Expert Systems with Applications 39 (2012) 7808–7821

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

# A logical analysis of banks' financial strength ratings

Peter L. Hammer [a,1], Alexander Kogan [a], Miguel A. Lejeune [b,*]

[a] Rutgers Business School, Rutgers University, 1 Washington Park, Newark, NJ 07102, USA
[b] Decision Sciences Department, The George Washington University, Washington, DC, USA

ARTICLE INFO

*Keywords:*
Data mining
Logical Analysis of Data
Credit risk rating
Decision support systems

ABSTRACT

We evaluate the creditworthiness of banks using statistical, as well as combinatorics-, optimization-, and logic-based methodologies. We reverse-engineer the Fitch risk ratings of banks using ordered logistic regression, support vector machine, and Logical Analysis of Data (LAD). The LAD ratings are shown to be the most accurate and most successfully cross-validated. The study shows that the LAD rating approach is (*i*) objective, (*ii*) transparent, and (*iii*) generalizable. It can be used to build internal rating systems that (*iv*) have varying levels of granularity, and (*v*) are Basel compliant, allowing for their use in the decisions pertaining to the determination of the amount of regulatory capital.



## 1. Introduction

Information-intensive organizations such as banks have yet to find optimal ways to exploit the increased availability of financial data (Stein, 2005; Zhu & Wu, 2004). Mathematical programming (Peng, Kou, Shi, & Chen, 2008), support vector machines (Lee, 2007), and machine learning, in particular statistical (Huang, 2011; Jain, Duin, & Mayo, 2000) and combinatorial pattern recognition (Hammer & Bonates, 2006; Hammer, Kogan, & Lejeune, 2006; 2011), provide a wealth of opportunities for the credit rating and scoring field, which lags behind the state-of-the-art methodological developments (Galindo & Tamayo, 2000; Huang, Chen, Hsu, Chen, & Wu, 2004). In this paper, we use the established combinatorial and logic-based techniques of Logical Analysis of Data (LAD) (Alexe, Alexe, Bonates, & Kogan, 2007; Boros, Hammer, Ibaraki, & Kogan, 1997; Crama, Hammer, & Ibaraki, 1988; Hammer, 1986) to develop credit risk rating models for evaluating the creditworthiness of banks.

The objective of this paper is to reverse-engineer the Fitch bank ratings to produce an (*i*) *objective*, (*ii*) *transparent*, (*iii*) *accurate*, and (*iv*) *generalizable* bank rating system. By the *objectivity* of a rating system we mean its reliance only on measurable characteristics of the rated banks. By its *transparency* we mean its formal explicit specification. By the *accuracy* of a rating system which is based on a widely used existing (proprietary and opaque) rating system we mean the close agreement of its ratings with those of the existing system. By its *generalizability* we mean its accuracy in rating those banks which were not used in developing the system.

In this study, we shall: (*i*) identify a set of variables which can be used to accurately replicate the Fitch bank ratings; (*ii*) generate combinatorial patterns characterizing banks having high ratings and those having low ratings; (*iii*) construct a model to discriminate between banks with high and low ratings using combinatorial optimization techniques and the identified patterns; (*iv*) define an accurate and predictive bank rating system using the discriminant values provided by the constructed model; (*v*) cross-validate the proposed rating system.

This study reveals the weakness of the results obtained with multiple linear regression and support vector machines, and shows that ordered logistic regression can provide excellent results in reverse-engineering a bank rating system. These results are not only matched but exceeded by utilizing the substantively different methodology of LAD, whose results, while remarkably similar, are shown to be much more robust compared to those given by ordered logistic regression. In view of the essential differences in techniques, the conformity of bank ratings provided by LAD and ordered logistic regression strongly reinforces the validity of both the obtained results and of these rating methods.

It is worth noting the additional advantages provided by the LAD approach. First, the LAD credit risk model, as opposed to the ordered logistic regression one, does not assume that the effect of the variables used as predictors is the same on each bank and on each bank rating category. This feature is particularly relevant, since Kick and Koetter (2007) have shown that the credit risk importance of banks' financial structure differs across bank rating categories. Second, while the ordered logistic regression approach can be used only to construct a rating system that has the same number of rating categories as the benchmarked system, the LAD approach can generate rating systems with varying granularity

* Corresponding author.
*E-mail addresses:* kogan@rutgers.edu (A. Kogan), mlejeune@gwu.edu (M.A. Lejeune).

[1] Peter L. Hammer tragically died in a car accident, after this research was essentially completed.

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2012.01.087

levels: (*i*) a binary classification model to be used for the pre-approval operations; (*ii*) a model with the same granularity as the benchmarked rating model; (*iii*) a model with a different granularity than that of the benchmarked rating model, to allow the bank to refine its pricing policies and allocation of regulatory capital.

We show that the LAD-based model cross-validates extremely well, and therefore is highly generalizable. Thus, this approach can be used by financial institutions to develop Basel-compliant rating models. The accuracy of the predictions is a particularly strong achievement in view of the opaqueness of the financial sector (Morgan, 2002). Financial institutions are highly leveraged and hold assets (e.g., structured financial securities), the risks of which fluctuate significantly and are very difficult to evaluate. Moreover, the proposed model is a cross-country one (see Table 1) whose prediction accuracy is verified for financial institutions spread across the world. In the literature, as reported in (Arena, 2008), most bank rating and failure models have been developed for a particular country (Germany (Kick & Koetter, 2007), Italy (Ughetta, 2006), Turkey (Canbas, Cabuk, & Kilic, 2005), Brazil (Barnhill & Souto, 2008)), thus not allowing for comparison within a common framework.

The structure of this paper is the following. Section 2 motivates the development of internal credit risk rating systems. In Section 3, we present the data used in this study. Section 4 provides a general overview of the Logical Analysis of Data (LAD) methodology used for reverse-engineering bank ratings. Section 5 develops an LAD model for discriminating banks with high and low ratings and presents a procedure for mapping the LAD numerical values reflecting the creditworthiness of banks to credit risk ratings. Section 6 assesses the accuracy and generalizability of the LAD model. Section 7 compares the LAD approach with other classification methods. Section 8 describes the broader impacts of the forward-looking LAD credit risk rating system. Finally, concluding remarks are presented in Section 9.

## 2. Motivation for developing internal credit risk rating systems

Although external credit risk rating systems (i.e., developed by rating agencies such as Moody's, Fitch, S&P's) continue to play a fundamental role in risk management practices, banks have been allocating increasing amounts of resources to the development of more accurate and granular risk rating models (Jankowitsch, Pichler, & Schwaiger, 2007). Some of the main reasons behind this trend are the following ones.

First, the work of rating agencies has recently come under intense criticism (Financial Stability Forum, 2008). Skepticism about rating agencies finds its root in their inability to spot some of the largest financial collapses of the decade (Enron Corp, WorldCom Inc, Lehman Brothers) which some observers attribute to the presence of conflicts of interest induced by the issuer-pay model, in which the rated company pays the rating agency a fee for the issued rating. A report of the Securities and Exchange Commission (2003) indicates that 90% of Moody's and Fitch's revenues come from fees paid by the issuers. Moreover, in many instances, key credit analysts in rating agencies participated directly in fee negotiation with issuers. The SEC reports that often the rating agency employees structuring a financial security were the same who were rating the product! The issuer-pay model creates moral hazard situations and has led to the so-called complacency effect, which makes raters, especially in a non-crisis period, very reluctant to downgrade an obligor (Schwarcz, 2008) and is viewed as one of the main reasons for the subprime financial crisis. The development of an objective accurate internal rating model would make banks less dependent on the whims of the rating agencies.

Second, increasingly intense international market environment and changes in the regulatory framework driven by the Financial Stability Forum and the Basel Committee on Banking Supervision called forth incentives for banks to improve their credit risk rating systems. While the Basel Committee initially (i.e., in the 1988 Capital Accord) favored the ratings provided by external credit rating agencies, Basel III is actually a risk-focused regulatory framework under which a bank can develop its own risk model to calculate the regulatory capital for its credit portfolio (Basel Committee, 2010) and stresses the importance of banks' liquidity. At the onset of the 2007 financial crisis, the problems of many banks were due to a non-prudent management of their liquidity. The 2007 turmoil showed how liquidity can quickly evaporate for a lasting period of time and cause severe stress on the financial markets. This led the Basel Committee on Banking Supervision, in line with the Financial Stability Forum's prudential oversight recommendations (2008), to strengthen its principles for banks' liquidity management in order to improve the resilience of banks to stress scenarios. Compliance with Basel III requires the internal risk models (rating, probability of default, loss given default, exposure at default) to be cross-validated and accepted by the legislator, and qualifies banks for the adoption of the Internal Rating Based approach (2001) to calculate their capital provisions.

Third, an internal rating system provides autonomy to a bank's management to execute credit risk policies in accordance with the bank's own core business goals and can potentially make credit operations more transparent and efficient. The development of an objective, internally derived model would allow the application of more thorough and homogeneous decision rules. Ozdemir (2009) points out that the enhancement of an internal rating system provides a foundation for business gains. In a recent study (Mitchell & Van Roy, 2007), it was shown that a moderate improvement in the rating system of midmarket loans could translate into an annual $5.6 million gain for a medium-sized US bank (with total assets between 10 and 50 billion USD).

The above discussion provides strong arguments for the development of internal models. However, it must be noted that internally developed models sometimes suffer from impaired data quality (i.e., bank mergers sometimes result in a series of redundant, inconsistent data marts populated by complex legacy systems), limited size of data sets available within the institution, as well as from moral hazard situations preventing their objective use (originate-and-distribute model), and sampling bias. Indeed, internal rating systems are constructed only on the basis of the loans that have been approved in the past by the institution, but are intended to be used for all future loan applications.

## 3. Credit risk ratings of banks

Credit risk ratings are derived for individual, sovereign as well as corporate obligors across industries. In this paper, we focus on the financial sector, a key category of corporate borrowers, and we construct a forward-looking rating system for the classification of banks with respect to their risk of defaulting over a given time horizon. Our approach is generalizable to other types of borrowers by the modification of the set of explanatory variables and the selection of appropriate data sets for model inference. As the financial sector typically assigns credit ratings for a one-year horizon (Grunert, Norden, & Weber, 2005; Wang & Weigend, 2004), we analyze how a set of financial variables measured at year $t$ (calendar year 2000) can be used to predict the credit risk rating in year $t + 1$ (calendar year 2001).