Predicting Bankruptcy in Private Firms: Towards a Stepwise Regression Procedure

Jonathan Bauweraerts[1]

[1] Warocqué School of Economics and Management, University of Mons, Mons, Belgium

Correspondence: Jonathan Bauweraerts, FNRS-FRESH Research Fellow, Warocqué School of Economics and Management, University of Mons, Place Warocqué, 17, 7000, Mons, Belgium. Tel: 32-65-373276.

Abstract

The aim of this paper is to investigate the relative importance of various bankruptcy predictors commonly used in the existing literature as well as ad hoc variables by applying a variable selection technique. Based on a sample of 4,796 Belgian private firms, a forward stepwise logistic regression procedure is employed. Our results confirm that lower levels of liquidity, solvency and profitability increase the probability of bankruptcy while younger and smaller firms are more likely to be bankrupt. Furthermore, the proportion of accruals in total assets is negatively related to the probability of failure and improves the accuracy of our model.

Keywords: corporate bankruptcy, corporate failure, private firms

1. Introduction

Corporate bankruptcy often implies considerable social costs that affect owners, employees, clients, suppliers, financial institutions and government. For instance, Graham, Kim, Li and Qiu (2014) showed that the magnitude of the decline in annual wages one year after bankruptcy is 30% of pre-bankruptcy wages. According to Eckbo, Thorburn and Wang (2015), two-thirds executives face a median present value income loss equal to five times their pre-departure income. As corporate bankruptcy can induce harsh consequences for many stakeholders, business and academic communities are deeply involved in the investigation of bankruptcy prediction. As a result, numerous studies have tried to explore the potential predictors of corporate bankruptcy over the last decades (Du Jardin, 2009).

Most of prior works on corporate bankruptcy employed accounting-based variables (Altman, 1968; Beaver, 1966; Lin, Ansell & Andreeva, 2012), i.e., financial ratios constructed from only accounting data, or a mix of accounting and market-based variables (Campbell, Lo & MacKinlay, 1997; Shumway, 2001; Tinoco & Wilson, 2013), i.e., financial ratios built from market and accounting data. Although these models offered significant improvements in predicting corporate bankruptcy, little attention has been paid to the importance of considering advanced selection techniques to select the most relevant and reliable bankruptcy predictors (Tian, Yu & Guo, 2015). In this study, we endeavor to fill this gap by adopting a forward stepwise logistic regression method that provides conclusive evidence of the role of accounting-based predictors to forecast bankruptcy in private firms.

Opting for predictor selection techniques enables us to identify relevant bankruptcy predictors and improve the accuracy of the predictive model (Fan & Li, 2001). By using a stepwise procedure to select bankruptcy predictors, we contribute to the literature in two ways. First, we answer to a recent call for more robustness in the selection of empirical predictors that perform well in predicting corporate bankruptcy (Du Jardin, 2009). Second, based on an exhaustive set of bankruptcy predictors frequently employed in the existing literature, we identify the most relevant ones. By so doing, we provide additional insights on the application of corporate bankruptcy theories in empirical research (Tian et al., 2015).

This paper is structured as follows. In the first section, we review the literature on bankruptcy prediction models. Research method and results are presented in the subsequent sections. In the concluding section, we discuss the results and identify several limitations and directions for future research.

2. Theoretical Background

Bankruptcy prediction has received increasing attention from the finance and accounting literature since the late sixties. Seminal research of Beaver (1967) started to analyze the antecedents of bankruptcy by leading a discriminant

analysis on a single ratio (cash-flow/total debt) while Altman (1968) developed a multidimensional approach that combined five accounting ratios to calculate the well-known "Z-score" in order to predict corporate bankruptcy. Over years, numerous modelling techniques have been designed to provide a more complete understanding of the bankruptcy phenomenon and improve the accuracy of the models. In that sense, Du Jardin (2009) reveals that more than 50 methods have been used to build bankruptcy prediction models (discriminant analysis, logistic regression, probit regression, rules induction, spline regression, neural networks, gambler's ruin model, hazard model, and so on).

One of the most frequently employed statistical techniques in bankruptcy forecasts is the logit model (first used in Ohlson, 1980). This model offers several advantages that make it superior to alternative procedure. For instance, logit models do not require the potential bankruptcy predictors to be normally distributed and allow to combine several bankruptcy indicators into a multivariate probability score which indicates the likelihood of corporate bankruptcy (Balcaen & Ooghe, 2006; Karlson, 2015). Given the reliability of logit models to assess corporate bankruptcy (Acosta-González & Fernández-Rodríguez, 2014; Gupta, Gregoriou & Healy, 2015), this statistical technique will be used in this study.

Beyond the regression technique, another point must be stressed to build accurate bankruptcy prediction model: variable selection. Usually, a two-step procedure is chosen to select the most accurate variables. Reviewing 190 papers on bankruptcy prediction models, Du Jardin (2009) showed that, during the first step, 40% of studies only used variables that have been found to be good predictors in prior research. In other words, the variables are included in the model because they were significant in past empirical works. However, this procedure is quite reductionist as bankruptcy predictors can be reliable in one context but not in another owing to their contingent nature (Balcaen & Ooghe, 2006; Du Jardin, 2015). To mitigate this concern, the first step of this research proposes to adopt a mix-method that includes variables whose predictive power has been demonstrated in prior studies as well as ad hoc variables with the aim to improve the accuracy of the model.

In the second step, an automatic procedure is commonly employed to build the final set of bankruptcy predictors. Dash and Liu (1997) suggested to distinguish between complete methods and heuristic methods. While the former enables to find an optimal solution provided the evaluation criteria is monotonic, the latter relaxes the monotonic assumption on the selection criteria. As a result, heuristic procedures allow researchers to explore all possible combinations for the selection criteria to finally restrict attention to a smaller number of potential bankruptcy predictors (Acosta-González & Fernández-Rodríguez, 2014). Some of the most popular methods are the forward or backward stepwise procedures, which sequentially include or exclude variables based on various criteria such as t-ratio statistics or the probability of F (Miller, 2002; Lussier & Corman, 2015). Despite their relevancy, few studies engage in such procedures. According to Du Jardin (2009), only 26% of prior works on bankruptcy prediction adopt stepwise selection procedures, which hampers the robustness of their results. As a consequence, this research uses forward stepwise logistic regressions to build the most accurate model of bankruptcy prediction (Karas & Reznakova, 2014)

3. Method

3.1 Data Collection

In this study, we used a sample of 4,796 Belgian private firms whose 826 companies were declared bankrupt between the years 2010 and 2014. The Bureau Van Dijk (hereafter, BVD) database was employed to identify the firms that had experienced a bankruptcy between 2010 and 2014. This database was also used to gather information about the financial and accounting ratios as well as firm's characteristics.

3.2 Regression Procedure

Since the dependent variable is a dichotomous qualitative variable, a binary logit regression model was used, as is the case in many studies regarding the occurrence of bankruptcy filing (Ohlson, 1980; Premachandra, Bhabra & Sueyoshi, 2009). A logit model describes the relationship between a dichotomous dependent variable that can take value 1 (bankrupt business) or value 0 (healthy), and k other explanatory variables x_1, x_2... x_k. These variables can be quantitative or qualitative. Since the dependent variable is binary (dichotomous), the latter follows the Bernoulli distribution such that $P_i = P(y_i = 1)$ is the probability of bankruptcy and $1 - P_i$ is the probability of non-failure. The estimated model requires the endogenous variable to be a linear combination of exogenous variables:

$$y_i^* = \beta\ X_i + \varepsilon_i \tag{1}$$

where ε is the error term and β the vector of coefficients

and where

yi = 1 if yi* > 0

yi = 0 if yi* ≤ 0

The probability of non-default (a posteriori) of business i is given by:

$$P(y_i = 0) = P(y_i^* \leq 0) = P(\beta X_i + \varepsilon_i \leq 0) = P(\varepsilon_i \leq -\beta X_i) = F(-\beta X_i) = 1 - F(\beta X_i) = 1 - P_i \quad (2)$$

Similarly, the probability of failure (a posteriori) of business i is represented by:

$$P(y_i = 1) = P(y_i^* > 0) = P(\beta X_i + \varepsilon_i > 0) = P(\varepsilon_i > -\beta X_i) = 1 - P(\varepsilon_i \leq -\beta X_i) = F(\beta X_i) = P \quad (3)$$

The logit model assumes that the errors follow a logistic distribution where the distribution function is:

$$F(x) = (1 + e - x) - 1 \quad (4)$$

Therefore, it is possible to calculate the probability of non-default of business I as follows:

$$P(y_i = 0) = F(-\beta X_i) = (1 + e^{\beta X_i}) - 1 = 1 - P_i \quad (5)$$

Similarly, the probability of the default of business i is:

$$P(y_i = 1) = F(X_i \beta) = (1 + e - \beta X_i) - 1 = P_i \quad (6)$$

The β coefficients were estimated using the method of maximum likelihood and the model is analysed with Stata software.

3.3 Variable Selection

Dependent variable. Bankruptcy is a dichotomous variable coded with the value of 1 if the company is bankrupt, 0 otherwise.

Independent variables. Numerous studies have included a large amount of accounting-based variables and market-based variables to improve the accuracy of bankruptcy forecast model (e.g. Altman, 1968; Beaver, McNichols & Rhie, 2005; Bharath & Shumway, 2008; Charitou, Dionysiou, Lambertides & Trigeorgis, 2013). However, most of them used sub-optimal selection criteria. According to Du Jardin (2009), only 35% of empirical research in the field employs an effective variable selection method. In this study, stepwise logistic regressions were used to identify and select the best combination of variables predicting bankruptcy (Shin & Lee, 2002; Shin, Lee & Kim, 2005).

Forward stepwise selection consists to find the single best predictor variable and add variables that meet specified criteria (Tsai, 2009). More specifically, this method sequentially includes variables based on F-statistic considerations until none improves the model (Miller, 2002). The final model only contains effective predictors with a significant coefficient. In building the model, 20 potential predictors were used based on prior studies such as Altman, (1968), Beaver (1966), Beaver et al. (2005), Ding, Song and Zen (2008), Ohlson (1980), Reznakova and Karas (2014), Tsai (2009), Tseng and Hu (2010), Wang and Lee (2008). 11 ad hoc variables were also included to take into account the contingent nature of bankruptcy predictors (Du Jardin, 2009, 2015).

To select the most accurate and relevant predictors during the stepwise selection procedure, we used several criteria. Following Tsai (2009), we employed .05 probability of F as a cutoff line of entry to select one of the variables which is crucial to the model. To avoid co-linearity problems with the variables selected in applying this procedure, we set .10 probability of F as a limit of removal (Tsai, 2009). Thus, one variable was included in the model if the probability of F is less than .05 and removal from the models if the probability of F is more than 0.1. The probability of F corresponds to the contribution of the variables to the model whether they reach the significance or not. Applying this forward stepwise technique to the accounting-based variables reported in Table 1, the following independent variables were included in our model:

Firm age corresponds to the number of years the firm has been in business. *Firm size* is the natural logarithm of total assets. *Accruals* is measured as accruals divided by total assets. *Current* represents a measure of the current ratio (current assets/current liabilities). *EBIT/TA* is a profitability ratio that is measured as earning before interests and taxes divided by total assets. *Solvency* corresponds to a commonly employed measure of the solvency ratio: (Net income + depreciation) / (Short-term liabilities + Long term liabilities). *VA/TW* captures labor productivity and is measured as the value added per worker.

Table 1. List of variables

Variable	Shortcut	Variable	Shortcut	Variable	Shortcut
Firm age	Firm age	Number of days of supplier credit	SupplierDays	Total liabilities/Total assets	TD/TA
Log of total assets	Firm size	Long term liabilities/Total assets	LTL/TA	Net income/Total liabilities	NI/TL
Shareholder equity/Total assets	Solvency	Gross sales margin	GSM	Net income/Current liabilities	NI/CL
Current ratio	Current	Net sales margin	NSM	Net income/Current assets	NI/CA
EBIT/Total assets	EBIT/TA	Net income/Sales	NI/S	Cash-flow/Current assets	CF/CA
Accruals/Total assets	Accruals	Net income/Total assets	NI/TA	Cash-flow/Total liabilities	CF/TL
Value added/Total workers	VA/TW	Cash-flow/Equity	CF/E	EBITDA/Total liabilities	EBITDA/TL
Value added/Tax expense	VA/TE	Cash-flow/Total liabilities	CF/TD	Current liabilities/Sales	CL/S
Acid test	Acid	Net Working Capital/Sales	NWC/S	Inventory turnover	InvTurn
Log of sales	LnS	Net Working Capital/Total assets	NWC/TA		
Number of days of client credit	ClientDays	Long term liabilities/Equity	LTdebt/E		

4. Results

4.1 Descriptive Statistics

Descriptive statistics and Pearson's correlation matrix are reported in Table 2. It appears that bankrupt firms are younger ($p < .01$) and smaller ($p < .01$). Additionally, it must be noted that the solvency ratio ($p < .01$) and the current ratio ($p < .01$) are negatively correlated with the probability of bankruptcy. Profitability seems to be negatively linked to bankruptcy since a negative correlation is found between both *EBIT/TA* ($p < .01$) and *VA/TW* ($p < .01$) and bankruptcy. It is also observed that accruals are positively correlated to bankruptcy ($p < .01$). Interestingly enough, larger firms display higher levels of solvency ratio ($p < .01$), current ratio ($p < .01$), *EBIT/TA* ($p < .01$) and *VA/TW* ($p < .01$). Older firms are only characterized by higher levels of solvency ratio ($p < .01$) and current ratio ($p < .01$). Furthermore, both firm age ($p < .01$) and firm size ($p < .01$) are negatively correlated to accruals.

Table 2. Means, standard deviations, and correlations

Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1. Bankruptcy	0.172	0.378	1							
2. Firm age	16.554	11.148	-0.076***	1						
3. Firm size	5.762	1.852	-0.233***	0.237***	1					
4. Accruals	0.027	0.071	0.159***	-0.071***	-0.219***	1				
5. Current	3.337	8.351	-0.123***	0.081***	0.057***	-0.015	1			
6. EBIT/TA	-2.232	93.549	-0.053***	-0.000	0.096***	-0.081***	0.010	1		
7. Solvency	36.149	38.841	-0.386***	0.152***	0.095***	-0.070***	0.381***	0.217***	1	
8. VA/TW	84.314	121.427	-0.193***	0.027	0.322***	-0.053**	0.064***	0.145***	0.151***	1

* $p \leq .10$. ** $p \leq .05$. *** $p \leq .01$.

4.2 Regression Analysis

The results of our regression are presented in Table 3. Both firm age ($p < .01$) and firm size ($p < .01$) are negatively related to bankruptcy. Regarding the relationship between profitability and bankruptcy, we observe that both *EBIT/TA* ($p < .01$) and *VA/TW* ($p < .01$) are negatively related to the probability of bankruptcy. A negative relation is reported between the degree of liquidity, assessed by the current ratio, and bankruptcy ($p < .01$) while a negative link exists between the solvency ratio and the probability of bankruptcy ($p < .01$). Furthermore, a positive relationship is observed between accruals and bankruptcy ($p < .01$).

Table 3. Logit regression

	Logit regression	
	Coef.	Std. Dev.
Current	-0.203***	(0.124)
EBIT/TA	-3.381***	(0.710)
Solvency	-0.026***	(0.004)
VA/TW	-0.026***	(0.005)
Accruals	4.212***	(1.336)
Firm size	-0.131***	(0.034)
Firm age	-0.003***	(0.000)
Intercept	1.731***	(0.007)
Observations	23 980	
Model Chi2	423.32*** (7 df)	
Log Likelihood	-377.966	

* $p \le .10$. ** $p \le .05$. *** $p \le .01$.

As robustness check, we led an out-of-sample analysis. As such, the sample was divided into two parts. The first part included 70% of the observed group (3,357 firms) and acts as the training group. The rest of the sample (1,439 firms) represented the control group that was employed to test the model obtained on the training group. The out-of-sample analysis revealed high levels of accurate prediction since the estimated parameters did not differ significantly from our initial regression. Furthermore, we run additional robustness tests by changing the division percentage of both groups. However, setting the observed group and the control group both at 50% , or even 25% of the initial sample for the observed group and 75% for the control group, did not change our percentage of accurate prediction significantly.

5. Discussion and Conclusion

Bankruptcy prediction is a critical issue that has been widely explored in the finance and accounting literature. Although numerous improvements have been noted in the construction of bankruptcy prediction models over the last decades (Balcaen & Ooghe, 2006; Du Jardin, 2015), a long way has still to be done regarding the accuracy of those models (Reznakova & Karas, 2014). Using a comprehensive Belgian bankruptcy database constructed from Belfirst, we adopt a forward stepwise logit regression procedures in order to extract the most accurate model based on an initial set of 31 variables containing the most commonly employed bankruptcy predictors as well as ad hoc variables whose inclusion was likely to improve the fit of the model.

Our results suggest that bankruptcy can be predicted by a subset of 7 variables: *firm age*, *firm size*, *EBIT/TA, VA/TW, Solvency, Current* and *accruals*. In addition to the variables related to solvency, liquidity and profitability whose predictive power has already been shown (e.g. Altman, 1968; Beaver, 1966; Beaver et al., 2005; Ohlson, 1980; Tsai, 2009), it is interesting to note that the proportion of accruals in total assets improves the predictive power of the model. This observation is in line with prior research suggesting that higher levels of accruals is an indication of the presence of errors in the accruals-estimation process (Richardson, 2003), which is likely to increase the probability of bankruptcy (Al-Attar, Hussain & Zuo, 2008).

The contribution of this article to the academic literature is twofold. First, by employing a stepwise forward logit regression procedure to build our bankruptcy prediction model, we answer to a recent call for more robustness in the variable selection process (Acosta-González & Fernández-Rodríguez, 2014). Moreover, we also included ad hoc variables to take into account the contingent nature of bankruptcy prediction, a procedure that has been overlooked in

empirical research so far (Du Jardin, 2009, 2015). Taken together, these elements contribute to the literature as they are oriented towards more accuracy in the construction of bankruptcy prediction models. Second, our findings also add a unusual bankruptcy predictor with the proportion of accruals in total assets. By so doing, we emphasize the importance to take into account ad hoc variables in order to extend corporate bankruptcy theories (Tian et al., 2015).

This study also suffers from several limitations that must be acknowledged. First, we used a forward stepwise procedure. Even if such using such a procedure has been found reliable (Acosta-González & Fernández-Rodríguez, 2007), over-identification concern can appear in the model. It means that false significant variables could be included in the final model (Lovell, 1983). Therefore, future research should adopt a method that alleviates this problem such as computational search procedures (Acosta-González & Fernández-Rodríguez, 2014) or data mining and machine learning techniques (Tsai, 2009). Furthermore, this study addressed bankruptcy prediction using a sample of Belgian private firms. Since bankruptcy prediction models must be contextualized to offer relevant and accurate forecasts (McSweeney, 2001), our study could be replicated in other institutional, legal or organizational contexts. Additionally, we used static bankruptcy predictors to build our model. As such predictors only capture an imbalance at a determined moment, an alternative method would be to use variation variables that consider year-on-year changes in the predictors to address bankruptcy in a dynamic way (Du Jardin, 2009).

In conclusion, we hope that, by developing a further understanding of bankruptcy prediction in private firms, this study will stimulate future research on this complex and important issue of finance and accounting studies.

References

Acosta-González, E., & Fernández-Rodríguez, F. (2007). Model selection via genetic algorithms illustrated with cross-country growth data. *Empirical Economics, 33*(2), 313–337. http://dx.doi.org/10.1007/s00181-006-0104-3

Acosta-González, E., & Fernández-Rodríguez, F. (2014). Forecasting financial failure of firms via genetic algorithms. *Computational Economics, 43*(2), 133–157. http://dx.doi.org/10.1007/s10614-013-9392-9

Al-Attar, A., Hussain, S., & Zuo, L.Y. (2008). Earnings quality, bankruptcy risk and future cash flows. *Accounting and Business Research, 38*(1), 5–20. http://dx.doi.org/10.1080/00014788.2008.9663317

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589–609. http://dx.doi.org/10.1111/j.1540-6261.1968.tb00843.x

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. *The British Accounting Review, 38*(1), 63–93. http://dx.doi.org/10.1016/j.bar.2005.09.001

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4,* 71–111. http://dx.doi.org/10.2307/2490171

Beaver, W. H., McNichols, M. F., & Rhie, J. W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies, 10*(1), 93–122. http://dx.doi.org/10.1007/s11142-004-6341-9

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies, 21*(3), 1339–1369. http://dx.doi.org/10.1093/rfs/hhn044

Campbell, J., Lo, A., & MacKinlay, A. (1997). *The Econometrics of Financial Markets.* PressPrinceton, NJ: Princeton University.

Charitou, A., Dionysiou, D., Lambertides, N., & Trigeorgis, L. (2013). Alternative bankruptcy prediction models using option-pricing theory. *Journal of Banking & Finance, 37*(7), 2329–2341. http://dx.doi.org/10.1016/j.jbankfin.2013.01.020

Dash, M., & Liu, H. (1997). Feature selection for classification. *Intelligent Data Analysis, 1*(1), 131–156. http://dx.doi.org/10.1016/S1088-467X(97)00008-5

Ding, Y., Song, X., & Zen, Y. (2008). Forecasting financial condition of Chinese listed companies based on support vector machine. *Expert Systems with Applications, 34*(4), 3081–3089. http://dx.doi.org/10.1016/j.eswa.2007.06.037

Du Jardin, P. (2009). Bankruptcy prediction models: How to choose the most relevant variables? *Bankers, Markets & Investors, 98*, 39–46.

Du Jardin, P. (2015). Bankruptcy prediction using terminal failure processes. *European Journal of Operational Research, 242*(1), 286–303. http://dx.doi.org/10.1016/j.ejor.2014.09.059

Eckbo, B.E., Thorburn, K.S., & Wang, W. (2014). How costly is corporate bankruptcy for top executives? *Tuck School of Business Working Paper*, 109.

Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American Statistical Association, 96*, 1348–1360. http://dx.doi.org/10.1198/016214501753382273

Graham, J.R., Kim, N.H., Li, S., & Qiu, J. (2014). The Labor Impact of Corporate Bankruptcy: Evidence from Worker-Firm Matched Data. Available at SSRN 2276753.

Gupta, J., Gregoriou, A., & Healy, J. (2015). Forecasting bankruptcy for SMEs using hazard function: To what extent does size matter?. *Review of Quantitative Finance and Accounting, 45*(4), 845–869. http://dx.doi.org/10.1007/s11156-014-0458-0

Karas, M., & Reznakova, M. (2014). A parametric or nonparametric approach for creating a new bankruptcy prediction model: The Evidence from the Czech Republic. *International Journal of Mathematical Models and Methods in Applied Sciences*, *8*, 214–223.

Karlson, K. B. (2015). Another Look at the Method of Y-Standardization in Logit and Probit Models. *The Journal of Mathematical Sociology, 39*(1), 29–38. http://dx.doi.org/10.1080/0022250X.2014.897950

Lin, S. M., Ansell, J., & Andreeva, G. (2012). Predicting default of a small business using different definitions of financial distress. *Journal of the Operational Research Society, 63*(4), 539–548. http://dx.doi.org/10.1057/jors.2011.65

Lovell, M. C. (1983). Data mining. *Review of Economic and Statistics, 65*, 1–12. http://dx.doi.org/10.2307/1924403

Lussier, R. N., & Corman, J. (2015). A business success versus failure prediction model for entrepreneurs with 0-10 employees. *Journal of Small Business Strategy, 7*(1), 21–36.

McSweeney, B. (2001). Narratives and numbers: from a contextual to contextualized financial analysis. *Accounting Forum, 25*(3), 246–263. http://dx.doi.org/10.1111/1467-6303.00065

Miller, A. (2002). *Subset selection in regression*. London: Chapman & Hall/CRC. http://dx.doi.org/10.1201/9781420035933

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*(1), 109–131. http://dx.doi.org/10.2307/2490395

Premachandra, I. M., Bhabra, G. S., & Sueyoshi, T. (2009). DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique. *European Journal of Operational Research, 193*(2), 412–424. http://dx.doi.org/10.1016/j.ejor.2007.11.036

Reznakova, M., & Karas, M. (2014). Bankruptcy prediction models: can the prediction power of the models be improved by using dynamic indicators? *Procedia Economics and Finance, 12*, 565–574. http://dx.doi.org/10.1016/S2212-5671(14)00380-3

Richardson, S. (2003). Earnings quality and short sellers. *Accounting Horizons, 17,* 49–62. http://dx.doi.org/10.2308/acch.2003.17.s-1.49

Shin, K. S., & Lee, Y. J. (2002). A genetic algorithm application in bankruptcy prediction modeling. *Expert Systems with Applications, 23*(3), 321–328. http://dx.doi.org/10.1016/S0957-4174(02)00051-9

Shin, K. S., Lee, T. S., & Kim, H. J. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications, 28*(1), 127–135. http://dx.doi.org/10.1016/j.eswa.2004.08.009

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model*. *The Journal of Business, 74*(1), 101–124. http://dx.doi.org/10.1086/209665

Tian, S., Yu, Y., & Guo, H. (2015). Variable selection and corporate bankruptcy forecasts. *Journal of Banking & Finance, 52*, 89–100. http://dx.doi.org/10.1016/j.jbankfin.2014.12.003

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis, 30*, 394–419. http://dx.doi.org/10.1016/j.irfa.2013.02.013

Tsai, C. F. (2009). Feature selection in bankruptcy prediction. *Knowledge-Based Systems, 22*(2), 120–127. http://dx.doi.org/10.1016/j.knosys.2008.08.002

Tseng, F. M., & Hu, Y. C. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications, 37*(3), 1846–1853. http://dx.doi.org/10.1016/j.eswa.2009.07.081

Wang, Y. J., & Lee, H. S. (2008). A clustering method to identify representative financial ratios. *Information Sciences, 178*(4), 1087–1097. http://dx.doi.org/10.1016/j.ins.2007.09.016