Identifying the most systemically important banks in a bank network using logistic regression -The method and preliminary results-

Jussi Lindgren, Aalto University School of Science,
jussi.lindgren@vm.fi

Introduction

Identifying systemically important banks (SIBs) is of paramount importance, especially from the regulatory point of view. For example, the Basel III capital requirements demand an extra capital buffer from G(global)-SIBs. There are many ways to identify such banks. The Basel Committee on Banking Supervision (BCBS) uses e.g. size and interconnectedness (interbank assets and liabilities) among others to identify (G)-SIBs [1].This study uses market data on probabilities of default (PD), extracted from CDS-spreads, and interbank exposure data to assess and identify the most important banks in a bank network.

The Model

The model is based around the concept of a perceptron from the neural networks literature. The model has two sets of data inputs, the market implied probability of defaults fom CDS-spreads and the capital-adjusted interbank exposures. Probability of default of bank i is denoted by p_i. The capital adjusted exposure of a bank i towards bank j is denoted by $A_{ij} = \frac{E_{ij}}{C_i}$. The capital of bank i is denoted by C_i and the loss given default by E_{ij}. The capital-adjusted expected loss for bank i stemming from bank j is therefore the matrix $EL_{ij} = A_{ij}p_j$. The probability of default of a bank i in the network is assumed to be determined through a sigmoid function as follows:

$$p_i(p_j) = \frac{1}{1+e^{-(\beta^j EL_{ij})}}$$

The specification works like a perceptron/simple neuron: the probability of default (PD) is assumed to depend continuosly on the expected loss stemming from all the other banks in the network. The incoming expected losses are weighted according to some parameter vector β^j.The sigmoid function then maps the weighted expected losses to the compact interval [0,1]. These values represent the probability of default of a bank in the network.

The model can be linearised by using the logit transform to obtain the regression model:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta^j EL_{ij} + \epsilon_i$$

We have used the so-called Einstein summation convention (upper and lower indices are to be summed over, when they have the same index). The error term obeys the usual simple assumptions. Multicollinearity- or heteroscedasticity related issues are ignored here.

Once the parameter vectors are estimated for each bank, we just add the coefficients together and rank the banks by associating the systemic importance of a bank with its magnitude of summed coefficients. In the model, the larger coefficient implies a larger impact on the logit of the probability of default.

The Data

The data consists of 5-year (1.8.2011-) daily CDS-spreads for large European banks. The implied probability of defaults are obtained using the simple formula $p = \frac{S}{1-R}$

Where S is the CDS-spread and R is the recovery rate (assumed to be 40%).

- The following 11 banks were in the sample: Deutsche Bank, BBVA,Credit Agricole, BNP Paribas, Unicredit,Intesa Sanpaolo, Santander, Societe Generale, UBS, Barclays, RBS
- As there was no interbank exposure data available, the regression assumed that each capital-adjusted exposure was =1.

The Results

The parameter vector β^j was estimated for each bank, and the results were statistically significant for 95 % of the estimated parameters. The goodness of fit was excellent (R^2 ~0.95). The most important bank in this study was found to be Santander and Barclays. There was a lot of variation across the banks in terms of importance.

Conclusions

This new method would be a useful addition to the toolkit of regulators and supervisors in order to identify the most important banks in a network. The main benefit of this method is that it is simple and straightforward. The main obstacle is the availibility of data. The interbank exposure data should be included in order to obtain more reliable results. However, for supervisors and central banks, the access to data should not be an obstacle.

Further work

Based on the robust results, it seems that the neural paradigm could be used more generally in the context of financial networks. Further research could be done on for example integrating Hopfield networks and Hebbian learning into financial networks.

[1] www.bis.org/bcbs/publ/d296.pdf