Expert Systems with Applications 39 (2012) 4007–4012

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

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

Decision tree-based technology credit scoring for start-up firms: Korean case

So Young Sohn *, Ji Won Kim

Department of Information & Industrial Engineering, Yonsei University, 134 Shinchon-dong, Seoul 120-749, Republic of Korea

ARTICLE INFO

Keywords:
Technology credit scoring model
Start-up
Small and medium enterprise
Decision tree

ABSTRACT

Various types of Technology Credit Guarantees (TCGs) have been issued to support technology development of start-up firms. Technology evaluation has become a critical part of TCG system. However, general technology credit scoring models have not been applied reflecting the special phenomena of start-ups, which are distinguishable from those of established firms. Furthermore, somewhat complicated approaches have been applied to existing models. We propose a rather simple decision tree-based technology credit scoring for start-ups which can serve as a-replacement for the complicated models currently used for general purposes. Our result is expected to provide valuable information to evaluator for start-up firms.

1. Introduction

Start-up firms are in need of an immense amount of funds for technology development (Sohn & Jeon, 2010). Many governments employ several support strategies to encourage start-up firms to accelerate economic growth and to decrease unemployment. Among many support schemes, the Technology Credit Guarantee (TCG) system is seen as one of the most important instruments (Kang & Heshmati, 2007). The TCG is a system that government gives warranty to private financial institutions such as banks which give loans to the SMEs that received the guarantee from TCG agency. This kind of system removes the risks of lending to start-up firms (Oh, Lee, Heshmati, & Choi, 2009). In order to enhance the technology competitive power of start-ups, continuous support based on the evaluation of applicant start-ups is required. Therefore, the importance of professional technology assessment cannot be over emphasized. Further, evaluation must achieve an appropriate level of precision so as to distinguish successful start-ups from those which would default the loan subsequent to funding.

Despite its importance, many existing technology credit scoring systems have not considered using a separate model for start-ups from that for established firms. In addition, existing technology credit scoring models are complicated, and it is not easy to understand the mechanism involved in.

Typically, a technology scorecard had been used to CEO's knowledge about technology and technology superiority, marketability and profitability with pre-assigned weight (Henderson & Cockburn, 1994; Korea Technology Transfer Association, 2005; Moon & Sohn, 2008a; Sohn, Kim, & Moon, 2005; Walsh & Linton, 2002). However high default rate of funded SMEs based on such scorecard has been reported (Boocock & Shariff, 1996; Cowling & Mitchell, 2003; Sohn & Kim, 2007). Therefore, accurate technology evaluation is crucial. The use of inadequate evaluation models could jeopardize the entire funding process, causing critical losses. As a preventative effort, many researchers have been studying how to select firms that will not default on their loans subsequent to technology funding.

Recently developed technology evaluation scorecards are as follows. Sohn, Moon, and Kim (2005) provided an improved version of the technology evaluation model by eliminating multicollinearity among the evaluation attributes. Kim and Sohn (2007) proposed a bivariate probit model to determine whether the rejected inference technique was more useful than existing models, which use only the history of accepted applicants. Sohn and Kim (2007) proposed a random effects logistic regression model for default prediction by considering not only the financial and non-financial characteristics of the SMEs, but also an element of uncertainty, which could not be explained by such characteristics. Sohn, Kim, and Moon (2007) further applied a structural equation model (SEM) to predict the financial performance of funded technology based SMEs by considering the relationship among various variables. Moon and Sohn (2008a) proposed a new CBR system for predicting multi-period financial performances for technology-based SMEs after funding and, Moon and Sohn (2008b) proposed a new technology-scoring model to reflect the phenomenon of total perception scoring, which occurs often in many technology evaluations. Jeon and Sohn (2008) proposed an expected loss model for the TCG fund, a model which takes into account defaults for various types of competing risks such as delay, bad credit, and bad checks, among others. Most recently, Moon and Sohn (2010)

* Corresponding author. Tel.: +82 2 2123 4014; fax: +82 2 364 7807.
E-mail address: sohns@yonsei.ac.kr (S.Y. Sohn).

0957-4174/$ - see front matter
doi:10.1016/j.eswa.2011.09.075

proposed new technology evaluation models, which consider not only technology-related variables, but also environmental variables such as enterprise characteristics and economic conditions.

However, in these studies, start-ups have not been separately considered for model development. Because start-up firms would behave differently from established firms, it is necessary build technology credit scoring model. Many previous studies also have focused on developing various evaluation methods, ranging from intuitive judgment to complex options models (Mitchell & Hamilton, 1996). Complex models have some drawbacks such as difficulty of delivering the meaning.

The decision tree method (classification tree) is known to be simple and appeal to lay practitioners who do not have heavy statistical backgrounds. It can also easily examine the interaction effects of predictor variables.

The main purpose of this study is to propose a decision tree based technology credit scoring model for start-up firms and identify significant predictors on technology loan default of start-ups. It is expected that the proposed model can be applied to a wide range of technology investment-related decision-making procedures.

This paper is organized as follows. In Section 2, we provide a literature review as well as the relevant theories related to credit scoring models and the data mining analysis method. In Section 3, we provide the empirical data and input variables used in this paper. In Section 4, new scoring models are proposed for start-up firms, and in Section 5, we discuss our study results and suggest areas for future research.

2. Literature review

2.1. Credit scoring model

The objective of quantitative credit scoring models is to assign credit applicants to one of two groups: a "good credit" group that is likely to repay their financial obligation or a "bad credit" group that should be denied credit because of a high likelihood of defaulting on their financial obligation (West, 2000).

Studies of credit scoring models have been performed for a long time. The linear discriminant model (Chen & Huang, 2003) was one of the first credit scoring models, and it is still commonly used today. However, linear discriminant analysis (LDA) for credit scoring has been challenged due to the categorical nature of the credit data and the fact that covariance matrices of the accepted and rejected classes are likely to be unequal (West, 2000). Practitioners and researchers have also applied statistical techniques to develop more sophisticated models for credit scoring, which involve logistic regression analysis (LRA) (Chen & Huang, 2003), k nearest neighbor (KNN) (Henley & Hand, 2007), neural network (NN) models (Desai, Crook, & Overstreet, 1996; Malhotra & Malhotra, 2002; West, 2000), genetic programming models (Ong, Huang, & Tzeng, 2005), and decision tree models (Bensic, Sarlija, & Zekic-susac, 2005).

Many researchers have indicated that the best model can be created through the comparison of various methods. Thomas (2000) and West (2000) indicated that both LDA and LRA can be used when the relationship between variables is linear. Hence, both methods may not reflect potential nonlinear relationship.

Over the last two decades, a number of studies has been conducted to compare NN model to other models such as LDA, decision tree and k-nearest. Coats and Fant (1993) suggested that the NN model was more accurate than LDA, especially, for predicting the default rate of firms in financial distress. Thus, NNs are the most popular tool used for credit scoring and it has been reported that their accuracy is superior to that of traditional statistical methods in dealing with credit scoring problems, especially with regard to nonlinear patterns (Desai et al., 1996; Mahlhotra & Malhotra, 2003). In contrast, NNs have been criticized for their poor performance when incorporating irrelevant attributes or small data sets (Feraud & Clerot, 2002; Nath, Rajagopalan, & Ryker, 1996).

In addition, Galindo and Tamayo (2000) performed a comparative analysis of CART decision-tree models, NNs, the k-nearest neighbor and probit algorithms on a mortgage loan dataset. They revealed that CART decision-tree models provided the best estimations for default.

2.2. Important variables

Performance of start-up firms has been investigated in terms of the relationship between growth and size of start-up firms (Audretsch, Santarelli, & Vivarelli, 1999). Recent researches have indicated that firm size as well as other firm-specific characteristics and managerial characteristics play important roles in growth of start-up firms. In particular, a talent for CEO of start-up firms has been shown to positively affect the growth of the firm (Almus, 2002; Wasilczuk, 2000). Also prior managerial experience of the founder has been demonstrated to positively affect firm growth and survival higher than those without prior experience (Storey, 1994).

Lynskey (2004) considered six firm characteristics for examining the determinants of innovative activity in Japanese technology-based start-up firms: 'technological capability', 'the availability of internal funds', 'the effectiveness of venture capital funding', 'joint research with universities', 'geographic location' and 'the age of the firm'. In addition to these firm characteristics, the author also considered six managerial characteristics: 'the CEO's educational background', 'the CEO's prior experience', 'whether the current CEO is the founding entrepreneur of the firm', 'the CEO's age', 'the CEO's involvement in a network of other researchers' and 'the CEO's experience of having managed other firms'.

Harada (2004) considered the firm characteristics in order to investigate the effects of productivity: 'type of industry', 'sales (million yen per month)', 'labor and capital input' and 'the age of the firm'. Also, managerial characteristics considered are: 'the CEO's age', 'previous occupational status', 'related business experience', 'the CEO's gender'. Benzing, Chu, and Kara (2009) considered firm characteristics for examining the determinants of motivation, success, and problems in Turkish start-up firms: 'How the business was established', 'average age of firms', 'average number of employees' and 'type of business'. They also considered managerial characteristics such as 'the CEO's gender', 'the CEO's age' and 'level of education'.

As summarized, many studies have considered the firm-specific characteristics and managerial characteristics for examining the determinants variables in various aspects such as growth, innovative activity, productivity, motivation, success and problems in start-up firms. Although, their purposes had some difference, variables considered are closely related to the success in start-up firms. Because increasing growth and productivity of start-up firms depend on innovation activity, also they contribute to success of start-up firms (Heunks, 1996).

In order to help success of start-up firms with a high degree of potential in technology, TCG agencies evaluate the firms which obtain high scores by a technology scorecard in Korea. The technology scorecard used in the current TCG program is as follows: the ability of a Chief Executive Officer (CEO), the level of technology, marketability of technology, and potential or realistic profitability of technology (Moon & Sohn, 2010; Sohn & Jeon, 2010; Sohn, Moon, et al., 2005). These attributes include the technology characteristics as well as the managerial characteristics. Recently, Moon and Sohn (2010) considered the firm characteristics as well as managerial characteristics in order to evaluate technology-based firms. In addition, they considered the economic conditions for more accurate evaluation. These indicators were selected on the basis of a discussion with experts from related fields (Korea Technology Credit Guarantee Fund; Small Business Corporation; Small and Medium Business Administration).

3. Data and input variables

3.1. Data

In order to analyze the decision tree based technology credit scoring for start-up firms, we used 4288 empirical data that had previously obtained a TCG from Korea from 1999 to 2004. The 4288 total cases include 3347 start-up firms and 947 established firms.

We predefined start-up firms as those which were younger than 3 years and established firms as those which were older than 3 years, following a definition adopted by the technology credit loan practice in Korea (Sohn, Moon, et al., 2005). For the purpose of research, thus we used 3347 start-up firms in our analysis.

Industry classification of about 3347 start-up firms has been provided in Table 1. As shown in Table 1, manufacturing start-up firms occupy approximately 70% of the data. However, other public, repair, and personal services start-up firms exhibit the highest default rates.

3.2. Input variables

Using a decision tree analysis, we constructed five models for start-up firms as described in Table 2. These models are compared in terms of classification accuracy.

Three groups of input variables are considered in this study: technology scorecard attributes, economic indicators, and firm characteristics. The technology scorecard attributes which are described in Table 3 are frequently used in technology evaluations (Benzing et al., 2009; Harada, 2004; Lynskey, 2004; Moon & Sohn, 2010; Sohn, Moon, et al., 2005) and they include not only the characteristics of the technology itself, but also the characteristics of a CEO, specifically, the level of management ability, the level of technology, the marketability of technology, and the potential or actual profitability of technology. All of the attributes were measured on a 5- or 10-point Likert scale by a committee of evaluators. Attributes evaluated on 10 point scale are considered to be worth two times more than those on 5 point scale. However, we rescaled variables measured in a 10 point Likert scale into a 5 point scale so that they can be initially treated the same as variables measured in a 5-point scale.

Attributes V1 through V14 were used for evaluation of both start-up and established firms. However, V15 and V16 were used differently according to a company's age, as shown in Table 3.

Table 2
Input variables for each proposed model.

Input variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technology scorecard	○	○		○	○
Economic indicators		○	○		○
Firm characteristics			○	○	○

Another group next input variables displayed in Table 4 consists of economic indicators (Moon & Sohn, 2010). The nine types of monthly economic indicators were supplied officially by KNSO (Korea National Statistical Office, 2005). These indicators were selected on the basis of a discussion with experts from related fields (Korea Technology Credit Guarantee Fund; Small Business Corporation; Small and Medium Business Administration).

The remaining input variables which are considered in this section are firm characteristics. These variables are binary variables with only 0 or 1 for a value (Table 5). Most variables are taken from the previous study by Moon and Sohn (2010) except for C7. The original variable, C7, in Moon and Sohn (2010) has been used to determine whether a company is a start-up firm. However, we already distinguish start-up from established firms, we replace this variable with the new variable, which indicates whether the company has any Intellectual Properties (IP) or not. Although IP is reflected partly on the experience of technology development which represent composite aspects such as performances in technology commercialization and technology development, however, we strongly felt that IP is a potential success indicator for start-up firms. Thus, we treat it separately and consider as one of predictor variables (Peña, 2002). In addition, we could not use the original variable, C6, given that only established firms are given the opportunity to apply for INNO-Biz.

4. Decision tree

In this section, we have constructed five kinds of models for start-up firms, using the three groups of input variables which were introduced in the previous section.

As shown in Table 2, Model 1 used only 13 technology scorecard attributes as predictor variables; in Model 2, we added economic indicators as predictor variables to Model 1; Model 3 used economic indicators and firm characteristics as predictor variables; Model 4 used technology scorecard attributes and firm characteristics as predictor variables; and Model 5 used all three kinds of input variables as predictor variables.

We analyzed the decision tree model which was applied to a classification model using a CART (Classification and Regression Tree) method. We used both train and validation data sets divided into 70:30, respectively.

As shown in Table 6, the best model is Model 5 due to its high classification accuracy. The classification accuracies of the Model 5

Table 1
Industry classification of start-up firms.

Industry classification	Frequency	Percentage	Default	Default rate
Construction	20	0.60	2	0.10
Mining	4	0.12	1	0.25
Education service	50	1.49	12	0.24
Other public, repair and personal services	16	0.48	9	0.56
Wholesale and retail	61	1.82	20	0.33
Real estate and rental	1	0.03	0	0.00
Business service	840	25.1	280	0.33
Transportation	3	0.09	0	0.00
Manufacturing	**2324**	**69.44**	**502**	**0.22**
Communication	28	0.84	5	0.18

Bold represent the majority category of industry classification.

Table 3
Technology scorecard attributes (Sohn, Moon, & Kim, 2005).

Categories	Variable name	Description	Scale
The ability of CEO (25)	V1	Level of technology knowledge	5
	V2	Level of technology experience	5
	V3	Management ability	5
	V4	Fund supply ability	5
	V5	Human resource and teamwork	5
The level of technology (25)	V6	Environment of technology development	5
	V7	Experience of technology development	5
	V8	Stage of new technology development	5
	V9	Technology superiority	10
	V10	Technology commercialization potential	10
Marketability of technology (30)	V11	Market Potential	5
	V12	Market characteristic	5
	V13	Product competitiveness	10
Realistic profitability of technology (20)	V14	Validity of sales plan	10
	V15	Business progress (new) or amount of sales (old)	5
	V16	Return on investment (new) or profitability (old)	5

New: start-up firms, old: established firms.

Table 4
Economic indicators (Moon & Sohn, 2010).

Variable name	Economic indicators
ECO1	Total business environment index
ECO2	Economic situations index of SMEs
ECO3	Economic preceding index
ECO4	Business survey index
ECO5	KOSPI (Korean Composite Stock Price Index)
ECO6	Operation index of SMEs
ECO7	Consumer price index
ECO8	An earning rate of the national bonds in 3 years
ECO9	The exchange rate of won per dollar

Table 5
Firm characteristics.

Variable name	Description	Value
C1	Stock market listed	KOSPI, KOSDAQ, or other exchange = 1, or not = 0
C2	External audit	External audit = 1, or not = 0
C3	Investment by foreigners	Investment by foreigners = 1, or not = 0
C4	Professional manager	Separation between capital and administration = 1, or not = 0
C5	Venture company	Certified by SMBA[a] = 1, or not = 0
C6	INNO-Biz	Certified by SMBA[a] = 1, or not = 0
C7	Intellectual Property (IP)	Having any type of IP = 1, or not = 0
C8	Production stage	After pilot production stage = 1, or not = 0
C9	Joint company	Consortium = 1, or not = 0
C10	Category of business	Service = 1, General Manufacturing = 0

[a] SMBA (Small and Medium Business Administration).

Table 6
Accuracy of the all models.

Misclassification rate	Model 1	Model 2	Model 3	Model 4	Model 5
Train	0.32	0.29	0.30	0.31	0.27
Validation	0.32	0.30	0.26	0.28	0.26
Train accuracy	0.68	0.71	0.70	0.69	0.73
Validation accuracy	0.68	0.70	0.74	0.72	0.74

are 73% and 74%, respectively for train and validation datasets. Hence, we discussed the pattern of Model 5. These results showed that when evaluating the technology credit scoring of start-up firms, three parts should be considered such as technology attributes, economic indicators and firm characteristics.

The result of decision tree analysis is presented in Fig. 1.

According to result of decision tree analysis, the following were identified as significant variables that distinguishes the default from non-default of the start-up firms in terms of loans: ECO7 (Consumer Price Index: CPI) from the economic indicators, V1 (level of technology knowledge), V2 (level of technology experience) of the top manager from the technology scorecard attributes and C7 (Intellectual Property (IP)) from firms characteristics.

Compared to Moon and Sohn (2010) whose logistic regression used the variables of the original attributes, our decision tree results are a lot simpler. Moon and Sohn (2010) did not distinguish start-ups from established firms and pre-processing of the original sixteen attributes was needed to form independent variables for the logistic regression model. Among those variables, seven variables in management (knowledge management, technology experience, fund supply and human resources), technology (environment of technology development), marketability (market potential) and profitability (sales plan, business progress and return on investment) turned out to be significant.

Looking into variables which were influential on non-default, they were stock market listed (C1), external audit (C2), venture company (C5), INNO-Biz (C6), category of business (C10) among the firm variables, and new company and all economy variables except for ECO9 (the exchange rate of won per dollar).

However, in the current decision tree model for start-ups, only four variables were used: C7 (IP), ECO7 (Consumer Price Index: CPI), V1 (level of technology knowledge), and V2 (level of technology experience).

The trained rules for the default or non-default pattern of start-up firms from decision tree analysis are as follows:

Pattern 1: ECO7 (Consumer Price Index: CPI) $\geqslant$ 104.85 → ECO7 (Consumer Price Index: CPI) < 107.9.

1. When start-up firms apply for the Technology Credit Guarantee Program while CPI is between 104.85 and 107.9, non-default rate is high.

Pattern 2: ECO7 (Consumer Price Index: CPI) $\geqslant$ 104.85 → ECO7 (Consumer Price Index: CPI) < 107.9 → V2 (level of technology experience) = 2, 3, 4, 5.

2. When start-up firms apply for the Technology Credit Guarantee Program while CPI (ECO7) is higher than 107.9 and CEO who has some degree of technology experience, non-default rate is the highest.

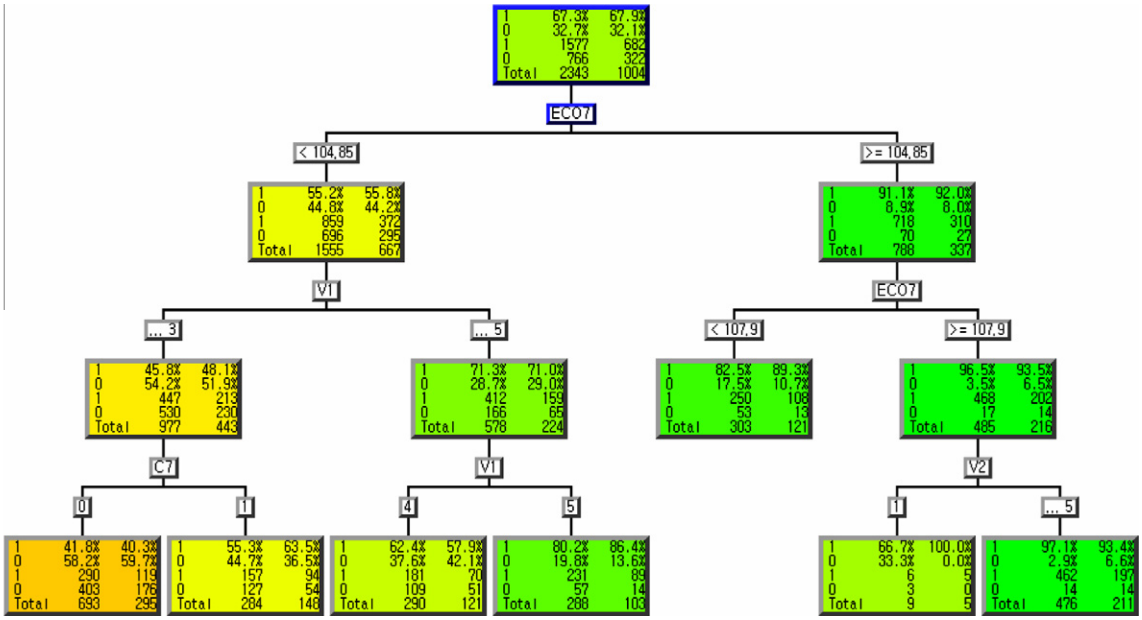

Fig. 1. Result of the decision tree analysis.

Pattern 3: ECO7 (Consumer Price Index: CPI) ⩾ 104.85 → V1 (level of technology knowledge) = 4, 5 → V1 (level of technology knowledge) = 5.

3. When start-up firms which have a CEO who has an excellent knowledge in technology apply for the Technology Credit Guarantee Program while CPI is lower than 104.85, non-default rates is high.

Pattern 4: ECO7 (Consumer Price Index: CPI) ⩾ 104.85 → V1 (level of technology knowledge) = 1, 2, 3 → C7 (Intellectual Property (IP)) = 0 or 1.

4. When start-up firms managed by CEO who has little knowledge in their technology apply for the Technology Credit Guarantee Program while CPI is lower than 104.85, non-default rate is high, as long as the firm has IP. However when start-up firms do not have IP, default rate is high.

As shown above, we found four patterns using the decision tree analysis. In particular, the Consumer Price Index (CPI) among influential variables is the most important variable affecting loan default or non-default of start-up firms. The CPI is a composite measure of price-level change over a period, either in a year-on-year basis or versus a base year. In this paper, we used a CPI that was adjusted on the basis of the year 2000. The CPI represented changes in prices of all goods and services purchased for consumption by households (Bureau of Labor Statistics, 2011). Qu (2008) examined expected default frequency using macro economic variables such as CPI, Interest rate, and Exchange rate and found that the CPI has a huge influence on the probability of default. In Norway, Germany and the US, when CPI increases by one percent, the probability of default on average decreases by 42.68%, 14.37% and 29.94%, respectively, all of which are much larger than the influence caused by other macro variables.

Interpreting the results of the decision tree analysis, when CPI is high, it can represent a burden for start-ups and as such funding can be of great help for start-ups during these times. Hence, the non-default rate of start-up firms is higher when CPI is higher; however, excessive growth of CPI can also cause negative economic growth.

The abilities of CEOs related to their levels of technological knowledge and experience were also important variables. Technological knowledge has been suggested as the foundation for economic growth and product performance (McEvily & Chakravarthy, 2002; SubbaNarasimha & Ahmad, 2003) given that it can help a firm not only attain, but also sustain its competitive advantage (Hitt, Ireland, & Lee, 2000). Moreover, some studies have revealed that a CEO's experience is positively associated with a firm's performance (Chandler, 1996; Reuber & Fischer, 1994; Westhead & Cowling, 1995). Among firm's characteristics, IP is an influential variable which could even overcome a CEO's relatively weak technological knowledge. Also according to Van Auken (2001) and Peña (2002), IP is important element in the start-up firms to raise capital and a good indicator of whether start-up firms will succeed. According to our study, a CEO who has lower capabilities could be offset by the power of IP.

5. Conclusion

The importance of technology in strengthening the competitiveness of a country is apparent and as such, the Korean government continues to fund SMEs which have the potential for superior technology. For effective management, an accurate default prediction model about funding program for SMEs is needed. Many financial institutions have utilized various default prediction models using logistic regression, multiple discriminant analysis, neural network and multidimensional scaling. In this paper, we proposed a decision tree based technology credit scoring model for start-up firms. We found the patterns using sixteen technology scorecard attributes, nine economic indicators and ten firm characteristics. We compared performances using different sets of predictors. Consequently, our Model 5 turns out to have the best prediction ability. The classification accuracy of this model, as based on the validation dataset was 74%. This represented a higher level of accuracy than what was reported as the best by a previous study (66%), which had been based on a logistic regression model (Moon & Sohn, 2010).

Our results for the start-up firms only can be compared to those of the general model in Moon and Sohn (2010) which revealed factors related to management (knowledge management, technology experience, fund supply and human resources), technology (environment of technology development), marketability (market potential) and profitability (sales plan, business progress and return on investment) and all economy factors except for the exchange rate of won per dollar are significant. Although it is hard to compare factors used in Moon and Sohn (2010) to individual attributes used in our decision tree analysis, it is interesting to note that both models found important management aspects such as level of technology knowledge and technology experience. In addition, our study found that IP ownership is crucial to protect start-ups from loan default along with economic condition reflected by CPI.

The resulting rules can be used to decide whether or not to guarantee applicant start-up firms for technology fund. It could also provide useful guidelines for people preparing to start a firm.

In the current study, we analyzed 3347 cases of empirical data covering TCG activities from 1999 to 2004. It is nonetheless limited because our sample did not represent all kinds of start-up firms. The current data set focused on two kinds of industries, business service and manufacturing. Additionally, how economic indicators influence on loan default of technology based start-ups may reflect Korean situation, hence, the ability to generalize these results to other countries is limited. Further analyses, with more extensive and diverse data set are required to derive more robust results or to customize it for individual countries. They are left for the areas for further studies.

Acknowledgment

This work (research) is financially supported by the Ministry of Knowledge Economy (MKE) and Korea Institute for Advancement in Technology (KIAT) through the Workforce Development Program in Strategic Technology.

References

Almus, M. (2002). What characterizes a fast-growing firm? *Applied Economics, 34*, 1497–1508.

Audretsch, D. B., Santarelli, E., & Vivarelli, M. (1999). Start-up size and industrial dynamics: Some evidence from Italian manufacturing. *International Journal of Industrial Organization, 17*, 965–983.

Bensic, M., Sarlija, N., & Zekic-susac, M. (2005). Modelling small-business credit scoring by using logistic regression, neural networks and decision trees. *Intelligent Systems in Accounting, Finance and Management, 13*, 133–150.

Benzing, C., Chu, H. M., & Kara, O. (2009). Entrepreneurs in Turkey: A factor analysis of motivations, success factors, and problems. *Journal of Small Business Management, 47*(1), 58–91.

Boocock, G., & Shariff, M. N. M. (1996). Loan guarantee schemes for SMEs the experience in Malaysia. *Small Enterprise Development, 7*(2), 25–36.

Bureau of Labor Statistics (2011). Available from: http://www.bls.gov.

Chandler, G. N. (1996). Business similarity as a moderator of the relationship between pre-ownership experience and venture performance. *Entrepreneurship: Theory and Practice, 20*, 51–65.

Chen, M. C., & Huang, S. H. (2003). Credit scoring and rejected instances reassigning through evolutionary computation techniques. *Expert Systems with Applications, 24*, 433–441.

Coats, P. K., & Fant, L. F. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management*, 55–142.

Cowling, M., & Mitchell, P. (2003). Is the small Firms loan guarantee scheme hazardous for banks or helpful to small business? *Small Business Economics, 21*, 63–71.

Desai, V. S., Crook, J. N., & Overstreet, G. A. (1996). A comparison of neural networks and linear scoring models in the credit union environment. *European Journal of Operational Research, 95*(1), 24–37.

Feraud, R., & Clerot, F. (2002). A methodology to explain neural network classification. *Neural Networks, 15*, 237–246.

Galindo, J., & Tamayo, P. (2000). Credit risk assessment using statistical and machine learning: Basic methodology and risk modeling applications. *Computational Economics, 15*, 107–143.

Harada, N. (2004). Productivity and entrepreneurial characteristics in new Japanese firms. *Small Business Economics, 23*, 299–310.

Henderson, R., & Cockburn, I. (1994). Measuring competencies. Exploiting from effects in pharmaceutical research. *Strategic Management Journal, 15*, 63–84.

Henley, W. E., & Hand, D. J. (2007). Construction of a k-nearest-neighbour credit-scoring system. *IMA Journal of Mathematics Applied in Business and Industry, 8*(4), 305–321.

Heunks, F. J. (1996). Innovation, creativity and success. *Small Business Economics, 10*, 263–272.

Hitt, M. A., Ireland, R. D., & Lee, H. (2000). Technological learning, knowledge management, firm growth and performance: An introductory essay. *Journal of Engineering and Technology Management, 17*(3/4), 231–246.

Jeon, H. J., & Sohn, S. Y. (2008). The risk management for technology credit guarantee fund. *Journal of the Operational Research Society, 59*(12), 1624–1632.

Kang, J. W., & Heshmati, A. (2007). Effect of credit guarantee policy on survival and performance of SMEs in Republic of Korea. *Small Business Economics, 31*, 445–462.

Kim, Y., & Sohn, S. Y. (2007). Technology scoring model considering rejected applicants and effect of reject inference. *Journal of the Operational Research Society, 58*(10), 1341–1347.

Korea Technology Transfer Association (2005). <http://www.kotec.or.kr>.

Lynskey, M. J. (2004). Determinants of innovative activity in Japanese technology-based start-up firms. *International Small Business Journal, 22*(2), 159–196.

Malhotra, R., & Malhotra, D. K. (2002). Differentiating between good credits and bad credits using neuro-fuzzy systems. *European Journal of Operational Research, 136*(2), 190–211.

McEvily, S., & Chakravarthy, B. (2002). The persistence of knowledge-based advantage: An empirical test for product performance and technological knowledge. *Strategic Management Journal, 23*, 285–305.

Mitchell, G., & Hamilton, W. (1996). Managing R&D as a strategic option. *Research Technology Management, 31*(3), 50–56.

Moon, T. H., & Sohn, S. Y. (2008a). Case based reasoning for predicting multi-period financial performances of technology-based SMEs. *Applied Artificial Intelligence, 22*(7), 1–14.

Moon, T. H., & Sohn, S. Y. (2008b). Technology scoring model for reflecting evaluator's perception within confidence limits. *European Journal of Operational Research, 184*, 981–989.

Moon, T. H., & Sohn, S. Y. (2010). Technology credit scoring model considering both SME characteristics and economic conditions: The Korean case. *Journal of the Operational Research Society*, 666–675.

Nath, R., Rajagopalan, B., & Ryker, R. (1996). Determining the saliency of input variables in neural network calssifiers. *Computers and Operations Research, 24*(8), 767–773.

National Statistical Office in Korea (2005). Available from: http://www.nso.gr.kr.

Oh, I. H., Lee, J. D., Heshmati, A., & Choi, G. G. (2009). Evaluation of credit guarantee policy using propensity score matching. *Small Business Economics, 33*, 335–351.

Ong, C.-S., Huang, J.-J., & Tzeng, G.-H. (2005). Building credit scoring models using genetic programming. *Expert Systems with Applications, 29*(1), 41–47.

Peña, I. (2002). Intellectual capital and business start-up success. *Journal of Intellectual Capital, 3*(2), 180–198.

Qu, Y. (2008). Macro economic factors and probability of default. *European Journal of Economics, Finance and Administrative Science* (13).

Reuber, A. R., & Fischer, E. M. (1994). Entrepreneurs' experience, expertise, and the performance of technology-based firms. *IEEE Transactions on Engineering Management, 41*(4), 365–374.

Sohn, S. Y., & Jeon, H. (2010). Competing risk model for technology credit fund for small and medium-sized enterprises. *Journal of Small Business Management, 48*(3), 378–394.

Sohn, S. Y., & Kim, H. S. (2007). Random effects logistic regression model for default prediction of technology credit guarantee fund. *European Journal of Operational Research, 183*(1), 472–478.

Sohn, S. Y., Kim, H. S., & Moon, T. H. (2005). Predicting the financial performance index of technology fund for SME using structural equation model. *Expert Systems with Application, 32*, 890–898.

Sohn, S. Y., Moon, T. H., & Kim, H. S. (2005). Improved technology scoring model for credit guarantee fund. *Expert Systems with Application, 28*(2), 327–331.

Storey, D. (1994). *Understanding the small business sector*. London: Routledge.

SubbaNarasimha, P. N., & Ahmad, S. (2003). Technological knowledge and firm performance of pharmaceutical firms. *Journal of Intellectual Capital, 4*(1), 20–33.

Thomas, L. C. (2000). A survey of credit and behavioral scoring: Forecasting financial risks of lending to customers. *International Journal of Forecasting, 16*, 149–172.

Van Auken, H. E. (2001). Financing small technology-based companies: The relationship between familiarity with capital and ability to price and negotiate investment. *Journal of Small Business Management, 39*(3), 240–258.

Walsh, S., & Linton, J. D. (2002). The measurement of technical competencies. *Journal f High Technology Management Research, 13*(1), 63–86.

Wasilczuk, J. (2000). Advantageous competence of owner/managers to grow the firm in Poland: Empirical evidence. *Journal of Small Business Management, 38*(2), 88–94.

West, D. (2000). Neural network credit scoring models. *Computers and Operations Research, 27*, 1131–1152.

Westhead, P., & Cowling, M. (1995). Employment change in independent owner-managed high-technology firms in Great Britain. *Small Business Economics, 7*(2), 111–140.