Neurocomputing 275 (2018) 2525–2554

Contents lists available at ScienceDirect

Neurocomputing

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

An Artificial Neural Network and Bayesian Network model for liquidity risk assessment in banking

Madjid Tavana[a,b], Amir-Reza Abtahi[c,*], Debora Di Caprio[d,e], Maryam Poortarigh[c]

[a] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA 19141, USA
[b] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, D-33098 Paderborn, Germany
[c] Department of Information Technology Management, Kharazmi University, Tehran, Iran
[d] Department of Mathematics and Statistics, York University, Toronto, Canada
[e] Polo Tecnologico IISS G. Galilei, Via Cadorna 14, 39100 Bolzano, Italy

ARTICLE INFO

Article history:
Received 1 February 2017
Revised 1 July 2017
Accepted 11 November 2017
Available online 23 November 2017

Communicated by A. Abraham

Keywords:
Artificial Neural Network
Bayesian Network
Intelligent systems
Liquidity risk
Banking

ABSTRACT

Liquidity risk represent a devastating financial threat to banks and may lead to irrecoverable consequences in case of underestimation or negligence. The optimal control of a phenomenon such as liquidity risk requires a precise measurement method. However, liquidity risk is complicated and providing a suitable definition for it constitutes a serious obstacle. In addition, the problem of defining the related determining factors and formulating an appropriate functional form to approximate and predict its value is a difficult and complex task. To deal with these issues, we propose a model that uses Artificial Neural Networks and Bayesian Networks. The implementation of these two intelligent systems comprises several algorithms and tests for validating the proposed model. A real-world case study is presented to demonstrate applicability and exhibit the efficiency, accuracy and flexibility of data mining methods when modeling ambiguous occurrences related to bank liquidity risk measurement.

1. Introduction

Banks are subject to many different potential risks that range from those related to the technological and financial structure, affecting also their reputation, to those derived from the institutional and social environment. These risks are not mutually exclusive and have some intersections that make them hard to isolate and identify.

Liquidity risk, together with credit risk, operational risk and market risk, is categorized as a financial risk. However, a full consensus on the definition of liquidity risk is still to be reached mostly due to its ambiguity and vagueness. The ambiguity of the term liquidity risk follows from the multiple probable meanings that it can be given according to the context; the vagueness is given by the fact that the term "liquidity" can refer to different dimensions at the same time especially when used together with market liquidity risk or systemic liquidity risk (SLR) [78].

There are diverse viewpoints on what the definition of liquidity risk should be, all of them referring mainly to whether or not liquidity risk considers (1) solvency, (2) cost of obtaining liquidity or (3) immediacy [98]. For example, liquidity risk could be interpreted as the "capability to turn an asset quickly without capital loss or interest penalty", or as the risk of being unable to raise funds on the wholesale financial market [98]. In this paper, we follow the first of these two approaches, that is, we assume that liquidity risk arises because revenues and outlays are not synchronized [51].

The commitments of banks to shareholders to maximize the profits lead to a development in the volume of investments, while the commitments to depositors to refund make necessary to retain adequate liquidity especially considering depositors' stochastic behavior. Such a conflict between shareholders and depositors impels the bank directors to make a balance between profitability by long term investment and risk due to short term commitments. Liquidity management and surveillance of maturity mismatch of deposits and loans can be considered the main concerns of bank managers. Management's task becomes even more critical when the bank faces early withdrawals. The reason of this challenge is that short term deposits are the main funding resources for banks. In addition, loans are usually invested in weak liquidation assets. Too much liquidity causes an inefficient allocation of resources,

* Corresponding author.
E-mail addresses: tavana@lasalle.edu (M. Tavana), abtahi@khu.ac.ir (A.-R. Abtahi), dicaper@mathstat.yorku.ca, debora.dicaprio@istruzione.it (D. Di Caprio).
URL: http://tavana.us (M. Tavana)

https://doi.org/10.1016/j.neucom.2017.11.034

while low liquidity can lead to a reduction in the deposits interest rate, a loss of market and credit, an increase of debt and, finally, to the bank's failure. In other words, insufficient liquidity can kill the bank suddenly, but too much liquidity will kill it slowly [75]. Thus, it is extremely important to handle liquidity risk prudently and evaluate it correctly by an efficient and systematic method.

Liquidity risk relates to a complex set of factors such as significant operational risk loss, deteriorating credit quality, overreliance on short-term borrowing, overreliance on borrowing from very confidence sensitive funds providers, market risk and so on. Also, banks that are part of financial groups or bank holding companies need to identify key risk indicators that are indicative of the group's risk and reputation [75]. Each bank has to select a set of indicators that is most relevant to its funding situation and strategies (bank specific indicators). In particular, a bank primarily funded by insured deposits has far less need for a risk indicator of liability diversification than a wholesale funded bank [75]. In addition, liquidity risk may be affected by global factors usually described via macroeconomic variables.

The standard framework to measure liquidity risk compares expected cumulative cash shortfalls over a particular time horizon against the stock of available funding sources [44]. This requires assigning cash-flows to future periods for financial products with uncertain cash-flow timing. However, on one side, there still is a lack of consensus on how to assign such cash-flows [98]. On the other side, plurality, multiplicity and diversity of accounts make the calculation of net cash-flows so difficult and time consuming that accessing such data in a short period of time is impossible.

The minimum liquidity standards under Basel III [13–17] are based on two complementary ratios: liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). Although these ratios reflect the concept of liquidity risk correctly, implementing them in a banking system is not practical. In fact, both the numerators and denominators of these ratios include some weights related to inflows and outflows that must be conveniently estimated (and sometimes manually adjusted). The complexity of calculations of these coefficients together with the problem of an actual classification for the concept of "stable assets", make LCR and NSFR useless for many practical purposes. Moreover, banks do not usually make available their information/datasets to external researchers.

1.1. Main goals and contribution

The main goal of the current study is the design of a simple, practical, easy to control and analyzable system capable of warning about probable liquidity risk based only on raw data available in the book or balance sheet of the bank without any predefined function.

Nowadays machine learning methods can solve problems like this quite easily and applications of these methods to large databases, data mining, can lead to accurate results. Fortunately, banks are a very rich source of historical data. Thus, we can implement these techniques for measuring a bank liquidity risk and analyzing its key factors and the interconnections among them. More precisely, Artificial Neural Networks (ANNs) and genetic algorithm can be used for an approximate measure of liquidity risk and Bayesian Networks (BNs) to estimate and analyze the distribution function of liquidity risk.

Despite the capacity of machine learning methods to model real situations where future results must be predicted starting on imprecise or missing data, their applications to bank liquidity risk measurement remain very sporadic in the literature.

Liquidity scenarios are modeled differently depending on the fact that they use bank-specific factors or market-specific factors. In this study, we focus on the definition of liquidity risk determined by the concept of solvency. As a consequence, we focus on endogenous factors to construct a model whose characteristics will allow us to specifically address loan-based liquidity risk prediction issues.

The proposed model is flexible and can be applied to any loan-based scenario. However, its main purpose is to promote a systematic analysis of bank specific measurements based on the balance sheet ratios. The choice of using the balance sheet data is justified by the fact that the balance sheets are the most accessible, reliable and official reports that any bank is obliged to compile and safely retain.

The current model uses ANNs and BNs to analyze and assess liquidity risk and its key factors. The resulting assessment method comprises the use of several genetic algorithms and numerous tests to train a suitable ANN and learn the optimal BN to analyze the data.

The ANN and BN approaches represent two complementary phases: while ANN is used to approximate the general trend of the risk and find the two most influential factors in a non-efficient way, BN finds the most influential factor and determines the probability that liquidity risk occurs even in situations where it is not possible to measure all the indicators. The liquidity risk results obtained by ANN complement and are complemented by those obtained by BN. Since, the data implemented in both phases are the same, the numerical results can be used to confirm one another.

A case study based on a real bank dataset is performed to show the validity of the proposed assessment method.

The numerical results of the case study show that loan-based factors are inevitable given their key role in the model. Both the case study and the dataset were carefully chosen to reflect the solvency-based definition of liquidity risk. Some complementary factors (see also Section 2) can be added like credit rating, downgrade, significant operational loss and so forth, but there may be no enough data available to use these factors in practice.

The loan-based constraint imposed by the definition adopted for liquidity risk represents a limitation of the model which should be compensated by its applicability to an already large number of banks (all those whose main funding strategy consists of loans and deposits) and the efficient implementation of data derived from the balance sheet ratios into a two-phase ANN-BN intelligent schema whose results complement and relatively confirm one another.

The remainder of the paper proceeds as follows. Section 2 reviews some of the most recent and relevant liquidity risk assessment methods in the literature. Section 3 provides a description of the problem, including main goals and model variables. Section 4 presents the proposed model including a brief theoretical overview of the main general features of ANNs and BNs. Section 5 presents the numerical results obtained by implementing the model at a U.S. bank to demonstrate applicability and efficacy of the proposed method. In Section 6, we present our conclusions and future research directions.

2. Literature review

Different definitions of liquidity risk lead to different risk measurements. Conceptually, this risk is related to the mismatch of cash inflows and outflows and unfortunately a significant portion of bank financial products have uncertain cash-flow timing [56]. Thus, to measure bank liquidity risk, one idea is to assign uncertain cash-flows to future periods by different methods like surviving models and lifetime models [78].

Assessing liquidity risk is scenario specific [14]. The occurrence of cash-flows from existing assets and liabilities considerably depends on the underlying liquidity risk scenario, since it is a major driver in the behavior of a firm and its stakeholders [75]. In principle, it is impossible to consider all possible scenarios while