

KIER DISCUSSION PAPER SERIES

KYOTO INSTITUTE OF ECONOMIC RESEARCH

Discussion Paper No. 941

“Networks of volatility spillovers among stock markets”

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May 2016



KYOTO UNIVERSITY

KYOTO, JAPAN

Networks of volatility spillovers among stock markets

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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 confirm 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. Our results also link spillovers of escalating magnitude with increasing market size, market liquidity and economic openness.

JEL Classification: C31, C58, F01, G01, G15

Keywords: volatility spillovers, stock markets, shock transmission, Granger causality network, spatial regression, financial crisis

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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. 1/0392/15). The paper was completed when Evžen Kočenda was a Visiting Professor at the Institute for Economic Research, Kyoto University, whose hospitality is gratefully acknowledged. The usual disclaimer applies.

1 Introduction

How does volatility propagate across stock markets over space and time? This question is central to portfolio diversification strategies and their management, as stock volatility has become a standard measure of risk in finance (Garcia and Tsafack, 2011; Aboura and Chevallier, 2014). Volatility is propagated across markets via spillovers that exert greater impact when markets are more connected (Diebold and Yilmaz, 2015). In the comprehensive approach presented in this paper, we answer the central question posed above by analyzing volatility spillovers across 40 stock markets over the 2006–2014 period. In so doing, we employ a network approach that has recently become a major technique for studying issues related to market connectedness.

Our analysis is further motivated by the need to better capture the underlying phenomena behind the elusive dynamics of volatility spillovers, namely crashes, distress and contagion. Crashes in financial markets are unexpected, by definition, 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 (Wu, 2001). The recent financial crisis (2008), the sovereign-debt crises (2010–2011), and the most recent Chinese stock market turmoil (2015) have shown us that even local market-specific problems might dramatically influence stock markets around the world (e.g., Arghyrou and Kontonikas, 2012; Beirne and Fratzscher, 2013). It seems that the growing interdependence between economies, markets, and asset classes has resulted in increased transmission of negative shocks across markets.

We are also motivated in this research by the fact that most economic agents are naturally interested in market linkages during times of market distress, which are frequently accompanied by increased market volatility. This is the domain of the transmission of negative shocks and of so-called “contagion”. Country-specific fundamentals generally fail to explain both the timing and the severity of financial contagion in individual countries (Fratzscher, 2002). Moreover, identifying contagion necessitates establishing a causal link – as opposed to the mere co-occurrence of crises that might simply result from common shocks (Allen and Gale, 2000; Kaminsky and Reinhart, 2000).

We contribute to the literature in several ways. We follow key motivational underpinnings and establish causal links in market interdependence. Using the network approach to analyze volatility spillovers, we show that spillovers in stock markets

significantly escalate during the financial crisis (2008) and the European sovereign debt crisis (2011). Volatility spillovers are highly persistent in general, but their size markedly diminishes as the time-distance (temporal proximity) among markets increases. Our results also link the escalating magnitude of spillovers with increasing market size, market liquidity and economic openness. There are numerous identified market-specific differences, and we argue that their correlations with the size and persistence of spillovers can be exploited more subtly in terms of international portfolio diversification.

The remainder of this paper is organized as follows. We provide a brief literature overview in Section 2. In Sections 3 and 4, we describe our data and methodology. In Section 5, we present and discuss our results. Section 6 briefly concludes with some implications.

2 Brief literature review

Recently, several studies have investigated volatility transmission across various markets. Mensi et al. (2013) examine return and volatility links among the S&P500 and commodity price indices for energy, food, gold, and beverages from 2000 to 2011 and find that the gold and oil markets appear to be strongly influenced by US stock market volatility. Nazlioglu et al. (2013) study volatility transmission between oil and selected agricultural commodity prices (wheat, corn, soybeans, and sugar) from 1986 to 2011. Their results from variance causality tests differ depending on the periods examined but reveal significant volatility spillovers from the oil market to the commodity markets (except for sugar) during the post-crisis period. Baruník et al. (2015) analyze volatility spillovers on the oil commodity market over the 1987–2014 period and show that spillovers increase after 2008. However, they also show that relatively balanced and low asymmetries in volatility spillovers correlate well with the ongoing financialization of oil commodities and the advent of heightened oil exploration and production in the US. In addition, Baruník et al. (2016a) analyze most liquid US stocks in seven sectors and offer ample evidence of the asymmetric connectedness of stocks at the disaggregate level. The asymmetries in spillovers propagate in such a way that although negative spillovers are often of substantial magnitude, they do not strictly dominate positive spillovers. As was the case in the commodities' markets, the overall intra-market connectedness of US stocks is shown to increase substantially over the recent financial crisis.

Hwang et al. (2013) investigate the recent financial crisis (which originated in the US) and aim to find the mechanism by which the crisis was transmitted into emerging markets;

moreover, these authors attempt to identify the determinants of co-movements between the US and ten emerging stock markets. The transmission mechanism is understood as the same is defined by Chiang et al. (2007), i.e., who reveal three different phases of crisis transmission: (i) the contagion period, i.e., a sudden significant increase in dynamic correlations; (ii) the herding phase, i.e., when correlations remain at high levels; and (iii) the post-crisis period, when correlations should adjust to pre-crisis levels. The transmission mechanism defined in this manner varies across the examined emerging markets; thus, not all phases have been identified in all countries. Moreover, the daily sovereign CDS spread, TED spread, VIX index for the US stock market, information on foreign institutional investments, and one month's volatility index for the exchange rate are used as exogenous variables to determine dynamic correlations. The first two variables are associated with a decrease in the dynamic correlations, whereas the remaining three accompany increased correlations.

Luchtenberg and Vu (2015) also investigate the determinants of worldwide contagion during the recent financial crisis. However, their sample includes developed stock markets, and the results confirm that mature markets transmit and receive contagion. Both economic fundamentals (such as trade structure, interest and inflation rates, industrial production, and regional effects) and investors' risk aversion are significantly related to the level of contagion. These findings are in line with those of Baur (2012), Kenourgios and Padhi (2012), and Bekaert et al. (2014) and suggest that investors should definitely consider diversifying by asset classes or sectors, as the benefits stemming from international diversification have been significantly reduced in recent years. Nonetheless, even diversification by asset classes might not yield desired outcomes, as Baruník et al. (2016b) show.

In terms of methodology, a dominant vehicle in research on volatility spillovers is a version of the GARCH model, which thus resembles research on volatility itself (for example, Beirne et al. 2013; Lin, 2013; Li and Giles, 2015, among others). Diebold and Yilmaz (2009, 2012) make a new contribution to the spillover literature by developing a volatility spillover index based on forecast error variance decompositions from vector autoregressions (VARs) to measure the extent of volatility transfer among markets. Our approach in assessing market connectedness via a network-model-based measure represents another step in the further employment of network models to measure volatility spillovers.

The rest of the paper is organized as follows. In Sections 3 and 4, we describe our data and methodology. In Section 5, we present and discuss our results. Section 6 briefly concludes and presents some implications.

3 Data description and return alignment procedure

Our sample covers the daily stock market index data 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 and stock market indices is available in Appendix A. Data on annual market capitalization and market capitalization to GDP are from the World Development Indicators database of the World Bank¹. Data on equity prices and exchange rates are from the Thomson Reuters Datastream. 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 (Mink, 2015).

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. For example, daily data downloaded from well-known financial databases provide closing prices for the US and Japanese stock market indices at the same time t . Assume that we want to test a bi-directional link (in the Granger sense) between these two markets. In one direction² (US \nrightarrow Japan), it is perfectly reasonable to explain returns/volatilities in the Japanese market at (calendar) date t with those from the US from date $t-1$. Any software application will perform the Granger causality test in this manner. However, in the second direction (Japan \nrightarrow US), trading in the Japanese market is already over, and including the value from Japan at date $t-1$ thus actually takes into account the second available value. The problem of different trading hours is even more severe when considering the closing prices from the same day collected from non-overlapping markets. For example, when computing the correlations between the US and Japanese market, the values from the same date from the US are actually subject to forward-looking bias. Different trading hours may, however, be useful in Granger causality testing and can be used to our advantage, but only after aligning the data properly.

Our return alignment procedure follows VÝrost et al. (2015), which we briefly summarize below:

¹ Appendixes B and C present a description of the data used in spatial models and their basic characteristics.

² Symbol " \nrightarrow " denotes Granger non-causality, i.e., it should be read as "does not Granger-cause".

- (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

4 Applied methodology

4.1 Granger causality networks

First, we outline our approach to assess links between volatilities of market pairs. Following Hong (2001) in testing for volatility spillovers, we formally set the “*causality in variance hypothesis*” in the following form:

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

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

The $I_t = (I_{1t}, I_{2t})$ 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} .

³ Further details are available in Vřrost et al. (2015).

In the following, we will describe a procedure to test for causality in variance based on Cheung and Ng (1996), Hong (2001) and Lu et al. (2014). 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–December 2006 and end with a subsample from January 2014–December 2014.

4.2 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 (Hong, 2001). 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 :

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

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:

$$r_t = \alpha_0 + \alpha_1 FX_{t-1} + \alpha_2 STX_{t-1} + \alpha_3 GOLD_{t-1} + \alpha_4 OIL_{t-1} + \alpha_5 VIX_{t-1} + z_t$$

$$\left(1 - \sum_{i=1}^p \phi_i L^i \right) (1-L)^d z_t = \left(1 + \sum_{j=1}^q \theta_j L^j \right) \varepsilon_t \quad (2)$$

$$\varepsilon_t = \sigma_t \eta_t, \quad \eta_t \sim iid(0,1),$$

where η_t follows the Johnson-SU distribution (Johnson, 1949a, b) with the probability density function:

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

where $z = \zeta^{-1}(\sinh^{-1}(x) - \lambda)$ and $J = \zeta^{-1}(x^2 + 1)^{-1/2}$. Here, λ and ζ are parameters that determine the skewness and kurtosis of the distribution. The motivation for this particular choice of the distribution of η_t was based on Choi and Nam (2008), who presented evidence that such distributions can account for asymmetries and extreme tail events, which are often found in

financial markets. 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 of Bollerslev (1986):

$$\sigma_t^2 = \omega + \sum_{k=1}^r \alpha_k \varepsilon_{t-k}^2 + \sum_{l=1}^s \beta_l \sigma_{t-l}^2, \quad (4)$$

we also consider the following specifications: AVGARCH (Taylor, 1986), NGARCH (Higgins and Bera, 1992), EGARCH (Nelson, 1991), GJR-GARCH (Glosten et al., 1993), APARCH (Ding et al., 1993), NAGARCH (Engle and Ng, 1993), TGARCH (Zakoian, 1994), FGARCH (Hentschel, 1995), and CSGARCH (Lee and Engle, 1999). The preferred model is chosen based on the following steps⁴:

- 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 based on the Peña and Rodríguez (2006) test with Monte Carlo critical values (see Lin and McLeod, 2006)⁵. 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; Schwarz, 1978).
 - 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.

⁴ The entire analysis is conducted in R software using the rugarch (Ghalanos, 2012b) packages.

⁵ Autocorrelation of standardized residuals and their squares was tested for up to 20 lags.

4.3 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 $j \not\Rightarrow i$) using standardized conditional demeaned variances $s_{ii}^2 = (\varepsilon_{ii} / \sigma_{ii})^2 - (\sum_{k=1}^T (\varepsilon_{ik} / \sigma_{ik})^2) / T$ from the preferred ARFIMAX-GARCH specifications estimated in the previous section. We calculate the cross-lagged correlations:

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

where

$$\hat{C}_{ij}(k) = \frac{1}{T} \sum_{t=k+1}^T s_{ii}^2 s_{jj}^2, k \geq 0. \quad (6)$$

It should be noted that prior to the calculation of cross-lagged correlations, standardized conditional mean returns were aligned as specified in Section 2.⁶

Next, the null hypothesis of Granger non-causality ($j \not\Rightarrow i$) is tested using the test statistic proposed by Hong (2001):

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

where we use the Bartlett weighting scheme:

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

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 (Hong, 2001), 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:

⁶ Note also that k may sometimes (in addition to cases described by Eq. 9) be equal to 0 and remain valid for testing the hypothesis $j \not\Rightarrow i$. The minimum k depends on the alignment of the standardized conditional mean returns (see Section 2).

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

A simple extension of Lu et al. (2014) allows for instantaneous volatility spillovers from market j to market i , by allowing $k = 0$ in calculating cross-lagged correlations, i.e.:

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

This extension is used for markets with the same closing hours. 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.

4.4 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.

4.4.1 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, $\text{deg}^{\text{in}}(i)$ defined as:

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

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

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

Here, the $|\cdot|$ 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 . The closeness of vertex i is based on measuring the total sum of shortest paths to all other vertices in the network. The betweenness of a vertex i is based on measuring the total sum of shortest paths between any pair of vertices (except i), which pass through vertex i . 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, which is also the most likely case of Granger causality volatility spillover networks constructed in this study. For example, in a simple system of three markets, the only two relationships might be $A \Rightarrow B$ and $A \Rightarrow C$, which means that market A is not reachable from market B nor from market C .

If there is no path between two vertices, we can set the shortest path to $d(i,j) = \infty$ and define conveniently that $1/d(i,j) = 0$. Boldi and Vigna (2014) use this approach and then proceed to define the harmonic centrality of market i as:

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

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

4.4.2 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 (Freeman, 1979). 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:

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

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

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

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

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

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

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 (Eq. 13–14). Similarly, if volatilities in the equity markets are dominated by a single event in one market, we might observe an increase in concentration measures (Eq. 15–16).

4.4.3 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 as in Onnela et al. (2003b). 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:

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

Multi-step survival ratio at time t is then:

$$SR(s, t) = \frac{|E_t \cap E_{t-1} \dots \cap E_{t-s}|}{|E_{t-s}|} \quad (19)$$

where s is the number of steps. Observing one- and multi-step survival ratios lets 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.

4.5 Spatial regression

4.5.1 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:

$$s_{ijt} = \begin{cases} \bar{\rho}_{ij}(M), & i \Rightarrow j \\ 0, & i \not\Rightarrow j \vee \bar{\rho}_{ij}(M) < 0 \end{cases} \quad (20)$$

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:

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

In our setting, the variable of interest (\mathbf{y}) corresponds to Eq. 19. 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 $j = l$)⁷ and 0 otherwise.

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 (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 (LeSage, 2008). 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 $S_k(\mathbf{W}) = (\mathbf{I} - \rho\mathbf{W})^{-1}\beta_k$, 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

⁷ 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.

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 .

4.5.2 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; the detailed definitions of the variables are presented in Appendix B. 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.

First, we employ the following set of explanatory variables to capture various angles of market size: log of the market capitalization expressed in current US dollars, log of the market capitalization to GDP, and log of the turnover ratio.

Then, we consider equity market conditions using two variables: equity market returns over the given subsample and realized volatility on the equity market calculated from daily returns over the given subsample.

In addition, we also consider conditions on the foreign exchange market with foreign exchange returns measured in terms of the local currency to the US dollar and realized volatility on the foreign exchange market calculated from daily returns over the given subsample.

Furthermore, we account for the external relationship of a given country by employing the following: net trade to GDP; and foreign direct investments measured as net inflows to GDP and net outflows to GDP.

Finally, to capture how distant markets are in terms of time, we use two time-proximity measures: temporal proximity between closing hours of two markets (always positive) and temporal proximity between the out-vertex market and the US market (always positive).

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. In the example above, the observation in 2009 received a weight of 0.75 and the observation in 2010 received a weight of 0.25. 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.

In Table 2, 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 .⁸

⁸ The analysis was performed in R using the `spdep` package (Bivand, 2012).

5 Empirical results and discussion

5.1 Connectedness of markets: A network approach to return spillovers

Before we present our results, we illustrate the need to use network variables to describe complex relationships between markets. To this end, we plot two Granger causality networks. Figure 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, Figure 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.

<< *Insert Figure 1 around here* >>

In Figure 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). A notable observation is the sharp drop after 2011, leaving only approximately 15% of the statistically significant volatility spillovers.

One possible explanation is that we actually observe a period of intense cross-market relationships beginning in 2007 and ending in 2012.

<< *Insert Figure 2 around here* >>

To further elaborate on the connectedness of the markets under study, 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.

<< *Insert Table 1 around here* >>

Another notable result revealed from a further analysis of in- and out-degree centralization is the correlation between these two connectedness measures (plotted in Figure 3). The left panel of Figure 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 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.

<< *Insert Figure 3 around here* >>

The stability of our Granger causality networks is assessed using survival ratios that are plotted in Figure 4. Although we use rolling subsamples, the structure of the volatility spillover network appears to be stable over time: more than half of the surviving spillovers remain even after a year, which indicates that the structure of the network changes only moderately.

<< *Insert Figure 4 around here* >>

Thus far, our results reveal that volatility spillovers are quite common around the world; moreover, there are some markets that tend to propagate shocks more intensively than others, while other markets are more prone to receive shocks or to be influenced rather than transmitting shocks or influencing other markets. The next two figures depict the most and least influential and influenced markets (Figures 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 ignore how closely they are trading, i.e., the temporal proximity effect. The most influenced markets (see Figure 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.

<< *Insert Figure 5 around here* >>

<< *Insert Figure 6 around here* >>

5.2 Determinants of volatility spillovers

Our baseline results that are based on specifications described in Section 3.5.2 are presented in Table 2, which summarizes model coefficients. The dynamics of the effects is presented as a complementary representation in graphical form in Figures 7–11.

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

5.2.1 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 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. We plot the dynamics of the market liquidity effect in Figure 8 and observe that markets with a higher turnover ratio propagate larger volatility spillovers in the network.

<< Insert Table 2 around here >>

<< Insert Figure 7 around here >>

<< Insert Figure 8 around here >>

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

<< Insert Figure 9 around here >>

We have also studied the effects of the equity and foreign exchange market conditions of the out-vertex market on volatility spillovers (Figure 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.

<< Insert Figure 10 around here >>

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 (Figure 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 (Figure 10).

5.2.2 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 Figure 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.

<< Insert Figure 11 around here >>

6 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 main findings can be summarized as follows:

- 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. A similar peak was also found for the period between 2011 and 2012 during the European debt crisis, where more than 35% of all possible volatility spillovers were statically significant (see Figure 2).
- 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, leading to decreases in the interconnectedness of markets at both the market and global levels (see Table 1).

- Volatility spillovers appear to be stable, as even after 12 months (non-overlapping subsample), over 50% of the relationships survive (see Figure 4). However, we conclude that volatility spillovers are less persistent than return spillovers, as the ratio of surviving return spillovers exceeds 70%, as shown by Lyócsa et al. (2015).
- 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 Figure 7 and the results shown in Table 2).
- 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 Figure 7 and the results in Table 2).
- 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. For example, a unit change in a variable affecting the volatility spillovers on several markets can have a much larger effect on the propagation of volatility spillovers into some other market (indirect effect) than a unit change of the same variable on the given market (direct effect). In fact, within our empirical framework, indirect effects were always larger than direct effects, sometimes over 20 times larger (see Figure 7 for the spatial coefficient and Table 2 for direct and indirect effects).
- 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).
- 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).
- More export-oriented countries are more likely to propagate larger volatility shocks (see Table 2).
- During times of higher equity and foreign exchange volatility, larger volatility spillovers are more likely to occur. However, these results are not entirely

unambiguous and should be taken cautiously, as for a few periods, the opposite effect was observed (see Table 2).

There are several implications that can be drawn from our study. For example, if the interconnectedness of markets (through volatility) depends not only on fundamentals but also on the temporal distance between trading sessions, then diversifying equity portfolios across the globe (with regard to temporal distances) might be beneficial. There are several explanations at hand for such an effect. Perhaps it takes time (a larger temporal distance) for new information to be correctly priced into assets. Another explanation might be that with increasing temporal distance between two markets, new relevant information arrives that counteracts or distorts the previous information leading to smaller volatility spillovers.

Our study also provides a strong link between market interconnectedness and portfolio diversification. When markets are interconnected, two types of events matter for volatility shock propagation. First, these events are happening on a given market. Second, these events are increasingly happening in other markets that are interrelated through market volatility. The evidence thus implies that choosing markets that exhibit lower levels of interconnectedness (measured via network characteristics) can be beneficial for international portfolio diversification purposes.

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Appendix A

Code	Country	Index
<i>Frontier markets</i>		
AR	Argentina	MSCI ARGENTINA
HR	Croatia	CROATIA CROBEX
EE	Estonia	OMX TALLINN (OMXT)
RO	Romania	ROMANIA BET
SL	Slovenia	SLOVENIA-DS Market
<i>Emerging markets</i>		
BR	Brazil	MSCI BRAZIL
CZ	Czech Republic	PRAGUE SE PX
HU	Hungary	BUDAPEST
CN	China	SHANGHAI SE COMPOSITE
IN	India	S&P BSE NATIONAL 200
ID	Indonesia	IDX COMPOSITE
MY	Malaysia	DJGL MALAYSIA
MX	Mexico	MEXICO IPC (BOLSA)
PL	Poland	WARSAW GENERAL INDEX 20
RU	Russia	RUSSIA-DS Market
ZA	South Africa	SOUTH AFRI-DS Market
KR	Republic of Korea	KOREA SE KOSPI 200
TH	Thailand	BANGKOK S.E.T.
TR	Turkey	TURKEY-DS Market
<i>Developed markets</i>		
AU	Australia	ASX 200
AT	Austria	ATX - AUSTRIAN TRADED INDEX
BE	Belgium	BEL ALL SHARE
CA	Canada	S&P/TSX Composite index
DK	Denmark	DENMARK-DS Market
FI	Finland	OMX HELSINKI 25
FR	France	FRANCE CAC 40
DE	Germany	DAX 30 PERFORMANCE
GR	Greece	GREECE-DS Market
IE	Ireland	IRELAND SE OVERALL
IT	Italy	MSCI ITALY
JP	Japan	NIKKEI 225 STOCK AVERAGE
NL	Netherlands	AMSTERDAM MIDKAP
HK	Hong Kong	HANG SENG
NO	New Zealand	AEX ALL SHARE
PT	Portugal	PORTUGAL PSI-20
ES	Spain	IBEX 35
SE	Sweden	OMX STOCKHOLM 30
CH	Switzerland	SSMI
UK	United Kingdom	FTSE ALL SHARE
US	United States of America	RUSSELL 2000

Appendix B

Indicator name	Definition
Market capitalization of listed companies (% of GDP)	Market capitalization (also known as market value) is the share price times the number of shares outstanding. Listed domestic companies are the domestically incorporated companies listed on the country's stock exchanges at the end of the year. This indicator does not include investment companies, mutual funds, or other collective investment vehicles.
Market capitalization of listed companies (current US\$)	Market capitalization (also known as market value) is the share price times the number of shares outstanding. Listed domestic companies are domestically incorporated companies listed on the country's stock exchanges at the end of the year. This indicator does not include investment companies, mutual funds, or other collective investment vehicles. Data are in current US dollars.
Net trade in goods and services (% of GDP)	Net trade in goods and services is derived by offsetting imports of goods and services against exports of goods and services. Exports and imports of goods and services comprise all transactions involving a change of ownership of goods and services between the residents of one country and the rest of the world. Data are in current US dollars and are divided by GDP.
Turnover ratio (%)	Turnover ratio is the total value of shares traded during the period divided by the average market capitalization for the period. Average market capitalization is calculated as the average of the end-of-period values for the current period and the previous period.
Foreign direct investment, net inflows (% of GDP)	Foreign direct investments are the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. Such investments are the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors and is divided by GDP.
Foreign direct investment, net outflows (% of GDP)	Foreign direct investments are the net outflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. Such investments are the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net outflows of investment from the reporting economy to the rest of the world and is divided by GDP.

Source: World Bank WDI database

Appendix C Descriptive statistics variables used in spatial regressions

	Equity returns		Equity volatility		Forex returns		Forex volatility		Market cap.		Market cap. to GDP		Net trade to GDP		FDI net outflows to GDP		FDI net inflows to GDP	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
<i>Frontier markets</i>																		
AR	0.318	0.540	0.943	0.260	0.139	0.156	0.695	0.756	24.637	0.314	2.398	0.565	0.029	0.012	0.310	0.170	1.872	0.374
HR	0.021	0.360	0.889	0.532	0.003	0.099	0.981	0.304	24.035	0.326	3.825	0.325	-0.023	0.034	0.519	0.880	4.020	2.824
EE	0.100	0.404	0.968	0.368	-0.002	0.095	0.977	0.311	21.711	0.389	2.528	0.428	0.002	0.056	4.495	4.075	8.183	3.624
RO	0.065	0.403	0.935	0.424	0.030	0.137	0.976	0.328	23.911	0.336	2.661	0.374	-0.069	0.047	0.103	0.150	3.513	2.369
SL	1.378	3.973	0.382	0.942	-0.002	0.095	0.977	0.311	23.040	0.482	3.044	0.484	0.021	0.030	0.980	1.637	1.301	1.227
<i>Emerging markets</i>																		
BR	0.059	0.262	0.925	0.400	0.022	0.162	0.931	0.372	27.763	0.212	4.068	0.220	-0.001	0.014	0.768	0.630	2.851	0.560
CZ	-0.016	0.247	0.932	0.437	-0.001	0.131	0.976	0.340	24.544	0.207	3.099	0.255	0.040	0.014	1.705	0.888	3.703	0.906
HU	0.015	0.313	0.956	0.357	0.024	0.149	0.981	0.322	23.971	0.283	2.969	0.298	0.043	0.029	11.935	20.587	13.187	20.459
CN	0.173	0.625	0.961	0.347	0.003	0.099	0.963	0.369	29.019	0.178	4.240	0.441	0.046	0.024	1.427	0.228	4.069	0.481
IN	0.148	0.321	0.938	0.390	0.044	0.113	1.001	0.261	27.817	0.203	4.368	0.244	-0.051	0.012	0.906	0.476	2.057	0.606
ID	0.217	0.327	0.979	0.292	0.038	0.113	0.897	0.418	26.290	0.459	3.668	0.217	0.022	0.019	0.905	0.240	1.967	0.525
MY	0.110	0.215	0.955	0.378	-0.011	0.065	1.005	0.194	26.569	0.296	4.948	0.170	0.164	0.048	5.323	0.922	3.595	1.247
MX	0.118	0.238	0.941	0.371	0.032	0.118	0.959	0.388	26.728	0.227	3.623	0.180	-0.015	0.004	0.983	0.447	2.398	0.460
PL	0.005	0.242	0.969	0.309	0.018	0.181	0.964	0.373	25.783	0.185	3.512	0.221	-0.013	0.020	0.960	0.995	2.971	1.912
RU	0.035	0.322	0.890	0.480	0.056	0.165	0.694	0.319	27.509	0.245	4.023	0.371	0.081	0.013	3.360	0.325	3.213	0.785
ZA	0.108	0.164	0.945	0.315	0.071	0.151	0.983	0.283	27.169	0.119	5.206	0.238	-0.007	0.012	0.666	0.820	1.817	0.797
KR	0.068	0.208	0.957	0.379	0.024	0.153	0.035	0.305	27.598	0.220	4.471	0.157	0.030	0.017	2.163	0.310	0.891	0.100
TH	0.130	0.284	0.993	0.272	0.010	0.050	0.682	0.595	26.161	0.437	4.327	0.297	0.045	0.025	2.027	0.909	3.047	1.034
TR	0.134	0.349	0.980	0.238	-0.017	0.064	0.898	0.494	26.212	0.246	3.529	0.212	-0.053	0.018	0.371	0.159	2.087	0.786
<i>Developed markets</i>																		
AU	0.026	0.185	0.965	0.357	0.033	0.152	0.959	0.392	27.807	0.162	4.637	0.238	-0.009	0.010	1.188	1.063	3.866	0.625
AT	-0.016	0.274	0.954	0.385	-0.002	0.095	0.977	0.311	25.319	0.417	3.209	0.449	0.034	0.009	6.072	5.298	3.662	4.941
BE	0.024	0.229	0.962	0.345	-0.002	0.095	0.977	0.311	26.352	0.195	4.039	0.236	0.003	0.009	13.099	12.547	15.786	13.241
CA	0.042	0.171	0.904	0.495	0.007	0.097	0.963	0.343	28.234	0.178	4.731	0.163	-0.004	0.016	3.341	0.852	3.485	1.834
DK	0.101	0.258	0.954	0.372	-0.003	0.095	0.977	0.312	26.062	0.159	4.165	0.189	0.045	0.011	2.977	1.472	0.834	1.715
FI	0.053	0.268	0.976	0.327	-0.002	0.095	0.977	0.311	25.820	0.370	4.153	0.388	0.024	0.023	2.946	3.251	1.799	3.570
FR	0.001	0.198	0.970	0.344	-0.002	0.095	0.977	0.311	28.281	0.154	4.264	0.187	-0.013	0.004	2.862	1.660	1.495	1.039
DE	0.086	0.214	0.961	0.356	-0.002	0.095	0.977	0.311	27.997	0.150	3.719	0.180	0.057	0.005	3.190	0.751	1.707	0.643
GR	-0.110	0.322	0.966	0.235	-0.002	0.095	0.977	0.311	25.005	0.647	3.215	0.595	-0.060	0.040	0.675	0.539	0.870	0.426
IE	-0.002	0.291	0.945	0.419	-0.002	0.095	0.977	0.311	25.249	0.341	3.664	0.353	0.165	0.052	14.470	7.104	17.124	4.151
IT	-0.047	0.223	0.971	0.323	-0.002	0.095	0.977	0.311	26.951	0.384	3.154	0.395	0.000	0.015	1.834	1.033	0.800	0.599
JP	0.028	0.257	0.964	0.337	-0.005	0.116	0.987	0.250	28.958	0.098	4.265	0.187	-0.002	0.016	1.987	0.475	0.200	0.173
NL	0.016	0.223	0.936	0.434	-0.002	0.095	0.977	0.311	27.176	0.190	4.323	0.228	0.090	0.012	38.298	19.815	35.289	22.405
HK	0.075	0.259	0.943	0.441	-0.019	0.155	0.975	0.333	27.697	0.097	6.127	0.137	0.057	0.040	33.905	6.653	31.100	4.278
NO	0.042	0.249	0.923	0.422	0.007	0.127	0.979	0.317	26.204	0.199	3.984	0.248	0.131	0.019	3.461	1.941	3.461	1.941
PT	-0.022	0.244	0.974	0.283	-0.002	0.095	0.977	0.311	25.108	0.230	3.538	0.221	-0.045	0.039	2.722	1.687	3.903	1.300
ES	0.011	0.228	0.987	0.300	-0.002	0.095	0.977	0.311	27.776	0.172	4.387	0.174	-0.016	0.033	3.778	3.060	3.122	1.170
SE	0.064	0.221	0.959	0.367	0.000	0.131	0.975	0.337	26.929	0.208	4.592	0.208	0.058	0.008	5.863	1.958	3.220	3.148
CH	0.026	0.184	0.955	0.390	-0.034	0.090	0.981	0.300	27.708	0.093	5.223	0.204	0.098	0.011	8.306	4.642	3.823	4.436
UK	0.034	0.165	0.954	0.397	0.063	0.138	0.942	0.333	28.718	0.156	4.736	0.156	-0.022	0.004	3.709	4.825	3.760	2.782
US	0.083	0.221	0.950	0.410	0.019	0.118	0.959	0.364	30.457	0.133	4.712	0.127	-0.037	0.009	2.528	0.379	1.686	0.419

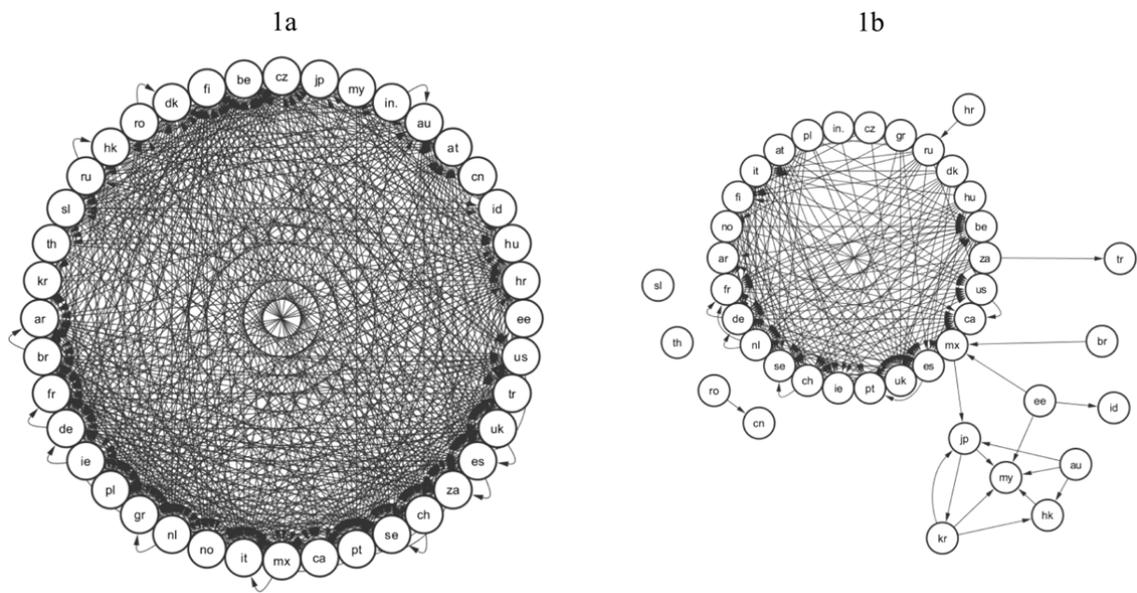


Figure 1: Granger causality networks

Note: 1a corresponds to a subsample beginning in January 2008 and ending in December 2008, and 1b corresponds to a subsample beginning in September 2013 and ending in August 2014.

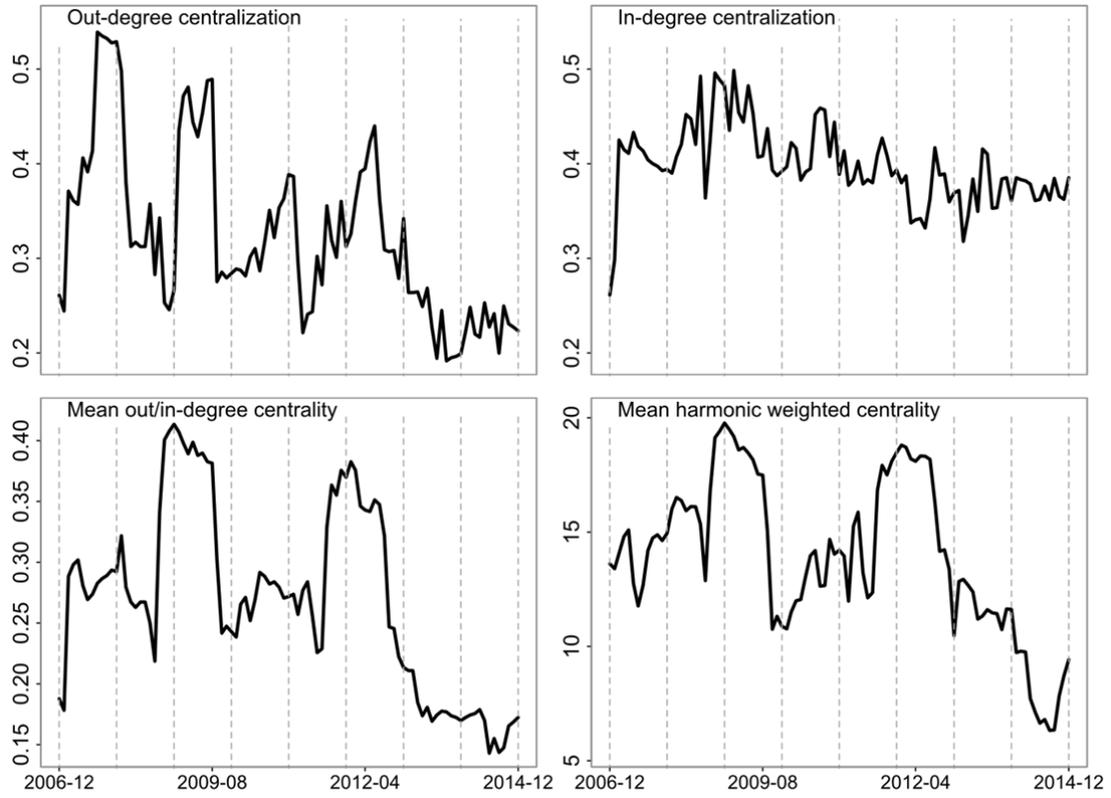


Figure 2: Time-varying spillovers: network centralization

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
<i>Frontier markets</i>															
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%
<i>Emerging markets</i>															
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%
<i>Developed markets</i>															
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%
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: 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. ^a, ^b, and ^c denote statistical significance at the 10%, 5%, and 1% level, respectively. We have used the HAC Newey-West standard errors estimated with automatic bandwidth selection and a quadratic spectral weighting scheme as in Newey and West (1994). MG corresponds to the pooled mean group estimator.

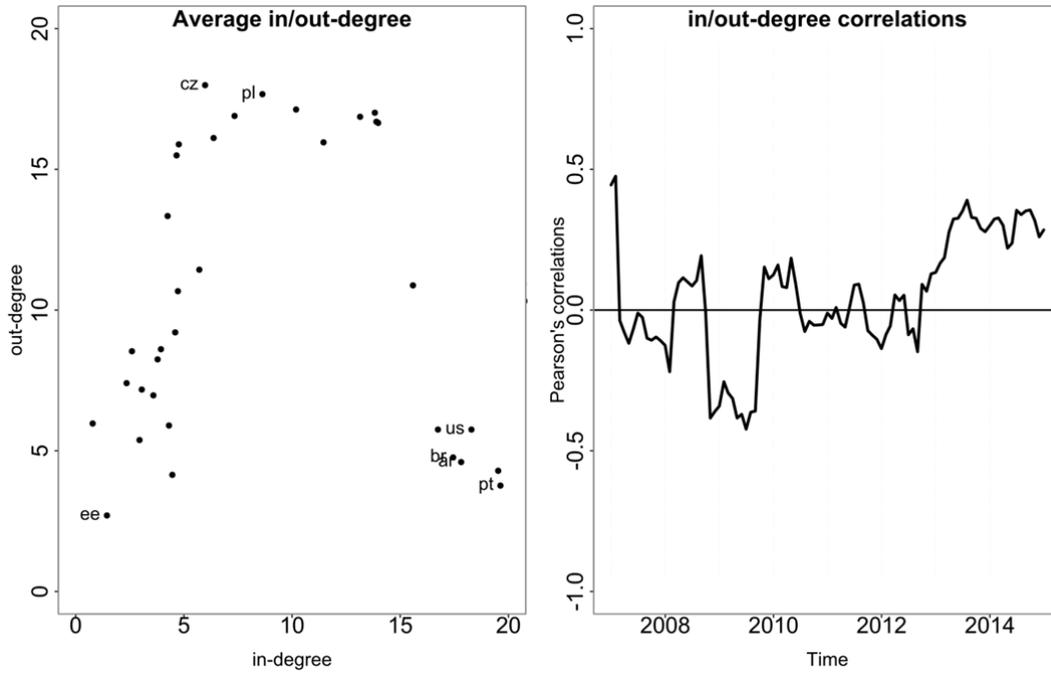


Figure 3: In-/out-degree relationship

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.

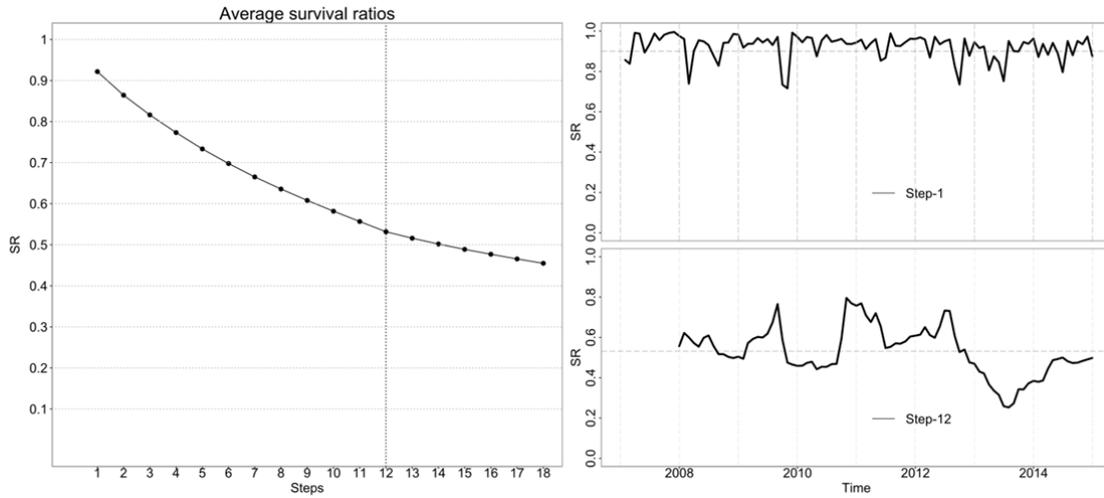


Figure 4: In-/out-degree relationship

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).



Figure 5: Top 3 markets with the highest out-degree $\text{deg}^{\text{out}}(i)$ 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.

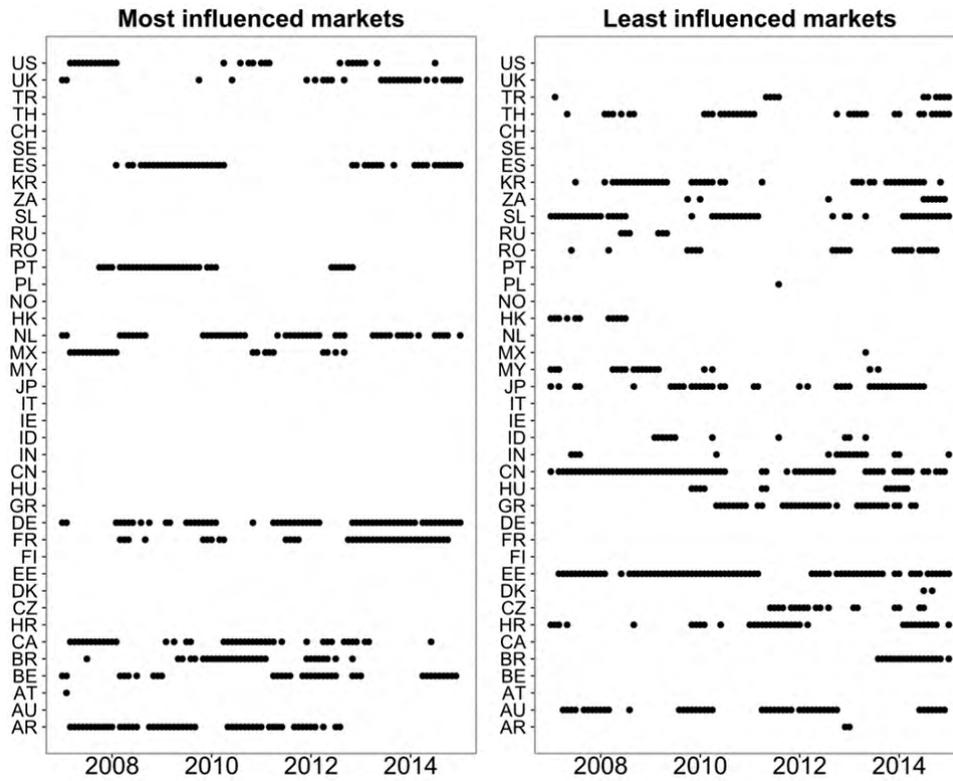


Figure 6: Top 3 markets with the highest in-degree $\text{deg}^{\text{in}}(i)$ over all subsamples
Note: A point is drawn at the time t for three markets with the highest (left panel) or lowest (right panel) in-degree.

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

(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	
<i>Temporal distance variables</i>										
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
<i>Out-vertex market variables</i>										
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
<i>In-vertex market variables</i>										
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
<i>Spatial coefficient (ρ)</i>	0.875 ^d		0.983 ^d		0.961 ^d		0.874 ^d		0.989 ^d	
<i>Spatial error model - fit statistics</i>										
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	
<i>Dependent variable</i>										
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
<i>Spatial tests</i>										
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	

Significance at 10%, 5%, 1%, and 0.1% is denoted by "a", "b", "c", and "d" superscripts, respectively.

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

(x1000)	31.12.2011		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	
<i>Temporal distance variables</i>								
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
<i>Out-vertex market variables</i>								
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
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
<i>In-vertex market variables</i>								
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	
<i>Spatial error model - fit statistics</i>								
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	
<i>Dependent variable</i>								
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
<i>Spatial tests</i>								
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	

Significance at 10%, 5%, 1%, and 0.1% is denoted by "a", "b", "c", and "d" superscripts, respectively.

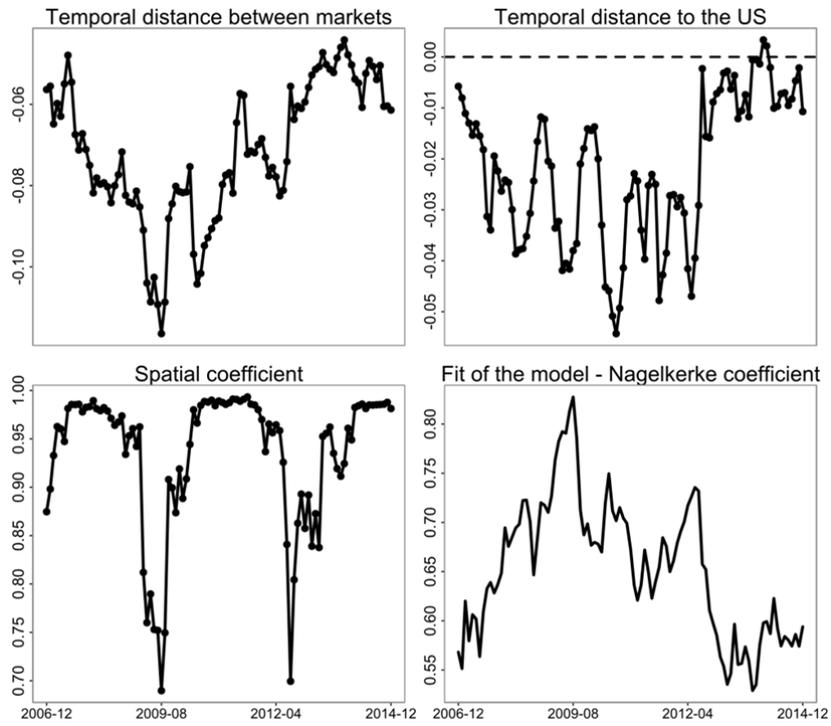


Figure 7: Average direct effects of temporal coefficients, spatial and Nagelkerke coefficients (out-vertex)

Note: Bullets denote statistically significant coefficients at the 5% significance level.



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

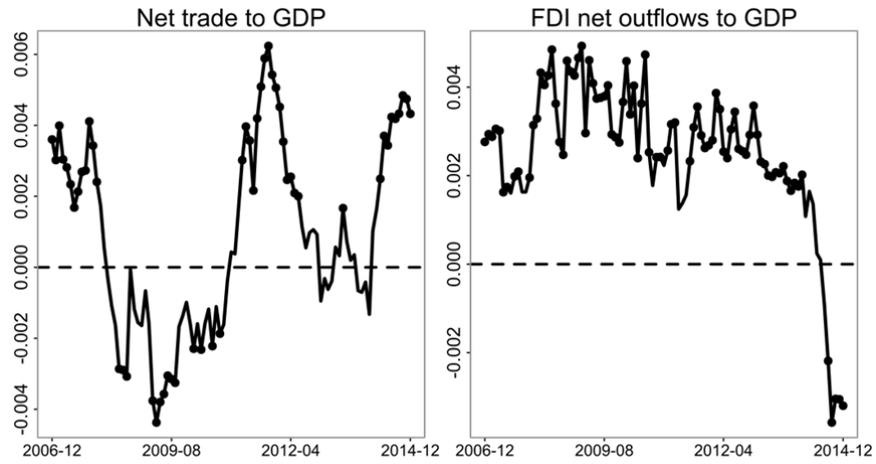


Figure 9: Net trade to GDP and FDI outflows to GDP (out-vertex)
Note: Bullets denote statistically significant coefficients at the 5% significance level.

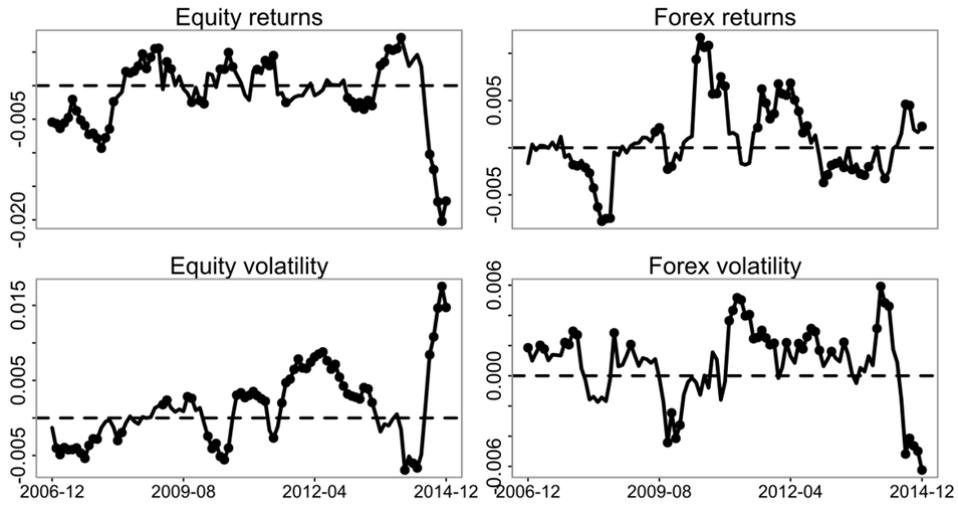


Figure 10: Equity and forex market returns and volatility direct effects (out-vertex)
 Note: Bullets denote statistically significant coefficients at the 5% significance level.

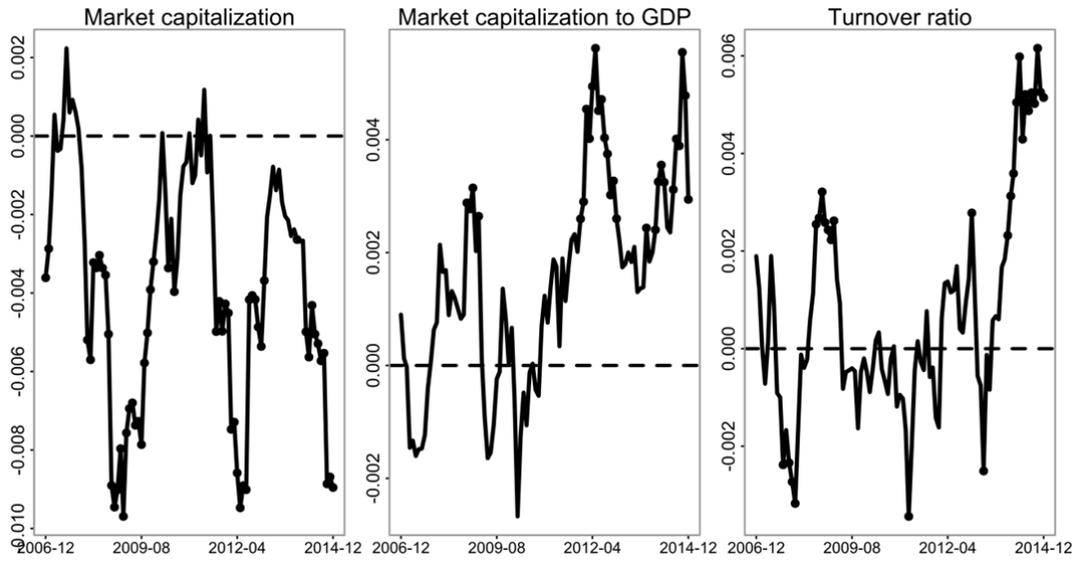


Figure 11: Average direct effects of market capitalization and market liquidity (in-vertex)
Note: Bullets denote statistically significant coefficients at the 5% significance level.