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Conditional graphical models for systemic risk estimation

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ABSTRACT

Financial network models are a useful tool to model interconnectedness and systemic risks in banking and finance. Recently, graphical Gaussian models have been shown to improve the estimation of network models and, consequently, the interpretation of systemic risks.

This paper provides a novel graphical Gaussian model to estimate systemic risks. The model is characterised by two main innovations, with respect to the recent literature: it estimates risks considering jointly market data and balance sheet data, in an integrated perspective; it decomposes the conditional dependencies between financial institutions into correlations between countries and correlations between institutions, within countries.

The model has been applied to study systemic risks among the largest European banks, with the aim of identifying central institutions, more subject to contagion or, conversely, whose failure could result in further distress or breakdowns in the whole system. The results show that, in the transmission of systemic risk, there is a strong country effect, that reflects the weakness or the strength of the underlying economies. Besides the country effect, the most central banks are those larger in size.

1. Introduction

During the latest financial crisis, started in 2007, impairment losses arising from loan books and security portfolios have substantially increased the probability of default of banks. Interconnectedness between financial institutions, through interbank lending and common sovereign or corporate exposures, have further amplified such probability, giving rise to the so-called "systemic risk" effect.

To enhance the future resilience of the banking sector, a new regulatory framework, the so-called Basel III package, has been proposed, implying more stringent capital requirements for financial institutions (Basel committee, 2011). The effectiveness of the new regulatory framework to prevent banking default and financial crisis is an open problem, particularly as regulations themselves are still in progress, and may thus benefit from the results of research findings in the field.

Research studies on bank failures can be classified in two main streams: scoring models and market models.

Scoring models are typically based on financial fundamentals, taken from publicly available balance sheets. Their diffusion has followed the seminal paper by Altman, 1978 and has induced the production of scoring models for banks themselves: noticeable examples are Sinkey (1975), Tam and Kiang (1992) and Cole and Gunther (1998). The development of the Basel regulation and the recent financial crisis have further boosted the literature on scoring models for banking failure predictions, especially under the so-called CAMELS framework (see e.g. Arena, 2005; Davis and Dilruba, 2008 and Klomp and Haan, 2012). Scoring models have been extended in different ways: interesting developments include the incorporation of macroeconomic components (see e.g. Kanno, 2013; Koopman, Lucas, and Schwaab, 2011; Mare, 2012 and Kenny, Kostka, and Masera, 2013) and the explicit consideration of the credit portfolio, as in the Symbol model of De Lisa, Zedda, Vallascas, Campolongo, and Marchesi (2011), that allows stress tests of banking asset quality and capital, as emphasized by Halaj (2013). Recent extensions are aimed at overcoming the rare nature of bank defaults: noticeable examples include Betz, Oprica, Peltonen, and Sarlin (2014) and Calabrese and Giudici (to appear).

The problem with scoring models is that they are mostly based on balance sheet data, which have, differently from the market, a low frequency of update (annual or, at best, quarterly) and do depend on subjective management choices. They may thus be good to predict defaults (especially in the medium term) but not in the assessment of systemic risks, which occur very dynamically and with short notice.

Market models originate from the seminal paper of Merton (Merton, 1974), in which the market value of a bank's assets, typically modelled as a diffusion process, is insufficient to meet its

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liabilities. Due to its practical limitations, Merton's model has been evolved into a reduced form (Vasicek, 1984), leading to a widespread diffusion of the resulting model, and the related implementation in Basel II credit portfolio models. In order to implement market models, diffusion process parameters and, therefore, bank default probabilities, can be obtained on the basis of share price data that can be collected almost in real time from financial markets. Market data are relatively easy to collect, are public, and are quite objective. On the other hand, they may not reflect the true fundamentals of the underlying financial institutions, and may lead to a biased estimation of the probability of failure, especially in the long-term (see e.g. Idier, Lamé, & Mésonnier, 2013).

The high frequency of market data makes them suitable to study systemic risks, which describe the additional probability of default that derives from the interconnectedness network of a bank. A comprehensive review on systemic risk models is provided in Benoit, Colliard, Hurlin, and Perignon (2015).

Specific measures of systemic risk have been proposed by Acharya, Pedersen, Philippon, and Richardson (2010) Adrian and Brunnermeier (2010) Brownlees, Hans, and Nualart (2014) Huang, Hao, and Haibin (2011) Segoviano and Goodhart (2009). All of these approaches are built on financial market price information, on the basis of which they lead to the estimation of appropriate quantiles of the estimated loss probability distribution of a financial institution, conditional on a crash event in the financial market. They however do not address the issue of how risks are transmitted between different institutions.

Trying to address this aspect of systemic risks, researchers have recently introduced network models. In particular, Billio, Getmansky, Lo, and Pelizzon (2012) propose several econometric measures of connectedness based on principal component analysis and Granger-causality networks; Diebold, Demirer, and Yilmaz (2014) propose Vector Autoregressive models, augmented with a LASSO type estimation procedure, aimed at selecting the significant links in a network model; Hautsch, Schaumburg, and Schienle (2013) and Peltonen, Piloiou, and Sarlin (2015) propose tail dependence network models aimed at overcoming the bivariate nature of the available systemic risk measures.

Network models, albeit elegant and visually attractive, are based on the assumption of full connectedness among all institutions, which make their estimation and interpretation quite difficult, especially when a large number of them is being considered.

To tackle the previous limitation, Ahelegbey, Billio, and Casarin (to appear) and Giudici and Spelta (to appear) have recently introduced graphical vector autoregressive models, which can account for partial connectedness, expressed in terms of conditional independence constraints. A similar line of research has been followed by Barigozzi and Brownlees (2013) and Brownlees et al. (2014) who have introduced multivariate Brownian processes with a correlation structure that is determined by a conditional independence graph.

Our contribution follows the latter perspective, and apply graphical network models to systemic risk. Besides the applied contribution, we add two main innovations. First, we consider a novel approach, that uses both financial market and balance sheet data, joining the financial market and the scoring perspective, in a single model. To our knowledge, this is the first paper that has such an integrated perspective. Second, we allow correlations between financial institutions to be decomposed into a systemic country effect plus an idiosyncratic bank-specific effect. This, following what assumed for the asset returns in CAPM models (Sharpe, 1964), improves substantially both model estimation and interpretation of the results.

The rest of the paper is organized as follows. In Section 2, we introduce our proposed model. In Section 2.1 we describe the empirical results obtained with the application of our model to data that concern the largest European banks. Finally, Section 2.2 contains some concluding remarks.

2. Methodology

In this section we first review graphical Gaussian models and, then, present our methodological proposal.

Graphical models are based on the idea that interactions among random variables in a system can be represented in the form of graphs, whose nodes represent the variables and whose edges show their interactions. For an introduction to graphical models see, for example, Lauritzen and Wermuth (1989) Pearl (1988) Wermuth and Lauritzen (1990) Whittaker (1990) and Edwards (1990).

2.1. Graphical Gaussian models

Let $g = (V, E)$ be an undirected graph, with vertex set $V = \{1, \ldots, n\}$, and edge set $E = V \times V$, a binary matrix, with elements e_{ij}, that describes whether pairs of vertices are (symmetrically) linked between each other ($e_{ij} = 1$), or not ($e_{ij} = 0$). If the vertices V of the graph g are put in correspondence with a vector of random variables $X = X_1, \ldots, X_n$, the edge set E induces conditional independence on X via the so-called Markov properties, see Wermuth and Lauritzen (1990). More precisely, the pairwise Markov property determined by the graph g states that, for all $1 \le i < j \le n$,

$$e_{ij} = 0 \Longleftrightarrow X_i \perp X_j | X_{V \setminus \{i,j\}};$$

that is, the absence of an edge between vertices i and j is equivalent to independence between the random variables X_i and X_j, conditionally on all other variables $X_{V\setminus\{i,j\}}$.

Here we are concerned with quantitative random variables and, therefore, the graphical model we assume is a graphical Gaussian model, specified as follows.

Let $X = (X_1, \ldots, X_n) \in R^n$ be a random vector distributed according to a multivariate normal distribution $\mathcal{N}(\mu, \Sigma)$. In this paper, without loss of generality, we will assume that the data are generated by a stationary process, and, therefore, $\mu = 0$. In addition, we will assume throughout that the covariance matrix Σ is non singular.

Let $K = \Sigma^{-1}$ be the inverse covariance matrix, or precision matrix, with elements k_{ij}. Whittaker (1990) proved that the pairwise Markov property implies that the following equivalence holds, for graphical Gaussian models:

$$X_i \perp X_j | X_{V \setminus \{i,j\}} \Longleftrightarrow \rho_{ijV} = 0,$$

where

$$\rho_{ijV} = \frac{-k_{ij}}{\sqrt{k_{ii}k_{jj}}}$$

denotes the ijth partial correlation, that is, the correlation between X_i and X_j conditionally on the remaining variables $X_{V\setminus\{i,j\}}$.

Therefore, given an undirected graph $g = (V, E)$, a graphical Gaussian model can be defined as the family of all N-variate normal distributions $\mathcal{N}(0, \Sigma_g)$ that satisfy the constraints induced by a graph g on the variance-covariance matrix, in terms of zero partial correlations.

Statistical inference for graphical models can be of two kinds: quantitative learning, which means that, given a graphical structure, with associated Markov properties, data are employed to estimate the unknown parameters of the model; and structural learning, which means that the graphical structure itself is estimated on the basis of the data.

Here we focus on structural learning, as our aim is to infer from the data the network model that best describes the interrelationships between the financial institutions we consider. To achieve this aim, we now recall the expression of the likelihood of a graphical Gaussian model, on which structural learning will be based.

For a given graph g, consider a sample X of size n from $P = \mathcal{N}(0, \Sigma_g)$, and let S be the corresponding observed variance-covariance matrix. For a subset of vertices $A \subset N$, let Σ_A denote the