Discussant comments on session IPM65: Statistical tools used in financial risk management

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There is great interest today in developing statistical tools to measure financial risk. Deregulation, innovation and globalisation in financial systems have changed the conception of the supervision process, which now centres on the evaluation of financial institutions' risk profile. Prevention has replaced the more reactive traditional approach. The new concepts are evident in the Basel II Capital Accord and have been in the spotlight with the recent sub-prime credit crises.

The authors propose a new bank failure prediction model based on a two-step approach. The first step uses a logit model to determine which banks are at risk. This allows for targeted monitoring, ie supervisors can concentrate on the "problematic" banks. In this step, the definition of "at risk" is crucial, and the authors have tested several options in order to obtain the best statistical solution. The second step involves a survival model, ie it estimates the time to default for at-risk banks. Such information, if available with sufficient lead time, would facilitate preventive action by supervisory institutions, designed to avert bank failure.

Though the authors were able to use a very large number of explanatory variables, based mostly on supervisory data, it could be that additional information covering specific features would improve the results. The issue of whether to collect key information on a legal-entity or group basis also arises, given the interdependency among financial entities.

This type of model can be used for off-site examinations, allowing for greater cost efficiency. Indeed, given that resources for on-site examinations are scarce, it is important to allocate them efficiently. In this case, the level and intensity of supervision devoted to each institution can be adjusted according to the institution's risk profile. This raises the question of whether the model will be implemented in Austria for supervisory purposes, and whether using this approach would influence the behaviour of financial entities.

As regards the authors' major findings, it is worth noting that the 2nd and 3rd years after a bank enters the at-risk category seem to be the most relevant ones in terms of its survival. This type of information would highlight the need for rapid intervention to avoid bank failure. However, there is a certain lack of statistical significance in these findings, perhaps as a result of the definition of "failure" adopted, since no actual defaults occurred in the sample. It could be useful to test an alternative and more practical rule, such as some financial ratio threshold that would define exactly when an incident occurs.

Nevertheless the two-step approach outperforms the one-step model, due to the fact that the variables determining whether a bank is at risk differ from those explaining how long it will survive. An interesting point here is the lack of statistical significance of the macroeconomic variables in predicting default in the at-risk sample, raising the question of whether they are offset by some other variables.

It should also be noted that credit risk is the most significant source of risk in the banking industry.

A final question concerns the feasibility of applying this model to other sectors, in particular to predict failure of non-financial corporations.

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