Corporate failure diagnosis in SMEs

A longitudinal analysis based on alternative prediction models

Kosmas Kosmidis
Department of Information Management, Kavala Institute of Technology, Kavala, Greece, and
Antonios Stavropoulos
Department of Applied Informatics, University of Macedonia, Thessaloniki, Greece

Received 14 January 2013
Revised 14 January 2013
Accepted 14 January 2013

Abstract

Purpose – The main purposes of this paper are to provide evidence about corporate failure diagnosis in SMEs, identify the predictor variables that enhance the accuracy of the corporate failure diagnosis models, and perform comparative analysis of the proposed models with the existing literature. The paper supports the proposition that the majority of the proposed corporate failure diagnosis models in the literature exhibit an endogenous drawback since their construction is based on large entities or listed corporations' samples.

Design/methodology/approach – The present study employs multiple discriminant analysis, logit analysis, and probit analysis to construct corporate failure diagnosis models based on SMEs longitudinal data from Greece.

Findings – The paper provides evidence that the contribution of human capital is immensely more important to the viability of SMEs than to the viability of large corporations. Moreover, this study identifies interactions among seemingly insignificant variables that exhibit incremental information content and attribute massive discriminant power to the proposed corporate failure diagnosis models.

Practical implications – The results of this study encourage regulatory authorities to adopt enhancements to the Basel II framework and financial institutions as regards to constructing their corporate failure diagnosis models. The models is based upon internal default experience and mapping to external data incorporating both quantitative and qualitative variables.

Originality/value – The contribution of this paper is the proposition of new value-relevant variables that enhance the accuracy of existing corporate failure diagnosis models for SMEs.

Keywords Greece, SMEs, Finance, Bankruptcy, Corporate failure, Prediction models

Paper type Research paper

1. Introduction

The diagnosis of corporate failure has been the apple of discord among researchers, academics and professionals for the last four decades since the pioneering work of Altman (1968), who employed multiple discriminant analysis methodology (MDA) in order to predict corporate bankruptcy. Apparently, this debate is becoming timelier nowadays due to the rampant spread of financial turbulence, which reinforces the

The authors are grateful to Konstantinos Terzidis, Evangelos Tsoukatos and two anonymous referees for their useful comments and suggestions.

International Journal of Accounting and Information Management
Vol. 22 No. 1, 2014
pp. 49-67

1834-7649
DOI 10.1108/IJAIM-01-2013-0001

proclaimed important role of corporate failure diagnosis. The prime causes of failure in mature companies are concerned with fatal corporate strategy decisions and especially with "defective response to change" (Argenti, 1976). Therefore, ability to adapt to a ceaselessly changing business environment is the cornerstone of a firm's potential to survive in the global arena.

Corporate failure affects a plethora of stakeholders such as employees, managers, shareholders, auditors, creditors, and, to the extent that failure results in breaking up a corporation's social and economic interaction with its host environment, the society as a whole. The devastating impact that the collapse of Enron, Worldcom, Barings Bank, Imarbank and others had on the Global economy supports the preceding argument about the plethora of interested parties affected by corporate failure. Numerous studies on financial distress signalling and corporate failure prediction have been reported in the literature. However, in their vast majority, these are confined to large entities or listed corporations.

Nevertheless, the birth of the current economic crisis was not the collapse of few colossal corporations but the massive default of US households in the sub-prime mortgage credit market. Consequently, research on corporate failure diagnosis should be expanded to small- and medium-sized enterprises (SMEs) and non-listed corporations, due to their large number and their impact on real economy. Especially in Europe, the majority of enterprises are considered small and account for a significant amount of European work experience and economic activity (Baixauli and Modica-Milo, 2010). In particular, this study focuses on Greece, which exhibits many similarities with other Southern European countries concerning the volume and frequency rate of SMEs in the economy (Commission of the European Union, 2007).

The main objectives of this paper are to:

- provide evidence on corporate failure diagnosis in SMEs;
- identify the financial ratios enhancing the predictive ability of corporate failure diagnosis models; and
- perform a comparative analysis of the proposed models in relation to existing literature.

The main contribution of this paper is to propose new value-relevant variables that improve the accuracy of existing models for SMEs. Evidence on bankrupt corporations was collected from the county courts in the region of Central and Eastern Macedonia in Greece.

The remainder of this paper is organised as follows: Section 2 presents an extensive literature review concerning corporate failure diagnosis and the current advances with the employment of experts systems. Our research methodology including sample and variable selection processes is provided in Section 3 of this paper. Section 4 reports the empirical results of our analysis. The discussion of the results and the practical implications of our study are embedded in Section 5. Finally, our concluding remarks are cited in Section 6 of this paper.

2. Literature review

There is a plethora of studies concerning financial distress signalling and corporate failure diagnosis. The ability to discriminate between financially distressed and viable corporations was enhanced by the use of financial ratios. The pioneering work of

Altman (1968), who employed MDA for corporate failure diagnosis purposes, served as a beacon for other researchers. The following two decades, academics were focused on finding out appropriate financial ratios that would maximise the accuracy and predictive power of their models (Altman *et al.*, 1977; Altman, 1984; Johnsen and Melicher, 1994) and testing these models in different sectors, industries (Espahbodi and Espahbodi, 1984) and markets (Peel and Peel, 1988; Keasey *et al.*, 1990; Tamari, 1984; Ugurlu and Aksoy, 2006).

However, the financial patterns of distressed corporations are more unstable than those of financially viable ones (Martikainen and Ankelo, 1991). In that sense, variable selection processes that seem to be appropriate for corporate failure diagnosis in a particular market, time and industry, may not be appropriate in all settings. Hence, the majority of corporate failure prediction models proposed in the literature embody a significant endogenous drawback as far as SMEs are concerned, since their construction was based on samples comprising large or listed corporations.

During the last two decades, researchers employed different methodologies attempting to improve the accuracy of their proposed models. The majority of existing literature supports the argument that artificial neural network approaches and support vector machines outperform traditional statistical models (MDA and logit – probit analysis) in different sectors, economies and eras (Altman *et al.*, 1994; Lin and McClean, 2001; Alfaro *et al.*, 2008; Yim and Mitchell, 2007; Tsukuda and Baba, 1994; Ozkan-Gunay and Ozkan, 2007; Etemadi *et al.*, 2008; Lin, 2009; Huang *et al.*, 2008; Wu *et al.*, 2010). In fact, traditional statistical models are based on assumptions such as linearity, normality and independence among predictor variables that rarely exist in the real world.

On the other hand, artificial neural networks learn and generalise by experience of complex and non-linear data while trying to minimise the misclassification rate empirically. Moreover, there is supporting evidence on vector machines outperforming even artificial neural networks due to the application of the structural risk minimisation principle (Hua *et al.*, 2007). Additionally, the interaction between "new" and "old" variables and their effect on the accuracy of proposed corporate failure diagnosis models has been examined. Factors such as economic cycle phase, e.g. recession (Richardson *et al.*, 1998), cash flow information (Sharma, 2001), quality of accounting and financial information (Gadenne and Iselin, 2000), and the detection of fraudulent financial reporting (Liou and Yang, 2008) can evidently enhance the predictive power of existing models. In conclusion, leverage and liquidity are considered as the most important predictor variables in corporate failure diagnosis.

Nevertheless, academia exhibits relative reluctance to engage in corporate failure diagnosis studies in SMEs, which can be easily justified by the scarcity of publicly available information on these corporations, especially the bankrupt ones (Sandin and Porporato, 2007). The potential underlying hazard of this phenomenon can be a repetition of the current economic crisis with a different starting point – not the sub-prime mortgage market but the SMEs' corporate loans market. According to the Basel II framework, the probability of default estimation can be based on internal default experience and/or mapping to external data and/or statistical default models (BCBS, 2004, par. 461). Since financial institutions choose to estimate the probability of default of their SME clients based on existing statistical default models through employing endogenously disadvantageous sampling processes, the gap between *ex ante* and *ex post* expected losses of financial institutions, will be enhanced due to the mitigated accuracy of existing models. Although Altman and Rijken (2004) illustrated how rating agencies achieve rating stability, the current economic crisis proves the fallacy of this stability.

The diagnosis of corporate failure can also be viewed within a corporate ethics framework. Managers of private corporations are responsible and accountable not only for making sufficient profits but also for contributing to the public interest by peacefully solving conflicts with their corporations' stakeholders which arise out of corporate strategy. This is because the license to operate a private company and to make profits should not be understood as being unconditionally granted by law. In this sense, corporate ethics:

- form a direct link between the public interest and corporate strategy when possible conflicts are not successfully settled by law; and
- depend on partners sharing the same culture (Steinmann, 2007).

Consequently, in cases where corporate bankruptcy has its roots in corporate ethics, the diagnosis of corporate failure should be explored within a cultural context. This perspective provides an alternative explanation on why evidently accurate corporate failure prediction models (e.g. Altman, Ohlson, Zmijewski) underperform when applied in different economies, markets and sectors (Wu *et al.*, 2010; Lin, 2009; Baixauli and Modica-Milo, 2010; Sandin and Porporato, 2007).

3. Methodology

As mentioned earlier, the paper lays emphasis on constructing accounting-based corporate failure diagnosis models with SMEs data from Greece. The inability to construct a market-based model for SMEs (the majority of SMEs abstain from capital markets) should not be intimidating since accounting-based models outperform in terms of differential error misclassification costs (Agarwal and Taffler, 2008). Evidence on failed corporations was originally collected from the county courts in the region of Central and Eastern Macedonia in Greece. The pre-requisites of the research study can be summarised to the following:

1. Sample comprises corporations complying with the definition of micro-, small- and medium-sized enterprises provided by the Commission of the European Union (2003). Such corporations employ fewer than 250 persons and have an annual turnover not exceeding €50 million, and/or an annual balance sheet total not exceeding €43 million.
2. The legal form of corporations in the sample is confined to limited liability (Ltd) and societe anonyme (s.a.) corporations. This particular methodological choice was made in order to overcome the scarcity of publicly available information about these corporations especially the bankrupt ones. According to the Greek Financial Reporting Standards only the preceding corporations are obliged to disclose financial statements such as balance sheets and the income statements. Moreover, the adoption of International Financial Reporting Standards is compulsory only for listed corporations in Athens Stock Exchange. However, the quality of financial statements is preserved since 85 percent of sample corporations (49 out of 58) are audited at least by one CPA or two certified

accountants, members of the Economic Chamber of Greece[1], [2]. Their quality is also not affected from upward revaluation of assets and fair value measurement (Cheng and Lin, 2009; Chong *et al.*, 2012) since managerial discretion is not an option[3].

3. Corporations engaged exclusively in retail, financial and other services were excluded from the sample, which primarily comprises manufacturing corporations.
4. The time span of the study extends from 2003 to 2009, a period before the outbreak of the crisis when Greek economy constantly witnessed positive growth rates. Hence, the impact of recession did not affect variable selection processes.
5. Failed corporations are considered those having been bankrupt or dissolved or discontinued operations.

The research population and sample contains only 29 failed corporations meeting the preceding five criteria; observations with missing values are deleted. Additionally, 29 non-failed corporations from corresponding sectors meeting the first four criteria are selected. Subsequently, the sample, consisting of 58 corporations, can be characterised as adequate since the failed corporations reflect 100 percent of the statistical population. Although over-sampling of failing corporations may lead to a non-random sample, the great majority of existing models embody this compromise due to the low frequency rate of failing corporations (Balcaen and Ooghe, 2006). The financial statements of these corporations are provided by the ICAP database. In particular, for failed corporations, the study incorporates the last available financial statements prior to failure; this implies that for failed corporations between 2004 and 2009, the last available financial statements derive from the 2003-2008 period. On the other hand, for non-failed corporations, a multi period approach is adopted. The approach is identical to incorporating the mean value of financial ratios derived from the financial statements of the entire 2003-2008 period. This refinement improves model performance (Wu *et al.*, 2010) by mitigating the impact of exceptional items on the financial position of the corporations.

The variable selection process is applied in four stages. The selection and computation of 37 financial ratios are embedded in the first stage. The definitions of these financial ratios are based on the current literature. In fact, the definition of eight liquidity ratios, 11 activity ratios, nine profitability ratios and nine viability ratios are shown in the corresponding Tables I-IV. For failed corporations, the computation of financial ratios derived from 29 firm-year observations while for non-failed corporations, the computation of financial ratios derived from 174 firm-year observations. At the second stage, one tail *t*-test is conducted for all these 37 financial ratios. The null hypothesis being that there is no significant difference in the mean values of these ratios between failed and non-failed corporations while the alternative hypothesis:

- for liquidity ratios is that non-failed corporations exhibit higher values than failed ones;
- for activity ratios is that non-failed are more efficient than failed corporations;
- for profitability ratios is that non-failed corporations exhibit higher values than failed corporations; and
- for viability ratios is that non-failed corporations are less leveraged than failed.

Table I.
Definition and *t*-test results of liquidity ratios

Ratios	Definition	Status	Mean	SD	Min.	Max.	*t*-val.	Signific.
Liquidity								
CR	Current assets to current liabilities	Non-failed	1.8143	1.0466	0.8700	5.0100	3.20	0.002***
		Failed	1.1606	0.3372	0.5450	2.0300		
QR	Current assets minus inventory to current liabilities	Non-failed	1.4072	1.0300	0.4700	4.7200	2.77	0.005***
		Failed	0.8535	0.3079	0.3470	1.9100		
DIR	Current assets minus inventory to daily operating expenses	Non-failed	278.1	207.6	81.0	1,186	0.51	0.307
		Failed	253.8	152.3	74.0	669.0		
LDIR	Natural logarithm of DIR	Non-failed	2.3699	0.2450	1.9085	3.0741	0.62	0.269
		Failed	2.3282	0.2661	1.8692	2.8254		
CFR	Distrib.earnings minus reserves and directors' reimburs.plus deprec.	Non-failed	1,072,665	2,261,621	−483,472	8,787,000	2.09	0.022**
		Failed	146,057	763,641	−1,164,816	3,674,320		
LCFR	Natural logarithm of CFR	Non-failed	4.0010	3.7570	−5.6840	6.9440	1.45	0.076*
		Failed	2.4950	4.1370	−6.0660	6.5650		
CFCLR	CFR to current liabilities	Non-failed	0.3130	0.7830	−0.6190	4.0300	2.04	0.025**
		Failed	0.0149	0.0710	−0.1700	0.1790		
CFTLR	CFR to total liabilities	Non-failed	0.2112	0.4362	−0.4580	2.0300	2.40	0.012**
		Failed	0.0147	0.0647	−0.1660	0.1790		

Note: Significant difference between failed and non-failed corporations at: *0.1, **0.05 and ***0.01 significance level

Table II. Definition and *t*-test results of activity ratios

Ratios	Definition	Status	Mean	SD	Min.	Max.	*t*-val.	Signific.
Activity								
ITR	Inventory to cost of goods sold multiplied by 360 days	Non-failed	114.0	88.9	10.0	391.0	−0.20	0.421
		Failed	119.5	117.3	0.0	584.0		
LITR	Natural logarithm of ITR	Non-failed	1.9094	0.3996	1.0000	2.5922	0.73	0.233
		Failed	1.8024	0.6747	0.0000	2.7660		
RTR	Receivables to annual sales multiplied by 360 days	Non-failed	212.9	164.4	46.0	869.0	0.63	0.264
		Failed	190.0	104.5	41.0	382.0		
LRTR	Natural logarithm of RTR	Non-failed	2.2402	0.2711	1.6628	2.9390	0.54	0.296
		Failed	2.2013	0.2796	1.6128	2.5821		
TCTR	Trade creditors to CoGs minus deprec. multiplied by 360 days	Non-failed	141.0	99.5	33.0	548.0	−1.26	0.107
		Failed	177.9	122.2	17.0	636.0		
LTCTR	Natural logarithm of TCTR	Non-failed	2.0686	0.2674	1.5185	2.7388	−0.88	0.193
		Failed	2.1406	0.3534	1.2304	2.8035		
CCR	ITR plus RTR minus TCTR	Non-failed	186.1	171.9	−93.0	743.0	1.17	0.124
		Failed	131.7	182.7	−331.0	682.0		
LCCR	Natural logarithm of CCR	Non-failed	1.8910	1.1220	−1.9680	2.8710	0.89	0.188
		Failed	1.6030	1.3250	−2.5200	2.8340		
ETR	Annual sales to equity	Non-failed	4.21	4.35	0.40	15.97	−2.51	0.009***
		Failed	10.52	12.84	0.73	53.85		
FATR	Annual sales to fixed assets	Non-failed	14.99	27.02	0.92	119.47	−1.16	0.127
		Failed	42.70	125.50	0.65	599.22		
TATR	Annual sales to total assets	Non-failed	0.9669	0.4094	0.2900	1.9100	−1.20	0.119
		Failed	1.1490	0.7090	0.3600	3.1500		

Note: Significant difference between failed and non-failed corporations at: *0.1, **0.05 and ***0.01 significance level

Table III.
Definition and *t*-test results of profitability ratios

Ratios	Definition	Status	Mean	SD	Min.	Max.	*t*-val.	Signific.
Profitability								
GMR	Gross profit to annual sales	Non-failed	0.2567	0.1000	0.0870	0.4860	1.23	0.112
		Failed	0.2180	0.1366	0.0210	0.7280		
NMR	Earnings before taxes to annual sales	Non-failed	0.0442	0.0697	−0.1346	0.2800	2.33	0.012**
		Failed	0.0057	0.0554	−0.1500	0.1800		
ROCE	Earnings before taxes plus interest paid to capital employed	Non-failed	0.0622	0.0418	−0.0392	0.1600	1.24	0.110
		Failed	0.0412	0.0805	−0.1200	0.2900		
ROE	Earnings before taxes to equity	Non-failed	0.1110	0.2137	−0.6500	0.5700	−0.01	0.498
		Failed	0.1130	2.2320	−5.4000	9.8300		
ROA	Earnings before taxes to total assets	Non-failed	0.0390	0.0480	−0.0660	0.1600	1.46	0.075*
		Failed	0.0136	0.0805	−0.1600	0.2600		
FLR	ROE to ROCE	Non-failed	2.6660	3.6030	0.43	18.94	−1.48	0.075*
		Failed	8.8700	22.3500	−23.24	100.0		
TIE	Earnings before taxes to internet paid	Non-failed	106.30	519.20	−4.34	2,803.0	1.06	0.150
		Failed	4.37	19.29	−4.00	100.00		
EBTPE	Earnings before taxes to number of employees	Non-failed	6,356	6,292	485	25,269	1.62	0.056*
		Failed	3,202	8,415	0	43,702		
LEBTPE	Natural logarithm of EBTPE	Non-failed	3.5926	0.4585	2.6854	4.4026	3.98	0.000***
		Failed	2.5504	1.3344	0.0000	4.6410		

Note: Significant difference between failed and non-failed corporations at: *0.1, **0.05 and ***0.01 significance level

Table IV. Definition and *t*-test results of viability ratios

Ratios	Definition	Status	Mean	SD	Min.	Max.	*t*-val.	Signific.
Viability/financial								
SR	Total liabilities to total assets	Non-failed	0.5987	0.2274	0.1650	0.9100	−3.55	0.000***
		Failed	0.7746	0.1388	0.4800	0.9800		
DER	Total liabilities to equity	Non-failed	3.1570	3.1860	0.1990	10.58	−2.22	0.017**
		Failed	7.7400	10.6800	0.9300	44.29		
LTDER	Non-currrent liabilities to equity	Non-failed	0.4170	0.6420	0.0000	2.6100	0.68	0.248
		Failed	0.3000	0.6630	0.0000	2.3100		
EDR	Equity to total liabilities	Non-failed	1.1110	1.2790	0.0980	5.0600	3.21	0.002***
		Failed	0.3290	0.2986	0.0220	1.0700		
FATAR	Fixed assets to total assets	Non-failed	0.2463	0.1886	0.0070	0.6400	1.02	0.155
		Failed	0.1991	0.1610	0.0030	0.5600		
LTCFAR	Equity plus non-current liabilities to fixed assets	Non-failed	3.9180	4.0100	0.8900	20.28	−0.35	0.365
		Failed	4.5600	9.0500	0.0570	32.14		
RSCR	Reserves to share capital	Non-failed	0.5670	0.8380	0.0040	3.5800	−0.46	0.323
		Failed	0.6710	0.8760	0.0000	3.7900		
POR	Dividends to earnings before taxes	Non-failed	0.2562	0.2186	0.0000	0.6640	−0.37	0.356
		Failed	0.3240	0.9610	0.0000	5.0900		
DY	Dividends to equity	Non-failed	0.0474	0.0754	0.0000	0.2600	−1.02	0.158
		Failed	0.3060	1.3660	0.0000	7.3600		

Note: Significant difference between failed and non-failed corporations at: *0.1, **0.05 and ***0.01 significance level

During the third stage, cluster analysis of variables is performed in order to detect possible inter-correlations among variables and thus avoid multicollinearity in model construction. Finally, in the fourth stage, univariate discriminant analysis is applied to identify the variables from each cluster exhibiting enhanced predictive power and thus reducing dimensionality (Hua *et al.*, 2007).

4. Empirical results

Besides the definition of financial rations, Tables I-IV also presents the descriptive statistics and *t*-test results of these ratios for failed and non-failed corporations. Table I reports the descriptive statistics and *t*-test results of liquidity ratios. As stated above, the null hypothesis states that there is no significant difference in the mean values of liquidity ratios between failed and non-failed corporations. On the contrary, the alternative hypothesis is that non-failed corporations exhibit higher values than failed corporations. The results provide evidence for the alternative hypothesis in all cases. However, statistically significant differences are witnessed in six out of nine ratios.

Accordingly, Table II presents the descriptive statistics and *t*-test results of activity ratios. Here, the null hypothesis is that there is no significant difference in the mean values of activity ratios between failed and non-failed corporations while the alternative hypothesis for positive (negative) *t*-values is that non-failed corporations exhibit higher (lower) values than failed corporations and vice versa. The results exhibit statistically significant difference between failed and non-failed corporations in only one out of 11 ratios.

Furthermore, the descriptive statistics and *t*-test results of profitability ratios are depicted in Table III. As mentioned earlier, the null hypothesis states that there is no significant difference in the mean value of the profitability ratios between failed and non-failed corporations while the alternative hypothesis for positive (negative) *t*-values is that non-failed corporations exhibit higher (lower) values than failed corporations and vice versa. The results exhibit statistically significant difference between failed and non-failed corporations in five out of nine ratios.

Finally, Table IV reports the descriptive statistics and *t*-test results of the viability ratios. Here, the null hypothesis is that there is no significant difference in the mean value of the viability ratios between failed and non-failed corporations while the alternative hypothesis for positive (negative) *t*-values is that non-failed corporations exhibit higher (lower) values than failed corporations and vice versa. The results report statistically significant differences between failed and non-failed corporations in only three out of nine ratios.

In conclusion, 15 financial ratios exhibit statistically significant differences between failed and non-failed corporations – results that are consistent with the existing literature. However, not all ratios are considered eligible for model construction due to multicollinearity problems. Cluster analysis of variables is performed on all 37 financial ratios in order to detect possible inter-correlations among variables. The Ward linkage method is employed to determine the distance between clusters. Based on the similarity level, four clusters are selected as the appropriate number. The final grouping of clusters is reported in Table V. Although there are significant differences with the initial grouping of ratios based on the existing literature, the results are not contradictory since the majority of ratios participating:

- in the first cluster are profitability ratios;
- in the second cluster are liquidity ratios;

Cluster 1		Cluster 2		Cluster 3		Cluster 4	
Ratio	Hit ratio % of UDA	Ratio	Hit ratio % of UDA	Ratio	Hit ratio % of UDA	Ratio	Hit ratio % of UDA
NMR	*74.10*	*CR*	*65.50*	DIR	50.00	*ETR*	*67.20*
ROCE	63.80	*QR*	*65.50*	LDIR	51.70	FATR	53.40
ROE	36.20	CFR	60.30	ITR	48.30	*TATR*	*55.20*
ROA	*67.20*	LCFR	56.90	LITR	48.30	*FLR*	*56.90*
DY	51.70	*CFCLR*	*65.50*	RTR	44.80	*SR*	*69.00*
EBTPE	*69.00*	*CFTLR*	*65.50*	LRTR	50.00	DER	53.40
LEBTPE	*67.20*	GMR	58.60	*TCTR*	*58.60*	LTCFAR	37.90
		TIE	50.00	*LTCTR*	*60.30*	POR	43.10
		EDR	*67.20*	CCR	53.40		
		FATAR	55.20	*LCCR*	*58.60*		
		RSCR	51.70	*LTDER*	*58.60*		

Note: Hit ratio of UDA is the percentage of correct classifications based on the univariate discriminant analysis model

Table V. Cluster analysis of variables

- in the third cluster are activity ratios; and
- in the fourth cluster are viability ratios.

The final step before proceeding to the model construction is to apply univariate discriminant analysis to identify the variables (ratios) from each cluster that exhibit enhanced discriminant power. The percentage of correct classifications for each ratio is also presented in Table V and the ratios of each cluster with the highest discriminant power are highlighted. From the comparison of the *t*-test results with the univariate discriminant analysis results, it is easy to comprehend that there are significant discrepancies. Although there are financial ratios (e.g. CFCLR, CFTLR, NMR, ROA, EBTPE, ETR, SR) appearing to be significant in both *t*-test and univariate discriminant analysis, there are also financial ratios with significant (insignificant) *t*-test results that exhibit low (high) discriminant power (e.g. DER) and vice versa (e.g. LTCTR, LCCR, LTDER). Moreover, these tests often fail to capture possible interactions among seemingly insignificant variables that attribute massive discriminant power to prediction models. Apparently, the model construction will be guided but not limited by these results.

These interactions among seemingly insignificant variables along with the estimates of the three alternative prediction models are depicted in Table VI. To avoid multicollinearity problems, only one variable from each cluster is selected. Although the accuracy of the MDA model is mitigated in the prediction of failed corporations leading to a 75.9 percent of correct classifications, the model performs better in regards to the prediction of non-failed corporations leading to a spectacular 93.1 percent of correct classifications. Since the number of failed and non-failed corporations is identical, the prior probability of each category equals to 50 percent. The overall accuracy of this prediction model is balancing to 84.5 percent which is satisfactory for in sample corporate failure diagnosis.

Consequently, Type I error (probability to misclassify a failed corporation as non-failed) increases to 24.1 percent and Type II error (probability to misclassify a non-failed corporation as failed) decreases to 6.9 percent. The assumption of equal

Table VI.
Estimates of the discriminant, logit and probit model

Variables	Discriminant analysis model		Logit model		Probit model	
	Non-failed	Failed	Coefficients	Significance	Coefficients	Significance
Intercept	−37.423	−38.878	1.584	0.722	1.036	0.688
LEBTPE	3.710	2.612	−3.350	0.001**	−2.039	0.001**
ETR	0.328	0.406	0.202	0.004**	0.124	0.002**
RSCR	3.368	4.097	1.109	0.034*	0.662	0.018*
LTCTR	27.479	29.286	3.470	0.036*	2.074	0.030*
χ^2	0.000			0.781		0.911
Accuracy						
Within groups	0.931	0.759				
Overall	0.845		0.810		0.810	
Type I error		0.241	0.207		0.207	
Type II error	0.069		0.172		0.172	

Note: Significant at: *0.05 and **0.01 level impact – cost between Types I and II errors is made although not always valid, particularly in credit exposure decisions. Moreover, the χ^2 statistic is sufficient to reject the null hypothesis that the mean values of the preceding classification functions are equal between failed and non-failed corporations. As for the variable selection, LEBTPE and ETR confirm both *t*-test and univariate discriminant analysis results. Surprisingly, the interaction of RSCR and LTCTR attribute to the model enhanced discrimination power, even though the former ratio is considered insignificant according to both *t*-test and univariate discriminant analysis, while the latter ratio is considered insignificant only in *t*-test results.

As far as the logit and probit models are concerned, the results of estimated coefficients and accuracy of the two models are considered as similar since they both achieve 81 percent of correct classifications and certainly their accuracy is mitigated in comparison to MDA. However, the Type I error is decreased to 20.7 percent and the Type II error is increased to 17.2 percent for both models. The χ^2 (Hosmer-Lemeshow and Pearson) statistics are sufficient (0.781 and 0.911) to accept the null hypothesis that the logit and probit models adequately describe the data.

The preceding analysis is based on a cut-off value of 0.50. Both the logit and probit models maximize their accuracy at the 28th percentile (cut-off value of 0.28) where they reach the hit ratio (84.5 percent of correct classifications) of MDA. For this percentile, the Type I error is minimized to 0 percent and the Type II error is increased to 31 percent. This massive increase of the Type II error is an indication that there is no sample selection bias since the non-failed corporations of the sample contain not only low-risk and profitable corporations but also medium risk corporations which temporarily suffer from losses. LEBTPE and ETR confirm both *t*-test and univariate discriminant analysis results in these models too. The informative content of the interaction of RSCR and LTCTR are also verified in the logit and probit model. In any case, Table VI also reports the significance of each variable for both models.

On the other hand, the signs of certain estimated coefficients may appear to be controversial and difficult to explain. In particular, the negative sign of LEBTPE is the most rational since the higher the profitability per employee the lower the probability of corporate failure. The positive sign of an activity ratio such as ETR is seemingly contradictory because it is expected that the higher the activity, the lower the probability of corporate failure. However, ETR should not be perceived as an activity ratio but rather more as a viability ratio since it shares many common characteristics with other viability ratios of the fourth cluster in Table V. Here, the impact of the denominator (equity) is dominant and thus, failed corporations exhibit much higher values of ETR because they are highly leveraged (trivial amount of equity due to severe losses). The positive sign of RSCR is difficult to explain because conservative dividend policy is expected to characterize non-failed corporations and not the opposite, which is the case (failed corporations exhibit much higher values of RSCR because they are probably highly leveraged). This ratio will be revisited in the next section. Finally, failed corporations enjoy higher trade credit due to default or inaccessibility of bank credit, and consequently, the positive sign of LTCTR is well justified. This is consistent with the prior work of Beck and Demirguc-Kunt (2006) who concluded that SMEs have limited access to formal sources (bank) of finance compared to large firms because SMEs have less collateral to offer and consequently, they resort to informal sources of finance such as moneylenders, trade credit and friends.

The preceding analysis concerning the signs of the independent variables is also supported by the correlation matrix cited in Table VII. Moreover, the absence of extreme correlation values (below the diagonal) attributes sufficient robustness to the proposed model even though multicollinearity is irrelevant in the MDA model (Eisenbeis, 1977).

5. Discussion and practical implications

Along with *t*-test and univariate discriminant analysis, a widely adopted methodology for variable selection process is to test the accuracy of existing popular models in new context. Although this practice verifies, validates, or impairs the robustness of existing "old" familiar variables, it distracts academia from identifying "new" value-relevant variables capable of enhancing the accuracy of corporate failure diagnosis models. Moreover, this practice usually fails to capture possible interactions among seemingly insignificant variables that exhibit incremental information content and attribute massive discriminant power to these models. As reported in Tables I-V, "old" familiar variables such as ROA, TATR, CR and SR employed by existing models (e.g. Altman, Ohlson, Zmijewski) are considered as significant in this study as well. However, their interaction does not attribute any incremental discriminant power to the prediction models especially in a SMEs context.

Alternatively, this study explores the impact of "new" value-relevant variables on the accuracy of the prediction models. One of these value-relevant variables is LEBTPE. Ironically, LEBTPE outperforms traditionally familiar profitability ratios like NMR and ROA not only in *t*-test and univariate discriminant analysis, but it also attributes incremental accuracy to the corporate failure diagnosis models. This study provides evidence that the contribution of human capital is immensely more important to the viability of SMEs than the large corporations or better yet, the contribution of human capital is higher in non-failed than in failed corporations. The main reason for this phenomenon is the employee well-being. Corporations with strong interest in employees' well-being (higher scores for employee involvement, health and safety policies and workforce reductions) exhibit significantly lower bankruptcy risk and leverage (Verwijmeren and Derwall, 2010).

The current literature which is confined to large or listed corporations prefers NMR and ROA to LEBTPE since it incorporates other financial ratios like the market value of equity to total liabilities (Altman, 1968) as proxies to capture the contribution of human capital to corporate viability. This contribution of human capital is perceived as the amount of goodwill created, "going concern". However, this rationale embodies two significant flaws because:

(1) it attributes the entire amount of goodwill to human capital and not to other factors such as the adoption of certain financial reporting standards (e.g. historical cost accounting, conservatism principle); and

Variables	LEBTPE	ETR	RSCR	LTCTR
LEBTPE	1.000			
ETR	−0.223	1.000		
RSCR	0.184	−0.038	1.000	
LTCTR	−0.108	−0.204	−0.330	1.000

Table VII. Correlation matrix of variables

(2) it pre-supposes that the market value of equity is feasible to be assessed when the vast majority of SMEs do not have access to capital markets and other secondary liquid markets are absent.

Consequently, the contribution of human capital to SMEs' viability is neglected by the existing prediction models even though it is more important to them than the large corporations.

As admitted in the previous section, the positive sign of RSCR is difficult to explain since conservative dividend policy and high degree of self-financing are presumably properties of non-failed corporations and not the opposite. One possible explanation for this ratio is the impact of the denominator (share capital) which is dominant and thus, failed corporations exhibit much higher values of RSCR because they are highly leveraged and their shareholders are less willing to contribute additional capital (trivial amount of share capital). In contrast, shareholders of non-failed corporations are more willing to raise additional capital to shield their investment. The question that arises here is, which are the latent variables that urge (avert) the shareholders of non-failed (failed) corporations (not) to contribute additional capital and vice versa? Nevertheless, the preceding hypothesis remains to be supported or falsified in a future study.

The accuracy of corporate failure diagnosis models is fundamental in credit risk management. In fact, Basel II allows financial institutions to choose between two principal options for the assessment of their credit risk: the standardised approach and the internal ratings based (IRB) approach (BCBS, 2004). There is evidence that low-risk corporations (customers – SMEs with lower probability of default) enjoy lower loan interest rates in large financial institutions which adopt an IRB model while higher-risk corporations (customers – SMEs with higher probability of default) enjoy relatively lower loan interest rates in small financial institutions which adopt the standardised approach (Ruthenberg and Landskroner, 2008). This is consistent with the prior work of Altman *et al.* (2002) who investigated the relative accuracy of the standardised model's risk weights under Basel II framework.

Thus, the majority of large financial institutions have an incentive to construct their corporate failure diagnosis models based on internal default experience and/or mapping to external data incorporating quantitative as well as qualitative variables (Kosmidis and Terzidis, 2011). In cases where financial institutions choose to estimate the probability of default of their SME clients based on existing statistical default models, which:

- derive from sample selection processes embodying an endogenous drawback;
- ignore the contribution of human capital; and
- miss the interaction among seemingly insignificant variables, these financial institutions will suffer excessive losses due to the mitigated accuracy of existing prediction models.

Accordingly, the Basel Committee on Banking Supervision (BCBS, 2009) should recognize the importance of the preceding analysis, which was merely neglected in its proposed enhancements to the Basel II framework.

6. Conclusions

The motivation of this paper is the inability of credit rating models to ascertain the risk associated with the US sub-prime mortgage market and the scarcity of corporate failure diagnosis models based on SMEs data. The main objective is to construct accounting-based corporate failure diagnosis models with SMEs data from Greece. The inability to construct a market-based model for SMEs due to their absence from capital markets should not be perceived as a drawback since accounting-based models evidently outperform in terms of differential error misclassification costs. The empirical results of our study show that the MDA model is more accurate than the logit and the probit model in terms of correct classification; no significant difference is witnessed between the results of the logit and the probit model. Only at the 28th percentile the logit and the probit model reach the hit ratio of the MDA model. In that case, they exhibit much lower misclassification costs since their Type I error is minimised to 0 percent while the Type I error of the MDA model is 6.9 percent.

A key issue in our analysis is the identification of "new" value-relevant variables that enhance the accuracy of corporate failure diagnosis models in an SMEs context. The contribution of human capital is significantly higher in non-failed corporations than in failed. The research results validate the existing literature, which supports the statistic that corporations with strong interest in employees' well-being exhibit much lower bankruptcy risk and leverage. Moreover, failed corporations enjoy higher trade credit because they have limited access to formal sources of finance such as bank credit and exhibit much higher values of ETR since they are highly leveraged. Additionally, the proposed models capture interactions among seemingly insignificant variables such as RSCR and LTCTR that exhibit incremental information content and attribute massive discriminant power to these models.

The scarcity of publicly available information about SMEs, especially the bankrupt ones, was one of the main obstacles of this study. However, the results of this paper encourage regulatory authorities to adopt enhancements to the Basel II framework in order to avoid the repetition of the current economic crisis in the future and financial institutions to construct their corporate failure diagnosis models for SMEs based on internal default experience and mapping to external data incorporating quantitative as well as qualitative variables by the provision of "new" value-relevant variables that enhance the accuracy of the existing models. Finally, the paper raises questions that remain to be supported or falsified in future studies.

Notes

1. Corporations employing more than 50 persons and/or have an annual turnover exceeding €5 million, and/or an annual balance sheet total exceeding €2.5 million (two out of preceding three criteria) are audited by CPAs (L.2190/1920).
2. Alternatively to note 1, corporations that have an annual turnover exceeding €1 million are audited at least by one CPA or two certified external accountants, members of the Economic Chamber of Greece (L.2190/1920).
3. According to Greek Financial Reporting Standards, revaluation of assets is compulsory every four years in compliance with ratios provided by the Ministry of Finance. This obligation applies also to corporations which adopted IFRS.

References

Agarwal, V. and Taffler, R. (2008), "Comparing the performance of market-based and accounting-based bankruptcy prediction models", *Journal of Banking and Finance*, Vol. 32, pp. 1541-1551.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008), "Bankruptcy forecasting: an empirical comparison of AdaBoost and neural networks", *Decision Support Systems*, Vol. 45, pp. 110-122.

Altman, E. (1968), "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", *Journal of Finance*, Vol. 23 No. 4, pp. 589-609.

Altman, E. (1984), "The success of business failure prediction models: an international survey", *Journal of Banking and Finance*, Vol. 8, pp. 171-198.

Altman, E. and Rijken, H. (2004), "How rating agencies achieve rating stability", *Journal of Banking and Finance*, Vol. 28, pp. 2679-2714.

Altman, E., Bharath, S. and Saunders, A. (2002), "Credit ratings and the BIS capital adequacy reform agenda", *Journal of Banking and Finance*, Vol. 26, pp. 909-921.

Altman, E., Haldeman, R. and Narayanan, P. (1977), "Zeta analysis: a new model to identify bankruptcy risk of corporations", *Journal of Banking and Finance*, Vol. 1, pp. 29-54.

Altman, E., Marco, G. and Varetto, F. (1994), "Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (the Italian experience)", *Journal of Banking and Finance*, Vol. 18, pp. 505-529.

Argenti, J. (1976), "Corporate planning and corporate collapse", *Long Range Planning*, Vol. 9 No. 6, pp. 12-17.

Baixauli, J.S. and Modica-Milo, A. (2010), "The bias of unhealthy SMEs in bankruptcy prediction models", *Journal of Small Business and Enterprise Development*, Vol. 17 No. 1, pp. 60-77.

Balcaen, S. and 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*, Vol. 38, pp. 63-93.

BCBS (2004), *International Convergence of Capital Measurement and Capital Standards*, A Revised Framework, Bank for International Settlements, Basel Committee on Banking Supervision, Basel.

BCBS (2009), *Proposed Enhancements to the Basel II Framework*, Consultative Document, Bank for International Settlements, Basel Committee on Banking Supervision, Basel.

Beck, T. and Demirguc-Kunt, A. (2006), "Small- and medium-size enterprises: access to finance as a growth constraint", *Journal of Banking and Finance*, Vol. 30, pp. 2931-2943.

Cheng, C.S.A. and Lin, S.W.J. (2009), "When do firms revalue their assets upwards? Evidence from the UK", *International Journal of Accounting and Information Management*, Vol. 17 No. 2, pp. 166-188.

Chong, G., Huang, H. and Zhang, Y. (2012), "Do US commercial banks use FAS 157 to manage earnings?", *International Journal of Accounting and Information Management*, Vol. 20 No. 1, pp. 78-93.

Commission of the European Union (2003), "Commission of the European Union Commission recommendation of 6 May 2003 concerning the definition of micro-, small- and medium-sized enterprises", *Official Journal of the European Union*, Vol. L 124, pp. 36-41.

Commission of the European Union (2007), *Observatory Survey*, The Observatory of European SMEs, Commission of the European Union, Brussels.

Eisenbeis, R.A. (1977), "Pitfalls in the application of discriminant analysis in business", *Journal of Finance*, Vol. 32 No. 3, pp. 875-900.

Espahbodi, H. and Espahbodi, R. (1984), "Predicting failure in the airline industry with financial models", *Transpn. Res. A.*, Vol. 18A Nos 5/6, pp. 455-475.

Etemadi, H., Rostamy, A.A.A. and Dehkordi, H.F. (2008), "A genetic programming model for bankruptcy prediction: empirical evidence from Iran", *Expert Systems with Applications*, Vol. 36 No. 2, pp. 3199-3207.

Gadenne, D. and Iselin, E. (2000), "Properties of accounting and finance information and their effects on the performance of bankers and models in predicting company failure", *Journal of Business Finance & Accounting*, Vol. 27 Nos 1/2, pp. 155-193.

Hua, Z., Wang, Y., Xu, X., Zhang, B. and Liang, L. (2007), "Predicting corporate financial distress based on integration of support vector machine and logistic regression", *Expert Systems with Applications*, Vol. 33, pp. 434-440.

Huang, S.M., Tsai, C.F., Yen, D.C. and Cheng, Y.L. (2008), "A hybrid financial analysis model for business failure prediction", *Expert Systems with Applications*, Vol. 35, pp. 1034-1040.

Johnsen, T. and Melicher, R. (1994), "Predicting corporate bankruptcy and financial distress: information value added by multinomial logit models", *Journal of Economics and Business*, Vol. 46, pp. 269-286.

Keasey, K., McGuinness, P. and Short, H. (1990), "Multilogit approach to predicting corporate failure – further analysis and the issue of signal consistency", *Omega*, Vol. 18 No. 1, pp. 85-94.

Kosmidis, K. and Terzidis, K. (2011), "Manipulating an IRB model: considerations about the Basel II framework", *EuroMed Journal of Business*, Vol. 6 No. 2, pp. 174-191.

Lin, F.Y. and McClean, S. (2001), "A data mining approach to the prediction of corporate failure", *Knowledge-Based Systems*, Vol. 14, pp. 189-195.

Lin, T.H. (2009), "A cross model study of corporate financial distress prediction in Taiwan: multiple discriminant analysis, logit, probit and neural networks models", *Neurocomputing*, Vol. 72, pp. 3507-3516.

Liou, F.M. and Yang, C.H. (2008), "Predicting business failure under the existence of fraudulent financial reporting", *International Journal of Accounting and Information Management*, Vol. 16 No. 1, pp. 74-86.

Martikainen, T. and Ankelo, T. (1991), "On the instability of financial patterns of failed firms and the predictability of corporate failure", *Economic Letters*, Vol. 35, pp. 209-214.

Ozkan-Gunay, E.N. and Ozkan, M. (2007), "Prediction of bank failures in emerging financial markets: an ANN approach", *The Journal of Risk Finance*, Vol. 8 No. 5, pp. 465-480.

Peel, M.J. and Peel, D.A. (1988), "A multilogit approach to predicting corporate failure – some evidence for the UK corporate sector", *Omega*, Vol. 16 No. 4, pp. 309-318.

Richardson, F., Kane, G. and Lobingier, P. (1998), "The impact of recession on the prediction of corporate failure", *Journal of Business Finance & Accounting*, Vol. 25 Nos 1/2, pp. 167-186.

Ruthenberg, D. and Landskroner, Y. (2008), "Loan pricing under Basel II in an imperfectly competitive banking market", *Journal of Banking and Finance*, Vol. 32, pp. 2725-2733.

Sandin, A.R. and Porporato, M. (2007), "Corporate bankruptcy prediction models applied to emerging economies: evidence from Argentina in the years 1991-1998", *International Journal of Commerce and Management*, Vol. 17 No. 4, pp. 295-311.

Sharma, D.S. (2001), "The role of cash flow information in predicting corporate failure: the state of the literature", *Managerial Finance*, Vol. 27 No. 4, pp. 3-28.

Steinmann, H. (2007), "Corporate ethics and globalisation, global rules and private actors", in Hanekamp, G. (Ed.), *Business Ethics of Innovation, Ethics of Science and Technology Assessment*, Vol. 31, Springer, Berlin, pp. 7-26.

Tamari, M. (1984), "The use of a bankruptcy forecasting model to analyse corporate behaviour in Israel", *Journal of Banking and Finance*, Vol. 8, pp. 293-302.

Tsukuda, J. and Baba, S. (1994), "Predicting Japanese corporate bankruptcy in terms of financial data using neural network", *Computers and Industrial Engineering*, Vol. 27 Nos 1/4, pp. 445-448.

Ugurlu, M. and Aksoy, H. (2006), "Prediction of corporate financial distress in an emerging market: the case of Turkey", *Cross Cultural Management: An International Journal*, Vol. 13 No. 4, pp. 277-295.

Verwijmeren, P. and Derwall, J. (2010), "Employee well-being, firm leverage, and bankruptcy risk", *Journal of Banking and Finance*, Vol. 34, pp. 956-964.

Wu, Y., Gaunt, C. and Gray, S. (2010), "A comparison of alternative bankruptcy prediction models", *Journal of Contemporary Accounting & Economics*, Vol. 6, pp. 34-45.

Yim, J. and Mitchell, H. (2007), "Predicting financial distress in the Australian financial service industry", *Australian Economic Papers*, Vol. 46 No. 4, pp. 375-388.

About the authors

Kosmas Kosmidis is a Lecturer in the Department of Information Management at the Kavala Institute of Technology. He is also the Quality Supervisor of the Department. He is a graduate of Aristotle University of Thessaloniki, Greece and Lancaster University, UK. He worked as an Accountant in Thrace Plastics s.a., as a Corporate Credit Officer in the Agricultural Bank of Greece and as a CEO of Rodopi Diary Industry. He was member of the Board of Directors of two companies and Vice-President of the Development Agency of Eastern Macedonia-Thrace s.a. His research interests include creative accounting, prediction of corporate failure, accounting-based valuation models, risk management, activity-based management and agency theory. He is a member of scientific committees of two conferences. Kosmas Kosmidis is the corresponding author and can be contacted at: kosmidis@teikav.edu.gr

Antonios Stavropoulos is an Assistant Professor in the Department of Applied Informatics at the University of Macedonia. He is a graduate of the University of Macedonia, Greece and received a PhD degree in the same university. He worked as a Corporate and Financial Consultant. He taught undergraduate and postgraduate courses in various universities and institutes. His research interests include advanced topics in financial accounting, taxation, prediction of corporate failure, accounting-based valuation models and information management systems. He is a member of scientific committees of many journals and conferences.