock market networks: Temporal proximity and preferential attachment, Physica A 427 (2015) 262–276.
[20] N. Al Rahahleh, M.I. Bhatti, Co-movement measure of information transmission on international equity markets, Physica A 470 (2017) 119–131.
[21] X. Liu, H. An, S. Huang, S. Wen, The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH–BEKK model, Physica A 465 (2017) 374–383.
[22] Q. Ji, J.F. Guo, Market interdependence among commodity prices based on information transmission on the internet, Physica A 426 (2015) 35–44.
[23] S. Lahmiri, Asymmetric and persistent responses in price volatility of fertilizers through stable and unstable periods, Physica A 466 (2017) 405–414.
[24] L. Liu, Y. Wang, Cross-correlations between spot and futures markets of nonferrous metals, Physica A 400 (2014) 20–30.
[25] S.H. Kang, C. Cheong, S.M. Yoon, Intraday volatility spillovers between spot and futures indices: Evidence from the Korean stock market, Physica A 392 (2013) 1795–1802.
[26] J.S. Kim, D. Ryu, Intraday price dynamics in spot and derivatives markets, Physica A 394 (2014) 247–253.
[27] S.H. Kang, C. Cheong, S.M. Yoon, Structural changes and volatility transmission in crude oil markets, Physica A 390 (2011) 4317–4324.
[28] T. Araújo, R. Louçã, The geometry of crashes a measure of the dynamics of stock market crises, Quant. Finance 7 (2007) 63–74.
[29] L. Sandoval Jr., I. De Paula Franca, Correlation of financial markets in times of crisis, Physica A 391 (2012) 187–208.
[30] M. Majapa, S.J. Gossel, Topology of the South African stock market network across the 2008 financial crisis, Physica A 445 (2016) 35–47.
[31] S. Lahmiri, A study on chaos in crude oil markets before and after 2008 international financial crisis, Physica A 466 (2017) 389–395.
[32] A. Sensoy, S. Yuksel, M. Erturk, Analysis of cross-correlations between financial markets after the 2008 crisis, Physica A 392 (2013) 5027–5045.
[33] G. Wu, The determinants of asymmetric volatility, Rev. Financ. Stud. 14 (2001) 837–859.
[34] R. Garcia, G. Tsafack, Dependence structure and extreme comovements in international equity and bond markets, J. Bank. Financ. 35 (2011) 1954–1970.
[35] S. Aboura, J. Chevallier, Cross-market spillovers with 'volatility surprise', Rev. Financ. Econ. 23 (2014) 194–207.
[36] G. Bekaert, C.R. Harvey, Emerging equity market volatility, J. Financ. Econ. 43 (1997) 29–77.
[37] G. Bekaert, M. Ehrmann, M. Fratzscher, A. Mehl, The global crisis and equity market contagion, J. Financ. 69 (2014) 2597–2649.
[38] N. Al Rahahleha, M. Ishaq Bhatti, Co-movement measure of information transmission on international equity markets, Physica A 470 (2017) 119–131.
[39] F.X. Diebold, K. Yilmaz, Financial and Macroeconomic Connectedness: A Network Approach To Measurement and Monitoring, Oxford University Press, Oxford, 2015.
[40] J. Baruník, E. Kočenda, L. Vácha, Gold, oil, and stocks: Dynamic correlations, Int. Rev. Econ. Financ. 42 (2016) 186–201.
[41] E. Baumöhl, E. Kočenda, Š. Lyócsa, T. Výrost, Networks of volatility spillovers among stock markets, in: KIER Working Papers 941, Institute of Economic Research, Kyoto University, Kyoto, 2016.
[42] M. Mink, Measuring stock market contagion: Local or common currency returns? Emerg. Mark. Rev. 22 (2015) 18–24.
[43] Y. Hong, A test for volatility spillover with application to exchange rates, J. Econometrics 103 (2001) 183–224.
[44] N.L. Johnson, Systems of frequency curves generated by methods of translation, Biometrika 36 (1949) 149–176.
[45] N.L. Johnson, Bivariate distributions based on simple translation systems, Biometrika 36 (1949) 297–304.
[46] D. Peña, J. Rodríguez, The log of the determinant of the autocorrelation matrix for testing goodness of fit in time series, J. Statist. Plann. Inference 136 (2006) 2706–2718.
[47] J. Lin, A.I. McLeod, Improved Peña–Rodriguez portmanteau test, Comput. Statist. Data Anal. 51 (2006) 1731–1738.
[48] G. Schwarz, Estimating the dimension of a model, Ann. Statist. 6 (1978) 461–464.
[49] A. Ghalanos, rugarch: Univariate GARCH Models, R Package Version 1.3-6., 2012.
[50] F. Lu, Y. Hong, S. Wang, K. Lai, J. Liu, Time-varying granger causality tests for applications in global crude oil markets, Energ. Econ. 42 (2014) 289–298.
[51] P. Boldi, S. Vigna, Axioms for centrality, Internet Math. 10 (2014) 222–262.
[52] L.C. Freeman, Centrality in social networks conceptual clarification, Soc. Networks 1 (1978) 215–239.
[53] J.P. Onnela, A. Chakraborti, K. Kaski, J. Kertész, A. Kanto, Dynamics of market correlations: Taxonomy and portfolio analysis, Phys. Rev. E 68 (2003) 056110.
[54] J.P. LeSage, An introduction to spatial econometrics, Rev. Econ. Ind. 123 (2008) 19–44.
[55] E. Hwang, H. Min, B. Kim, H. Kim, Determinants of stock market comovements among US and emerging economies during the US financial crisis, Econ. Model. 35 (2013) 338–348.

[56] K.F. Luchtenberg, Q.V. Vu, The 2008 financial crisis: Stock market contagion and its determinants, Res. Int. Bus. Financ. 33 (2015) 178–203.
[57] A. Mobarek, G. Muradoglu, S. Mollah, A.J. Hou, Determinants of time varying co-movements among international stock markets during crisis and non-crisis periods, J. Financ. Stabil. 24 (2016) 1–11.
[58] R. Bivand, spdep: Spatial Dependence: Weighting Schemes, Statistics and Models, R Package Version 0.5-46, 2012.
[59] W.K. Newey, K.D. West, Automatic lag selection in covariance matrix estimation, Rev. Econ. Stud. 61 (1994) 631–653.