Int. J. Production Economics 177 (2016) 77–100

Contents lists available at ScienceDirect

Int. J. Production Economics

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

Corporate credit-risk evaluation system: Integrating explicit and implicit financial performances

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ARTICLE INFO

Article history:
Received 24 September 2015
Received in revised form
20 March 2016
Accepted 17 April 2016
Available online 23 April 2016

Keywords:
Credit-risk
Decision analysis
Dynamic evaluation
Incentive point
Explicit incentive
Implicit incentive

ABSTRACT

Traditional credit-risk evaluation methods focus mainly on static credit evaluation and rarely consider incentive factors. This paper proposes a comprehensive method of credit-risk evaluation based on dynamic incentives. First, an "explicit incentive" model is constructed based on the firm's current financial standing, and an "implicit incentive" model is subsequently developed focusing on the trend of the firm's past performance. Geometric (or arithmetic) procedures are applied to integrate the two models. To validate the proposed approach, we apply it to 12 publicly traded companies, each with 24 quarters and 20 indicators. We find the proposed integrated evaluation model outperforms the conventional models by better reflecting the key credit-risk management concept of "motivation and guidance".

1. Introduction

Credit plays an important role in the lives of most people and in almost all organizations that involve monetary investment in some form (Chirinko et al., 1991; Koch, 1995; Selwyn, 1999). Obtaining credit is essential for the smooth and effective operation of businesses (Liu and Cruz, 2012; Feng et al., 2014). The value of credit depends on its necessity and urgency. These two factors are especially critical when the present value of that credit is multiple times its future value. In other words, if credit is not obtained immediately, its value decreases precipitously due to the loss of opportunities for which the credit was needed in the first place (Selwyn, 1999). In industries reliant on rapidly growing technology where today's technology becomes outdated tomorrow, the importance of timely credit is even more evident. Credit is also essential for the acquisition of capital-intensive investment which would otherwise be difficult to obtain.

Credit evaluation is inherently complex due to the various forms of risk involved (Babic and Plazibat, 1998; Selwyn, 1999). The numerous and varied risks stem from the many factors that could lead to default on payment obligations when they are due (Reed et al., 1980). Owing to these complexities, even with great care, the likelihood of making mistakes in credit-risk evaluation is significant (Lando, 2004). Despite the possibility of denying credit from deserving clients, the credit grantor often choose to err on the safe side by denying any risky ones (Altman & Saunders, 1998; Selwyn, 1999). This caution is especially important when the stakes associated with a wrong decision are high.

For example, the global financial chaos caused by the US subprime mortgage crisis in 2007 lead to huge economic losses. Neither the global stock market nor foreign exchange or futures markets were spared. Subprime mortgages are a type of mortgage granted to borrowers with lower credit ratings. The borrowers, compared with those with higher credit ratings, lack sufficient income or carry high levels of debt and have a larger-than-average risk of defaulting loans. Bank loss results when borrowers with lower credit ratings are unable to repay loans. The risk of financial products derived from subprime mortgages increased and eventually caused the financial markets to collapse. Thus, effectively monitoring and managing credit risks are crucial for the survival and success of the economy.

Credit-risk evaluation is essential for risk control. It requires a scientific index system that is rigorous and concise to objectively assess the borrower's trustworthiness and payback ability. Credit-risk evaluation can not only detect credit-risk early and make fitting decisions, but also optimize lender's investment portfolio (balancing returns and risks). Thus, credit evaluation has been of great interest to researchers. Beaver (1966) was the first to use a univariate analytical tool to predict financial stress on a firm-by-firm basis. To analyze credit risk, Messier and Hansen (1985) and Bryant (2001) developed expert systems, and Desai et al. (1996) introduced a neural network model. Hashemi et al. (1998) proposed a heterogeneous intelligent system for predicting bank holding patterns. Furthermore, Earky

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http://dx.doi.org/10.1016/j.ijpe.2016.04.012
0925-5273/

(1977) adopted a series of financial ratios to predict corporate bankruptcy and default probability using a logistic regression model. West (2000) investigated the credit scoring accuracy of five neural network models: multilayer perceptron, mixture-of-experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance. Yurdakul and Ic (2004) developed a credit evaluation and decision-making model for banks to determine the credibility of manufacturing firms by using AHP approach. Still, Martens et al. (2007) introduced the Trepan and G-REX methods to develop Support Vector Machine (SVM) rule extraction techniques to derive credit scores. On the other hand, Pavlenko and Chernyak (2010) demonstrated how probabilistic graphs could be used for modeling and assessing credit concentration risk. Zhang et al. (2010) proposed a new vertical bagging decision trees model (VBDTM) for credit evaluation. Bellotti and Crook (2009) tested SVMs against traditional methods on a large credit card database. Finally, Zhang et al. (2014) proposed a multi-criteria optimization classifier based on kernel, fuzzification, and penalty factors (KFPMCOC).

The above credit-risk evaluation methods can be classified into five categories as summarized in Table 1. Among the credit evaluation methods, decision theory is considered to be the most popular approach and has been widely used in practice. Statistical methods and neural network have broad application and high accuracy but require more modeling skills to determine proper model parameters and network topologies. Alternatively, DEA provides a flexible method by producing relative performance measures using input–output ratios. However, its results could vary significantly when credit assessors value inputs and outputs differently, resulting in very different weights and outcomes. Finally, SVM-based models seem promising for credit risk evaluation. But the SVM classifier involves solving a convex quadratic programming problem, which is computationally costly in real world applications.

All the conventional credit-risk evaluation methods discussed above have ignored the multi-period credit data and the progress trend. Namely, the extant techniques are static in nature and do not reward firms which have managed to gradually and systematically improve their financial performances. To address such deficiencies, we propose a comprehensive and forward-looking dynamic evaluation model that incorporates incentives, and takes into consideration firms' dynamic data and credit evolution history. The proposed method can better reflect the dynamic nature of a firm's evolution and align with the credit-risk management philosophy – "motivation and guidance", thus attaining a more objective decision while employing sound judgment.

The remainder of this paper is organized as follows: In Section 2, we propose the explicit and implicit incentive models, and integrate both the explicit and implicit incentives to form the dual-incentive model. Using financial data, we illustrate and validate the proposed method through numerical study in Section 3. Finally, we summarize our work, highlight our contribution, and offer managerial implications in Section 4.

Table 1
Different types of credit-risk evaluation methods.

Types of methods	Representative literature
Statistical method	Bolton (2009), Diakoulaki et al. (1992)
Decision theory	Messier and Hansen (1985), Bryant (2001), Yurdakul and Ic (2004), Zhang et al. (2010)
Neural networks	Desai et al. (1996), West (2000), Pavlenko and Chernyak (2010), Malhotra and Malhotra (2002)
Support vector machine (SVM)	Gestel et al. (2003), Klaus and Ralf (2005), Huang et al. (2007), Bellotti and Crook (2009), Zhang et al. (2014)
Data envelopment analysis (DEA)	Shanmugam and Johnson (2007), Premachandra et al. (2011), Avkiran (2011), Iazzolino et al. (2013)

2. Dynamic incentive model

For ease of reference and understanding of the proposed model, we summarize the various notations and symbols in Table 2.

2.1. Time series data for credit evaluation

We now propose the index system for credit risk evaluation using four first-level indicators and twenty second-level indicators. A summary of these indicators and relevant literature are given in Table 3.

To evaluate a firm's overall credit, we need to analyze the corresponding time series. Table 4 shows the data structure. The data $\{x_{ij}(t_k)\}$ is arranged in chronological order.

The $s_i(i = 1, 2, \cdots, n)$ in Table 4 denotes the ith firm; $t_k(k = 1, 2, \cdots, T)$ indicates the kth time period; $x_j(j = 1, 2, \cdots, m)$ is the jth evaluation criterion (the second level indicators) as defined in Table 1; and $x_{ij}(t_k)$is the original data. The data under certain criteria may have the- smaller-the-better attribute, while others may have the-bigger-the-better feature. To ensure their compatibility, we normalize the data under each criterion so that they are consistent and uni-dimensional (Figueira et al., 2005).

In Sections 2.2–2.4, we introduce the concept of "motivation and guidance" and integrate the management theory to develop comprehensive and dynamic credit-risk evaluation models, so as to scientifically and systematically reflect the firm's risk tendency.

2.2. The "explicit incentive" dynamic evaluation model

To derive the weight (importance) of each criterion, we apply the "entropy weight" method, a more objective approach to quantify the information contained in the data under each criterion (Mon et al., 1994). Combining the weights derived by the

Table 2
Summary of notations and symbols.

Notations	Meaning
$s_i(i = 1, 2, \cdots, n)$	the ith firm
$t_k(k = 1, 2, \cdots, T)$	the kth time period
$x_j(j = 1, 2, \cdots, m)$	the jth evaluation criterion
$\upsilon_i^+(t_k)$	The amount of $y_i(t_k)$ deviating from the positive-incentive values $y_i^+(t_k)$
$\upsilon_i^-(t_k)$	The amount of $y_i(t_k)$ deviating from the negative-incentive values $y_i^-(t_k)$
$\eta^{\max}$, $\eta^{\min}$, and $\bar{\eta}$	The highest, the lowest, and the average mean change rate among all n firms over all T periods
$\eta^+$and η^-	A firm's positive and negative deviations from the threshold credit point
$y_i^+(t_k)$、 $y_i^-(t_k)$	Positive and negative incentives
h^+andh^-	The positive- and negative-incentive factor
$z_i^{\otimes}(t_k)$	The "explicit incentive" value
$z_i^{\odot}(t_k)$	The "implicit incentive" value
$z_i^{**}(t_k)\left(z_i^{**}(t_k) = z_i^{\otimes}(t_k) + z_i^{\odot}(t_k)\right)$	The "arithmetic" dual incentive value
$z_i^{\Delta\Delta}(t_k)\left(z_i^{\Delta\Delta}(t_k) = z_i^{\otimes}(t_k) + z_i^{\odot}(t_k)\right)$	The "geometrical" dual incentive value
$\Delta_i(t_k)$	The average growth
$\Delta_i'(t_k)$	The relative growth rate
$\alpha/(1 + e^{-\Delta_i(t_k)})$	The growth-based coefficient
$\beta/(1 + e^{-\Delta_i'(t_k)})$	The relative-growth-rate
ξ	The "explicit incentive" and "implicit incentive" magnitude parameter
r	The vertical and horizontal incentive volume proportional parameter
η_q	The credit rating discrimination index