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# Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks

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We develop a model of neural networks to study the bankruptcy of U.S. banks, taking into account the specific features of the recent financial crisis. We combine multilayer perceptrons and self-organizing maps to provide a tool that displays the probability of distress up to three years before bankruptcy occurs. Based on data from the Federal Deposit Insurance Corporation between 2002 and 2012, our results show that failed banks are more concentrated in real estate loans and have more provisions. Their situation is partially due to risky expansion, which results in less equity and interest income. After drawing the profile of distressed banks, we develop a model to detect failures and a tool to assess bank risk in the short, medium and long term using bankruptcies that occurred from May 2012 to December 2013 in U.S. banks. The model can detect 96.15% of the failures in this period and outperforms traditional models of bankruptcy prediction.



## 1. Introduction

The recent financial crisis, the generalization and propagation of systemic risk in a more and more global financial environment, and the high social costs of bank failures have drawn attention to the mechanisms of control of banks solvency (Wang, Ma, & Yang, 2014). The 2009 Basel Committee on Banking Supervision papers, widely known as the Basel III Accord,[1] advise banking regulators to develop capital and liquidity rules sufficiently rigorous to allow financial firms to withstand future downturns in the global financial system.

The Basel III Accord follows the capital agreement found in the 1988 accord, commonly known as Basel I. Basel I is enforced by law in the G10 and adopted by over 100 other countries. The goal of this 1988 roundtable was to minimize credit risk. However, innovation and financial changes in the world led to the need in 2004 for a more comprehensive set of guidelines known as Basel II. The purpose of this new framework was to promote greater stability in the financial system and reduce the social costs of financial instability. To fulfill this aim, the accord requires banks to classify their loan portfolio and identify the risks that they may face through their lending and investment practices to ensure that they hold enough capital reserves. Basel II put in place a broader view of financial risk that incorporated the differences among credit, operational, and market risk. In addition, the accord gave both supervisors and markets a wider range of action.

The collapse of a number of financial institutions in the United States at the beginning of the crisis in 2007 due to the emergence of new financial products and risks, the fall of real estate prices, and biased pricing methods of real estate premises exposed Basel II's shortcomings. The industry clearly required new standards for supervision of financial intermediaries and new metrics of financial risk. Our paper joins the stream of analysis that examines the failures of U.S. banks in recent years. In so doing, we follow the recommendations of the G20 Finance Ministers and Central Bank Governors who met June 3–5, 2010, in Busan, Korea, and "[welcomed] the progress on the quantitative and macroeconomic impact studies which will inform the calibration of…new rules.".

We develop a hybrid neural network model to study the bankruptcy of U.S. banks by combining a multilayer perceptron (MLP) network and self-organizing maps (SOMs). With this contribution, we complement previous evidence and update the methods of risk assessment (Oreski & Oreski, 2014). Our aim is twofold: descriptive and predictive. First, we describe the main characteristics of U.S. distressed banks and how bank failures have evolved from the onset of the financial crisis in 2007. The implementation of our model and the analysis of the most descriptive variables provide

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[1] In December 2009, the Basel Committee on Banking Supervision published two consultative documents entitled "Strengthening the Resilience of the Banking Sector" and "International Framework for Liquidity Risk Measurement, Standards and Monitoring." Although these papers retain no other official designation, they have been widely dubbed Basel III.

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interesting insights about the most critical features of distressed banks relative to nondistressed banks. Second, we provide a tool to predict the probability of bank failures some time before they happen. In so doing, we define three different models that are conditional on the period of time before the failure. These two objectives lead to the development of a visual tool that can assess the strengths and weaknesses of a bank in the short, medium and long term by combining the outputs of the three models in a bi-dimensional map using SOMs (Kohonen, 1993). This tool offers not only a method to detect failures but also a visual representation of when weaknesses can arise. This procedure also provides a dynamic perspective as it can assess the probability of bank failure along a period of time, unlike most previous models that are limited to a single point in time.

Reliability is concern for models of failure prediction when the time horizon goes beyond the near short term because few models achieve stable results over the time. Our work makes advances in three directions relative to previous research. First, we widen the selection of variables and implement better selection criteria based on the experience and performance of previous research. In this way we avoid the loss of predictive power due to single-period data. Second, we explicitly take into account the specific features of the recent crisis and measure credit risk in conjunction with the Basel accords. Finally, we provide three different time-horizon scenarios for failure prediction (up to three years before bankruptcy). We then combine the joint likelihood of default from each model into a visual SOM that allows us to create different profiles of risk and to extend the time horizon to evaluate the potential risk of bank failure.

We test the predictive power of our model on a sample of U.S. banks that went bankrupt between May 2012 and December 2013. We also compare our MLP-SOM results with both traditional classification models (the discriminant and logit analyses) and with more recent techniques such as support vector machine and random forest procedures. Our model, which exhibits high predictive power, predicted one year ahead 96.15% of the 52 banks that failed between May 2012 and December 2013.

Our results show that distressed banks were heavily concentrated on the real estate at the explosion of the mortgage bubble. Distressed banks carried out a strategy of quick expansion and had to pay back higher interest rates to raise enough money. The business downturn and the fall of the prices of real estate collateral resulted in a growing default rate. The poor quality of the loan portfolios of distressed banks relative to their counterparts required higher provisions. The liquidity crisis constrained the possibility of improving the solvency of the banks through equity issuance and led to a negative margin. This vicious circle could not be maintained for long, and finally financial authorities intervened.

The paper is divided into five sections. Section 2 reviews previous research on models of bankruptcy prediction. Section 3 describes the main characteristics of our hybrid NN model: the MLP and SOM methodologies. In Section 4, we provide the results. We provide descriptive results and the storyline of the failed banks. In this section we also compare the predictive power of the NN models with the output from traditional techniques and from other more recent approaches. Finally, in Section 5, we draw some conclusions from our results and offer some directions for future research.

## 2. Review of bankruptcy prediction models

Corporate and specially banks bankruptcy prediction is an important and widely studied topic in the business intelligence field (Chen, 2011b; Serrano-Cinca & Gutiérrez-Nieto, 2013; Sun, Li, Huang, & He, 2014; Yu, Miche, Séverin, & Lendasse, 2014; Zhou, 2013). Models of prediction have become more sophisticated to account for the effects of financial crises or other outstanding business episodes (Mokhatab Rafiei, Manzari, & Bostanian, 2011; Nassirtoussi, Aghabozorgi, Wah, & Ngo, 2014). Although a sharp line cannot be easily drawn, broadly speaking, two approaches exist to bankruptcy prediction: structural and empirical (Angelini, di Tollo, & Roli, 2007). The structural approach is based on modeling the dynamics of firm characteristics and derives the default probability based on these dynamics. The empirical approach, rather than modeling bankruptcy on firm characteristics, gleans the default relation from the data (Atiya, 2001).

The foundations of the empirical approach can be traced to Davies and Bouldin (1979) and Ingaramo, Leguizamón, and Errecalde (2005). Beaver (1966) pioneered the prediction of bankruptcy using financial statement data. His univariate analysis focused on the evolution of certain financial ratios such as financial leverage, return on assets, and liquidity and showed how these ratios worsened as long as firms faced bankruptcy. Altman (1968) and Ohlson (1980) use linear models that classify firms using financial ratios as inputs. These authors widened the scope of the model by introducing a multiple discriminant credit scoring analysis. Their models identify financial variables that have statistical explanatory power. They also introduced the logistic regression approach and used a novel set of financial ratios as inputs. Yin (2005) contributed further to the empirical approach by using a step-wise multiple discriminant analysis to distinguish between corporate future failures and successes.

From the late 1980s, artificial intelligence techniques, particularly rule-based expert systems, case-based reasoning systems, and machine learning techniques such as artificial neural networks (ANNs) have been successfully applied to bankruptcy prediction (Angelini et al., 2007; Atiya, 2001; Mukta & Kumar, 2009). Empirical approaches have been improved along the time, from the simplest and the most restrictive models to more flexible and recent ones. Some of these approaches are the statistical techniques, the neural networks, the random forest, the support vector machine, the genetic algorithm and, even, some hybrids techniques.

Compared to other empirical approaches to bankruptcy prediction, NNs have some advantages. First, as previously stated, NNs do not make assumptions about the distribution of the data. Second and interestingly, NNs allow a nonlinear set of relations. This allowance is especially important for bankruptcy predictions because the relation between the likelihood of default and the explanatory variables do not have to be linear. NNs are quite powerful and flexible modeling devices that do not make restrictive assumptions on the data-generating process or the statistical law relating variables of interest. Oreski and Oreski (2014) argued that a nonlinear approach outperforms linear models for two reasons: first, saturation effects can occur in the relation between financial ratios and the prediction of default. Second, multiplicative factors may become problematic.

The comparison between traditional models and NNs remains an open question within the literature and has led to mixed results (Bernhardsen, 2001; Fulmer, Moon, Gavin, & Erwin, 1984; Ohlson, 1980). Furthermore, the choice of one method over another is usually based on several heterogeneous criteria, such as data availability. Nevertheless, in recent years, some authors have shown the superiority of NNs relative to other techniques (Hol, 2006; Lee & Choi, 2013; Levy-Yeyati, Martínez Pernía, & Schmukler, 2010; Mokhatab Rafiei et al., 2011). In particular, du Jardin (2010) who uses more than 500 ratios taken from approximately 200 previous papers, shows that an NN-based model that uses a set of variables selected with a criterion specifically adapted to the network leads to better results than a set chosen with criteria used in the financial literature.