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Granger causality stock market networks: Temporal proximity and preferential attachment

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HIGHLIGHTS

- Granger causality networks are constructed among 20 developed stock markets.
- A detailed procedure of handling the non-synchronicity of daily data is proposed.
- The spatial probit model is used to study the structure of the created networks.
- Relationships between markets depend on a temporal proximity of closing times.

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ABSTRACT

The structure of return spillovers is examined by constructing Granger causality networks using daily closing prices of 20 developed markets from 2nd January 2006 to 31st December 2013. The data is properly aligned to take into account non-synchronous trading effects. The study of the resulting networks of over 94 sub-samples revealed three significant findings. First, after the recent financial crisis the impact of the US stock market has declined. Second, spatial probit models confirmed the role of the temporal proximity between market closing times for return spillovers, i.e. the time distance between national stock markets matters. Third, a preferential attachment between stock markets exists, i.e. the probability of the presence of spillover effects between any given two markets increases with their degree of connectedness to others.

1. Introduction

In empirical finance literature, one is only rarely faced with an analysis of several hundreds or thousands of relationships. However, early works of Mantegna [1] and Mantegna and Stanley [2] introduced graphs into the financial literature as a means to cope with the scale and number of complex relationships between/within economic agents. Suppose a graph $G = (V, E)$, $V \subset \mathbb{N}$, where vertices V correspond to markets, and each edge (i, j) from a set of edges E, $E \subset V \times V$, corresponds to an interaction between two markets i and j. Such a graph represents a structure of interactions between markets. Using graph specific indicators and statistical methods, one could answer empirically or theoretically motivated questions, e.g. which markets tend to be clustered together, what type of markets tend to be on the periphery, but also why and when this happens.

Most of the network studies on financial markets study correlation based networks. Assume N assets and a correlation matrix $\mathbf{C}$ of returns (with elements $\rho_{ij} \in \mathbf{C}$) with $N(N-1)$ mutual correlations ρ_{ij} (excluding diagonal elements). Using

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suitable filtration methods, one can extract the most important correlations, which results in a much more parsimonious representation of market correlations (Mantegna [1], Coelho et al. [3]), which are in turn used to construct market graphs ready for further statistical analysis. The two dominant approaches for filtering the most important relationships are: (i) hierarchical methods and (ii) threshold methods.

Among the hierarchical methods, the most prominent representatives are minimum spanning trees (MST, for a more detailed treatment see Mantegna and Stanley [2]), and the planar maximally-filtered graph (PMFG, Tumminello et al. [4]). Numerous studies have shown that after such reductions, the vertices (asset classes) formed meaningful (usually incomplete) clusters based on industry classification or the geographical proximity of markets, e.g. Onnela et al. [5], Tumminello et al. [6], Tabak et al. [7], Lyócsa et al. [8], Bonanno et al. [9], Coelho et al. [10], Gilmore et al. [11], Eryiğit and Eryiğit [12], Song et al. [13], Mizuno et al. [14], Naylor et al. [15].[1]

Networks resulting from threshold methods are much more diverse. For example, Onnela et al. [17] has suggested the asset graph, which is created by retaining n-largest correlations.[2] Kullmann et al. [18], Boginski et al. [19], Huang et al. [20], Tse et al. [21], Bautin et al. [22], Nobi et al. [23], Heiberger [24], Curme et al. [25] constructed networks, where for any pair of vertices, an edge is created if the corresponding correlation coefficient increases some threshold value θ, say $|\rho_{ij}| > \theta$. Sometimes, the threshold varies or is determined via statistical tests. Threshold networks were also created in Yang et al. [26] and Tu [27], where an edge was created if a standard Engle and Granger [28] test suggested a presence of a co-integration between the prices of the two assets.

The main disadvantage of the hierarchical approaches described above (MSTs and PMFGs) is that the topological constraints on these networks do not necessarily have economic or statistical rationale. On the other hand, threshold approaches need a critical value above/below which all edges are retained. Either an arbitrary value is chosen or a statistical validation is performed (e.g. Curme et al. [25], Yang et al. [26], and Tu [27]).

In this paper we use *Granger causality networks* to model the complex relationships of return spillovers between 20 developed stock markets around the world. We contribute to the existing literature in several ways. First, our construction of stock market networks is based on Granger causality testing. Second, our approach enhances the literature on threshold stock market networks by providing a sensible alternative for the choice of the threshold value. Third, we show that the role of the US market within the networks has declined over time and that the markets have become less centralized. Fourth, using the spatial probit model, we are able to confirm that the time distance between markets influences return spillovers, thus also the topology of the Granger causality networks. Even small markets, which are localized near important markets, may gain great importance in the resulting network. Fifth, we found evidence for preferential attachment between markets.

Although our approach is unique, the idea of exploiting lead–lag relationships was already used in the econophysics literature as early as in 2002 by Kullmann et al. [18], and later used in Curme et al. [25] and discussed in length by Sandoval [29]. Two recent, related studies of interest are also from Fiedor [30], who uses partial mutual information, derived from an important measure in information theory, in the study of some securities in the NYSE and from Sandoval [31], who deals with certain stocks of companies within the world's financial sector using yet another tool based on information theory, which has Granger causality as a limiting, linear case. Moreover, Granger causality networks were also already used in the finance literature of an influential paper by Billio et al. [32] and are a common tool in human brain mapping, e.g. Bullmore and Sporns [33].

2. Data and methodology

2.1. Data sources

In our analysis we use daily closing prices from $N = 20$ stock market indices from four continents (Austria, Australia, Belgium, Canada, Switzerland, Germany, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Sweden, and United States).[3] Our sample starts in 2nd January 2006 and ends on 31st December 2013. Markets were selected on the basis of the availability of data and closing hours, including information on changes in closing hours (see Section 2.3). Prior to the analysis, all prices were converted into US dollars, to mimic the perspective of a US-based investor. As we are working with daily closing prices, exchange rates should have a negligible impact on the resulting time series.

Our analysis requires that all the series under consideration are weakly stationary. A time series $\{x_{i(t)}\}$ is weakly stationary if the mean of $x_{i(t)}$ is constant and $cov(x_{i(t)}, x_{i(t-k)})$ are invariant under time shift. Financial time series are often tested for the presence of the unit-root as this implies that the assumption of the weak stationarity does not hold.[4]

1 An exception is perhaps the study of Jung et al. [16], but even in this case the stocks on the Korean equity market had a tendency to cluster based on their membership in the MSCI Korea Index. This might be explained by behavioural tendencies of foreign investors, who are perhaps more trusting and therefore trade more stocks in the MSCI Korea Index compiled by an international institution than others.

2 Or n-smallest distances from a distance matrix $\mathbf{D}$, where $d_{ij} \in \mathbf{D}$, $d_{ij} = (2(1 - \rho_{ij}))^{0.5}$, see Mantegna and Stanley [2].

3 According to the Dow Jones Country Classification System (as of September 2011) all these countries are considered to be developed countries.

4 A simple example is a random walk model $x_t = x_{t-1} + e_t$, where $\{e_t\}$ is a white noise is an example of a unit-root process. As many economic and financial time series are assumed to be such processes, testing for the presence of a unit root is often the first step in economic analysis. If we write $x_t = \rho x_{t-1} + e_t = e_t + \rho e_{t-1} + \rho^2 e_{t-2} + \cdots$. Using he fact that $\{e_t\}$ is a white noise, $\text{var}(x_t) = \sigma_e^2 + \rho^2\sigma_e^4 + \rho^6\sigma_e^2 + \cdots$. The sum converges only if $|\rho| < 1$.