Systemic risk models
Modelli di rischio sistemico

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Abstract The latest financial crisis has stressed the need of understanding financial systems, as network of interconnected institutions, where financial linkages play a fundamental role in the spread of systemic risks. The statistical estimation of financial networks is a rather challenging data analysis task, due to the presence of big data, in two main dimensions: a) the number of institutions may be quite large and, therefore, the number of possible networks from which to select the most representative one becomes a huge number; b) the number of data variables on financial institutions is very large, and may come from different sources: for example, balance sheet data, actual and expected; market prices of shares, bonds and options; macroeconomic data; financial analysts and rating agency evaluations; news and media data. In this paper we propose a modelling strategy aimed at estimating financial networks, within a structured statistical framework, that of graphical Gaussian models and suggest ways to reduce data complexity by means of conditional independence arguments. We use financial market share prices as the variables on which to base the estimation of linkages between institutions. We then show how conditioning on a country effect can reduce cross border links between banks. Second we show, for a country that maintains many linkages between banks, how such linkages can be reduced conditioning on the available idiosyncratic (quarterly) balance sheet information of each bank.

Abstract *La recente crisi finanziaria ha evidenziato la necessit di comprendere i sistemi finanziari come network di istituzioni interconnesse, i cui legami finanziari giocano un ruolo determinante nella trasmissione dei rischi sistemici. La stima dei network finanziari e' piuttosto complessa, a causa della presenza di big data, in due principali dimensioni: a) il numero di istituzioni considerate puo' essere elevato e, dunque, il numero di networks fra cui scegliere il pi rappresentativo di-*

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viene un numero elevatissimo; b) il numero di variabili descrittive delle istituzioni finanziarie puo' essere elevato, ed i relativi dati possono provenire da differenti fonti: dati di bilancio, prezzi di mercato, dati macroeconomici, rating, opinioni degli analisti, dati mediatici. Nel paper proponiamo una strategia modellistica per tale stima, nell'ambito di un ambiente statistico strutturato, quello dei modelli grafici gaussiani. Utilizziamo i prezzi azionari come variabili sulle queli stimare i legami fra le istituzioni. Mostriamo quindi come ridurre le dipendenze fra istituzioni condizionando i prezzi di mercato al fattore paese, ed alle relative variabili macroeconomiche, nonch ai fondamentali caratteristici delle istituzioni, ed agli indici di bilancio da essi derivati.

Key words: Big data, Network modelling, Systemic risk

1 The problem

In the latest financial crisis, started in 2007, the core capital of banks has proved to be insufficient to cover impairment losses arising from loans and security portfolios. Consequently, several banks have been strengthened their capital base or reduced their asset exposure. Other banks have been bailed out by state aids or have defaulted. To reduce the risk of similar crises in the future and to enhance the 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. 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 filed.

Research studies on bank failures can be classified into three main streams: financial market models, scoring models and macroeconomic models.

Financial market models originate from the seminal paper of Merton (1974), in which the market value of a bank's assets, typically modeled as a diffusion process, is insufficient to meet its liabilities. Due to its practical limitations, Merton's model has been evolved into a reduced form (see e.g. Vasicek, 1984), leading to a widespread diffusion of the resulting model, and the related implementation in Basel II credit portfolio model. 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.

Scoring models are based only on financial fundamentals, taken from the publicly available balance sheet information (see e.g. Altman, 1968). Their diffusion has induced the production of scoring models for banks themselves. The development of the Basel regulation (www.bis.org) and the recent financial crisis have

further boosted the literature on scoring models for banking failure predictions. 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 strategic choices. They may thus be good to predict defaults (especially in the medium term) but not in the assessment of systemic risks, which occurr very dynamically and with short notice.

Our focus here will not be on the prediction of single defaults but rather, on how such prediction are correlated with each other, in a systemic perspective. The research literature on systemic risk is very recent, and follows closely the developments of the recent financial crisis. Specific measures of systemic risk have been proposed, in particular, by Acharya et al. (2010), and Billio et al. (2012). 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 on the financial market. These literature developments have lead and are still contributing to the identification of the Systemically Important Financial Institutions (SIFIs), at the global and regional level. They however do not address the issue of how risks are transmitted between different institutions.

Systemic risk can indeed also be defined as the risk that the failure of one significant financial institution can cause or significantly contribute to the failure of other significant financial institutions, as a result of their linkages to each other (see e.g. Billio, 2012). Trying to address this aspect of systemic risks, researchers have recently proposed network models, that can help model the systemic risk in financial systems which display complex degrees of connectedness. In particular, Billio et al. (2012) propose several econometric measures of connectedness based on principal component analysis and Granger-causality networks. They find that hedge funds, banks and insurance companies have become highly interrelated over the past decade, likely increasing the level of systemic risk through a complex and time-varying network of relationships.

To learn financial networks from the data we propose empowering network models with multivariate graphical models. Graphical models embed the idea that interactions among random variables in a system can be represented in the form of graphs, whose nodes represents the variables and whose edges shows their interactions. For an introduction to graphical models see, for example, Lauritzen, 1996.

Graphical models can be employed to accurately estimate the adjacency matrix, aimed at measuring interconnectedness between different financial institutions and, in particular, to assess central ones that may be the most contaged or the strongest source of contagion (as in Billio, 2012). Network models use the correlation matrix estimated from the data to derive the adjacency matrix. Although useful, this approach takes into account only the marginal (indirect) effect of a variable on another, without looking at the (direct) effect of other variables. In our context, it does not distinguish between the direct and the indirect effect of a country on other ones. Graphical models, instead, focus on the partial correlation matrix, that is obtained by measuring only the direct correlation between two variables. A partial correlation coefficient can express the change in the expected value of a dependent variable,

caused by a unitary change of the independent variables, when the remaining variables are held constant. In so doing, the effect of a bank on another is split into a direct effect (estimated by the partial correlation) and an indirect effect (what is left in the marginal correlation). Here we follow this approach and derive the adjacency matrix, the main input of a financial network model, not from the correlation matrix but, rather, from the partial correlation matrix obtained from the application of graphical models to the available data.

To achieve this aim we consider multivariate Gaussian graphical models, defined in terms of Markov properties, that is, conditional independencies associated with the underlying graph. While traditional network models assume fixed graphical structures (such as fully connected graphs), the structure of a graphical model is typically random, and can be learned from the data, as a good fitting structure. Such a model selection can be performed by testing, in a stepwise procedure, the statistical significance of conditional independencies, which are equivalent to specified zeroes among certain partial correlation coefficients which, in turn, are equivalent to missing edges in the network representation.

The use of graphical models can thus help to have a deeper understanding of the relationships between variables, by distinguishing direct from indirect relationships. From their appearance in the 90's, several methodological advances have been made for graphical models. Less so in terms of applications, especially in financial economics. In our opinion, this requires to solve two main problems.

First, the assumption of a random graph may be an important added value in situations where little a priori knowledge is present, as is the case for systemic risk. In addition, results should not be conditioned on single models, but, rather, should be model averaged, to avoid suboptimal inferences.

Second, graphical models do not allow to decompose asset return correlations into market specific and idiosyncratic effects, as in the classical CAPM models (Sharpe,1964). This assumption seems to be restrictive in finance.

The first problem can be solved with the use of more advanced, Bayesian, graphical models, as shown in Madigan and York, 1995, who propose a Bayesian model able to consider all possible graphical structures, choose the best fitting ones and, if necessary, average inferential results over the set of all models.

The methodological contribution of this paper can solve the second problem as well. We propose hierarchical graphical models, that allow correlations to be decomposed, as in a CAPM-like model, into a country (market) effect plus bank-specific (idiosyncratic) effects.

On the other hand, the applied contribution of this paper is in the understanding of whether and how a distress probability is transmitted between different banks, that belong to different countries, with different regulatory systems. The world financial market is not perfect: many frictions exists between different countries, mainly due to different regulations, given the fundamental relevance of banks for the economies to which they belong. A very interesting case study, in this respect, is the Eurozone, where the European Central Bank (ECB) has recently taken over the supervision of the largest banks (with total assets greater than 30bn euro) in each of the member states. Thus, eventually, the euro banking market will evolve into a single market

but, at the time being, it is still fragmented. It thus becomes timely and rather interesting to study the degree of convergence towards a European banking union, looking at the comovements between stock returns of the banks in the European area, that may give important insights.

2 The proposal

Financial network models are a useful tool to model interconnectedness and systemic risks in financial systems. Such models are essentially descriptive, and based on highly correlated networks.

In this paper we provide a stochastic framework for financial network models, aimed at a more parsimonious and more realistic representation.

The paper contains two main research contributions in this direction. First we introduce Bayesian Gaussian graphical models in the filed of systemic risk modelling, thus estimating the adjacency matrix of a network in a robust and coherent way. Second, we propose a hierarchical graphical model that can usefully decompose dependencies between financial institutions into correlations into between countries and correlations between institutions, within and/or across countries.

We have applied our proposed methods to 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.

Our results, that cannot be presented here for lack of space, show that, in the transmission of the perceived default risk, there is a strong country effect, that reflects the weakness and the strength of the underlying economies. Besides the country effect, the most central banks appear the largest ones, especially if from a relatively small country. Figure 1 describes an example of our results. It represents the graphical Gaussian model selected for the 12 considered Italian banks, using their observed returns for the period 2009-2013. From the Figure note the pivotal role of MB-MedioBanca which is directly related, besides to UCG-UNICREDITO and ISP-INTESA SAN PAOLO, the two largest Italian banks, also to many other banks. On the other hand, small banks such as BPE-BANCA POPOLARE DELL'EMILIA ROMAGNAM CVAL-CREDITO VALTELLINESE ,BPSO-BANCA POPOLARE DI SONDRIO and CE-CREDITO EMILIANO are less connected.

Future applied research include the extension of the model to different information on financial institutions and on countries.

These extension require the development of a a graphical model able to model different types of data signals: besides price shares, balance sheet data, analysts opinions and other sources of "soft" information.

More generally, the field of financial systemic risk modeling is an area where good statistical thinking and statistical analysis can contribute substantially to reach conclusions that are more and more important and timely for policy makers, both at the national and international levels.

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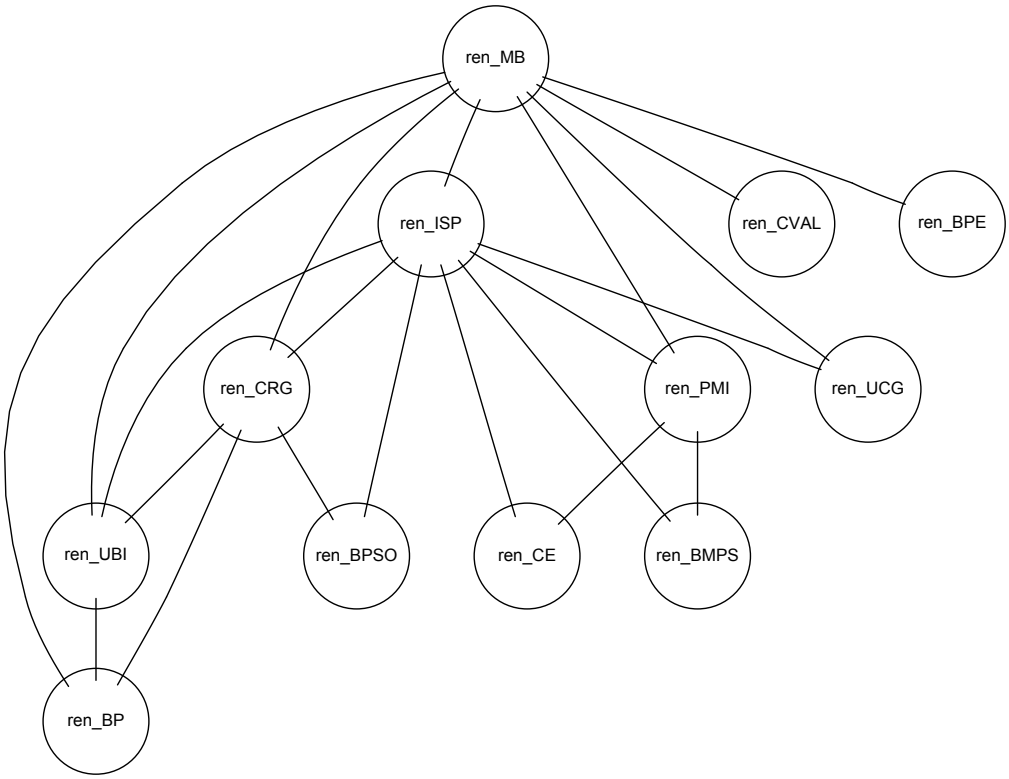

Fig. 1 Selected graphical network for the Italian banks