PREDICTING FINANCIAL FAILURE: SOME EVIDENCE FROM NEW BRUNSWICK AGRICULTURAL CO-OPS

by

Jorge DIETRICH*

Faculty of Administration, University of New Brunswick, Canada

F. J. ARCELUS

University of New Brunswick, Canada and Departamento de Gestión de Empresas, Universidad Pública de Navarra, Spain

and

G. SRINIVASAN

Faculty of Administration, University of New Brunswick, Canada

Received December 2004; final revision accepted January 2005

ABSTRACT**: *Given the essential role co-ops play in the Canadian economy, the primary purpose of this paper is to develop methods to forecast their likelihood of insolvency. However, investor-owner firms form the basic unit of analysis of most popular bankruptcy predictors used in Canada. The question is whether the key underlying elements that differentiates the latter from co-ops justifies deriving specific bankruptcy prediction formulas exclusively for each type of business organization. To that effect, this research evaluates the efficacy of these current predictors and suggests an improved predictor for agricultural co-operatives.*

* Financial assistance from the Natural Sciences and Research Council of Canada for the completion of this work is gratefully acknowledged. Special thanks go to Ms. Claire Gagnon, of the New Brunswick Justice Department for her invaluable help at the data collection stage and to Richard Audas and Wojciech Nasierowski, for their constructive criticisms of earlier versions of this research. Corresponding author: F. J. Arcelus, E-mail: arcelusf@yahoo.com

** *Résumé en fin d'article; Zusammenfassung am Ende des Artikels; resumen al fin del artículo.*

1 Introduction

The two most widely used Canadian and US Business Bankruptcy Predictors (www.bankruptcyaction.com/insolart1.htm; www.bankruptcycanada.com/bankpred1.htm) are the Springate (Sands 1980, Sands et al. 1983, Springate 1978) and the Fulmer (Fulmer et al. 1984, 1985) models, respectively. These models generate bankruptcy/insolvency probability estimates, using financial data that span several years and that cover mainly investor-owned firms (IOFs). However, banks, investors, creditors, government regulators, auditors and many other stakeholders use these methods to evaluate the bankruptcy probabilities of co-ops in much the same way as they do it for IOFs. This paper questions the appropriateness of such practice, because the key underlying structural elements that clearly differentiate these two types of organizations justify deriving specific bankruptcy prediction formulas for each type of business entity. More specifically, the purpose of this paper is to assess whether a model based on co-op data yields higher predictive ability for the forecast of co-op bankruptcy than its current IOF-based counterparts. The resulting analysis illustrates empirically the superiority of our newly developed Co-op Bankruptcy Predictor (BP), when applied to our database composed of agricultural co-operatives from New Brunswick, Canada.

The organization of the paper is as follows. The next section presents the basic hypothesis to be tested, its rationale and the operational definitions of its two key elements, namely that of a firm's bankruptcy and of a model's prediction accuracy. Section 3 develops the BP model subject of the present study, based exclusively on co-op data. Section 4 tests an early warning system, by replicating the studies of the previous section, using the same bankruptcy explanators, but lagged two or three years, depending upon the limited time-series data available. Conclusions complete the paper.

The process to discriminate between 'bankrupt' (B) firms and their 'on-business' (OB) counterparts began with Beaver (1966), but was popularized by Altman's (1968) Z-score based on multiple discriminant analysis (heretofore MDA) (e.g. Hair et al. 1998). Recent reviews of this literature appear in Cybinski (2000, 2001) and a recent bibliography, in http://www.defaultrisk.com/ps_crscoring.htm. These models have proven beneficial in a variety of applications, including portfolio selection (e.g. Platt and Platt 1990), credit evaluation (e.g. Altman and Haldeman 1995, Platt and Platt 1991), and turnaround management (e.g. Platt et al. 2000). Their popularity has also spread worldwide (e.g. Altman and Narayanan, 1997).

Criticisms of this research abound. Primary among them is the reliance upon static, single-period classifications schemes, such as MDA, that may produce biased and inconsistent bankruptcy probability estimates, causing inaccurate predictions (e.g. Platt and Platt 2002, Tyler 2001). However, the hazard-type models proposed by these critiques as alternative formulations may also result in biased estimated coefficients. Other techniques, such as artificial neural networks (e.g. Platt et al. 2000) and chaos theory (Lindsay and Campbell 1996), have not yet realized their potential. One of the main reasons for this state of affairs is that the data requirements for their use are often prohibitive, given the difficulty of obtaining sufficiently ample time-series data especially for failed firms. This normally renders the task of testing more dynamic models, tremendously difficult if not often impossible. Hence, there is no consensus as to an appropriate replacement. Nevertheless, the present study demonstrates that a very high prediction rate is certainly achievable with an easy-to-use single-period model.

2 The hypothesis and related operational definitions

The statement of the hypothesis is as follows:

Given the differences in ownership structure and goals, a bankruptcy model based on coop data yields a higher level of predictive ability for co-ops than do the current models, all based upon IOF data.

The interest in this hypothesis arose from the empirical observation that co-ops enjoy in general a higher survival rate than do IOFs. As an example, Bond et al. (1999) reports that more than 60 per cent of co-ops in Quebec survive more than 5 years, as compared to only 40 per cent in the IOF sector and more than 40 per cent of co-ops survive over 10 years, compared to 20 per cent for the IOFs. The differences are still wider for consumer-owned co-ops, where the five and ten year survival rates are 82 per cent and 66 per cent, respectively, and for producer-owned, with survival rates of 77 per cent and 58 per cent.

For the purposes of this paper, the crucial difference in ownership structure between co-ops and IOFs rests on the one-member/one-vote system of the former, *vis-à-vis* the one-vote-per-share system used by the latter. This tends to leave the control of the co-op (www.coopcca.com) in the hands of its members, thus rendering easier the process of working together to pool capital, as well as share risks, expertise and interest. It also results in differences in the profit distribution system, which emphasizes improvements in service to its membership and in promoting the well being of their communities. As a result, most of the borrowings done by co-ops come from financial co-ops (www.umich.edu), which share a similar business philosophy. These characteristics contribute to a lessening of the typical agency conflicts between stockholders and creditors. Bond et al. (1999), Hart and Moore (1998), among many others, present a more in depth analysis of these and other traditional agency factors. Arguably the most beneficial outcome of these interrelationships is the increase in the trust built by the co-operative and its customers. Such trust is at the core of the cooperative advantage (e.g. Spear 2000), because it lowers the usual agency, monitoring and contract costs (e.g. Fairbairn 2003), with the corresponding positive influence on the survival rate of this form of business.

With respect to an operational definition of bankruptcy, the Canada Co-operative Act (http://www.gnb.ca/acts/acts/c-22-1.htm) requires that all co-ops file at least one financial statement with the assigned Registrar's Office. The number of statements filed per year depends upon the size of the co-op. In addition, Part 17, Liquidation and Dissolution, of the Act sets the conditions under which a co-op may be considered as bankrupt. These are by petition of creditors, by its own will or by 'default' after three years interregnum without filing with the Registrar's Office any financial statement. In any case, the Court has the last word on dissolution.

This report uses the following operational definitions of B and OB, based upon the legislation:

> *Any co-op that: (i) has filed a financial statement with the Registrar's Office in 2000 or later; and (ii) has not asked for voluntary liquidation; and (iii) has not been dissolved by the Court, is considered to be in the 'on business' or OB category.*

Alternatively,

> *Any co-op that: (i) was listed as bankrupt by the Registrar's Office of Co-operatives Associations of the Credit Unions, Co-operatives & Trust Companies Branch of the Department of Justice of New Brunswick; or that: (ii) failed to produce a financial statement after 1999 (i.e. for at least three years) is considered in the Bankruptcy or B category.*

To derive a predictive accuracy criterion, observe that the application of a predictor model to a financial report may lead to two different conclusions, namely that the firm in question is Bankrupt/

inactive (B) or is On Business or active (OB). On the other hand, the co-op may turn out to be On Business or Bankrupt. The combination of these two possible predictions and the two possible real situations yield the standard four possible outcomes, characteristic of any hypothesis testing procedure (e.g. Lind et al. 2003). Two of the outcomes, denoted by $W1$ and $W2$, lead to the wrong prediction. $W1$ predicts that the co-op will be OB when in fact it will be bankrupt, whereas $W2$ predicts the failure of an active firm. Observe that $W1$ and $W2$ correspond to Type II and Type I errors, respectively, in hypothesis testing. The other two lead to accurate predictions, either because the model forecasts the success of an active firm ($R1$) or the failure of a B co-op ($R2$). Then, the percentage of correct predictions over the total number of tested financial statements measures the prediction accuracy rate, denoted by $AR\%$, i.e.

$$AR\% = [(R1 + R2)/(R1 + R2 + W1 + W2)]*100 \tag{1}$$

3 The Bankruptcy Predictor Model

This section starts with a brief description of the data set. It follows with a listing and some descriptive statistics of the variables used in the development of the BP model subject of the current study. The starting point is the evaluation of various prediction models characterized according to three criteria. The first considers whether they use the Fulmer and Springate variables. The second evaluates the appropriateness of including all Fulmer and all Springate variables or only the most efficient in discriminating between B and OB co-ops. The third relates to the advisability of carrying out the estimation process with co-op data developed exclusively for this study. These models are intermediate steps to the generalized BP, shown to have the highest predictive accuracy. The research methodology used for the evaluation of the models rests upon two components. The first, used to compute the coefficients of each model, consists of the use of MDA (e.g. Hair et al. 1998); the second relates to the estimation of the prediction accuracy, as measured by the $AR\%$ of (1).

The data set draws upon the income statements and the statements of financial position for the 67 agricultural cooperatives obtained from the Department of Justice of the province of New Brunswick, Canada, for the years 1999, 2000 and 2001. From these data, Table 1 lists the Fulmer and Springate variables needed to construct the predictor models plus the Equity/Total Liabilities ratio of Altman (1968) excluded by the other two. This set comprises the variables used in the literature cited earlier. Justification for their selection appears in the said works. Observe that the construction of these variables from the financial statements was not a straight-forward process. Four problems were particularly salient. First, cash flow statements were often missing. Hence, the creation of the CF variable required adding net income to depreciation (e.g. Anthony et al., 1999). Second, most of the very small co-ops (total assets less than \$100,000) do not differentiate between earnings before interest and tax, EBIT, and/or earnings before tax, EBT, in their income statement reports. The solution to this problem requires a detailed examination of each financial statement. Third, a similar statement-by-statement search was required to discriminate between tangible and intangible assets. Fourth, the EBIT variable was often negative in value. Evidence of this fact appears in the minimum value of EBIT/TA in Table 1. When this happens, the variable log EBIT/I cannot be computed. The transformation of EBIT/I into a deprivation index, as done in the generation of the Human Development Index and of its various components (e.g. UNDP 2003) avoids this shortcoming, through the computation of the index as the difference between the observed value and a lower limit, divided by the difference between the maximum observed ratio and the lower limit. For this procedure to yield only positive ratios, the lower limit is set at a value slightly lower than the minimum observed value. This procedure renders the resulting ratios amenable to the logarithmic transformation.

Table 1 also includes some descriptive statistics for the entire set as well as for the inactive and active co-ops separately. Most are relatively small co-ops, with average sales of Cnd\$363,743.10 (\$500,668.30 for the active and \$194,868.80 for the inactive) and average total assets of 206,606.30 (\$289,312.40 for the active and \$104,602.10 for the inactive). These figures compare are roughly equivalent to the IOFs in the Fulmer sample, with an average total asset size of US\$455,000. However, they are considerably smaller than the Springate firms, with an average total asset size of US\$2.5 million for the small firms. The most striking characteristic is the large differences in the financial results between the active and the inactive co-ops. These disparities hold true for both the mean and the variance of the various ratios. The p-values of the last two columns corroborate their significance. The first tests for differences between the means of each ratio and the second does likewise for the ratio of the two variances. That the financial ratios are much more negative for the inactive co-ops is not surprising, since Table 1 includes the variables most likely to reflect the financial position of the co-ops and hence, their respective probabilities of bankruptcy. Further, the

Table 1 – Descriptive analysis

Variable name[1]	All co-ops (n = 67)					Inactive (B) co-ops (n = 30)					Active (OB) co-ops (n = 37)					p-values[3]	
	Mean	Min	Max	Var	CV^2	Mean	Min	Max	Var	CV^2	Mean	Min	Max	Var	CV^2	Means	Var.
WC/TA	–0.08	–6.38	1.13	1.63	16.0	–0.55	–6.38	0.94	3.06	3.2	0.29	–1.38	1.13	0.19	1.5	0.01	0.00
EBIT/TA	0.00	–1.98	2.32	0.34	—	–0.11	–1.98	2.32	0.57	6.8	0.08	–1.17	1.16	0.14	4.8	0.20	0.00
EBT/CL	–0.75	–41.43	57.20	122.48	14.8	–1.34	–38.03	57.20	206.18	10.7	–0.26	–41.43	11.40	57.93	29.3	0.71	0.00
S/TA	4.32	0.00	43.30	60.43	1.8	7.10	0.11	43.30	119.99	1.5	2.06	0.00	6.46	2.46	0.8	0.02	0.00
RE/TA	–0.19	–13.74	4.20	4.55	11.2	–0.60	–13.74	4.20	9.14	5.0	0.15	–4.13	1.00	0.71	5.6	0.20	0.00
EBT/Eq	0.90	–86.18	93.74	264.98	18.1	–0.15	–4.31	3.37	1.93	9.3	1.76	–86.18	93.74	482.56	12.5	0.60	0.00
CF/TL	0.08	–34.03	53.84	70.48	105.0	–0.37	–34.03	53.84	151.88	33.3	0.45	–10.34	7.62	6.55	5.7	0.72	0.00
TL/TA	1.00	0.00	15.46	5.13	2.3	1.75	0.00	15.46	10.39	1.8	0.40	0.02	2.12	0.21	1.1	0.03	0.00
CL/TA	0.60	0.00	6.48	1.45	2.0	1.03	0.00	6.48	2.83	1.6	0.24	0.00	1.48	0.08	1.2	0.02	0.00
WC/TL	4.11	–1.07	79.91	140.96	2.9	5.34	–1.07	79.91	293.70	3.2	3.12	–0.78	15.19	19.58	1.4	0.50	0.00
log TgA	4.29	1.70	6.24	1.04	0.2	4.08	1.70	6.24	0.99	0.2	4.46	2.31	6.19	1.04	0.2	0.13	0.46
log EBIT/I	–0.05	–2.28	0.00	0.08	1.4	–0.10	–2.28	–0.02	0.17	4.22	–0.02	–0.03	0.00	10^{-5}	0.19	0.31	0.00
Eq/TL	4.50	–0.94	76.02	147.57	2.7	7.19	–0.94	76.02	302.91	2.4	2.31	–0.52	18.63	15.57	1.7	0.14	0.00

1. Variable names: WC = working capital; TA = total asset; EBIT = earnings before interest and tax; EBT = earnings before interest; CL = current liabilities; S = sales; RE = retained earnings; Eq = Equity; CF = cash flow; TL = total liabilities; log TgA = logarithm of tangible assets and I = interest.
2. CV = coefficient of variation = |standard deviation / mean|
3. p-values for the tests of differences between means and between variances for the B and OB co-ops.

variables with the lowest p-values encompass standard solvency/liquidity ratios normally used to characterize failing firms. As a result, the evidence in Table 1 tends to substantiate the proposition that the solvency/liquidity characteristics of the B firms are those from what it is usually labelled as failing firms and that those for the OB co-ops characterize non-failing firms. Also as expected, the coefficients of variation indicate that the inactive firms exhibit much larger variability than the active co-ops in most indices of financial performance. Finally, the value 105.0 for the coefficient of variation of CF/TL indicates the possible presence of outliers, identified later as three inactive co-ops. To avoid any potential bias in the results, we carried out the analysis of sections 3 and 4, with and without these outliers. Due to the statistical insignificant of the CF/TL variable, the results were almost identical. Hence, the remainder of this paper reports only the results with outliers.

Table 2 contains the standardized DMA weights/coefficients and their respective measures of statistical significance. The dependent variable, C, is whether or not the co-op in question was listed as active ($C = 1$) or inactive ($C = 0$) in 2001. The table lists the coefficients for two models, denoted as C13 and C7. For C13, the independent variables are the 13 financial ratios of Table 1, measured as of 2001. Further, the DMA stepwise method of SPSS helped determine which of the 13 variables are the most efficient in discriminating between B and OB co-ops. This method begins with all the variables excluded from the paradigm and selects the variable that maximizes the Mahalanobis distance between B and OB co-ops. In addition, only those variables with a minimum F value of 1.00 qualified for entry in the DMA function. This resulted in the variables included in the C7 columns. Further, the 'Importance' column identifies the discriminating power of the stepwise variables. Thus, Eq/TL is the most effective variable when used to classify co-ops into the active or inactive categories, whereas TL/TA ranks as the least effective. In addition, Table 2 includes also the p-values of the test for differences among the means of the C13 and C7 discriminant groups. For further details on the use of this methodology, see for example Hair et al. (1998).

The difference between the coefficients in C13 and C7 reflect the advantage of stepwise methodology and the dangers of multicolinearity on the values and, more importantly, on the sign of the coefficients. Two clear illustrations are the negative signs of WC/TA and of EBIT/TA. Such negative signs are in clear violation of standard financial theory that suggests that the higher the incidence of liquidity and of return on assets the better the financial position of

Table 2 – Discriminant analysis results

Variables	C13 C < 0 (B); C >= 0 (OB)		C7 C > 0 (B); C >= 0 (OB)		Importance
	Coefficient	p-value	Coefficient	p-value	
constant	–0.900	—	–1.253	—	
WC/TA	–0.379	0.006	—	—	
EBIT/TA	–0.394	0.169	—	—	
EBT/CL	0.007	0.695	—	—	
S/TA	0.082	0.007	0.082	0.000	2
RE/TA	0.214	0.156	0.232	0.000	5
EBT/Eq	–0.004	0.636	—	—	
CF/TL	0.040	0.691	0.047	0.000	6
TL/TA	0.275	0.014	0.211	0.000	7
CL/TA	–0.036	0.006	0.535	0.000	3
log TgA	–0.021	0.451	—	—	
WC/TL	0.001	0.135	—	—	
log EBIT/I	–1.330	0.256	–1.358	0.000	4
Eq/TL	0.070	0.102	0.074	0.000	1

the firm and thus the lower the chances of going bankrupt. For example, WC/TA is highly correlated (correlation coefficients over .5) with RE/TA, TL/TA and CL/TA. Once the stepwise process eliminates the first variable, the other three appear with the expected highly significant and positive coefficients. The negative sign of log EBIT/I is also expected, because the lower its value, the lower the interest coverage of the firm and thus the higher the likelihood of insolvency.

4 Assessing the quality of the Bankruptcy Predictor

This section uses *AR%*, the prediction accuracy rate defined in (1) as the main tool for the assessment of the quality of the BP developed in Table 2, thereby providing a way to validate the BP results. One is the prediction accuracy approach, which uses (1) to determine how well the C7 and C13 models forecast bankruptcy. The other is the early-warning approach, which determines the success of predicting today's bankruptcy probabilities with whatever past data is available.

The prediction accuracy approach uses (1) to compute the accuracy of the various models discussed so far, namely Springate, Fulmer and the BP results of Table 2. The procedure to obtain AR% is as follows. From the original sources and using the notation in Table 1, the first two models take on the following forms:

Springate: $Z = 1.03\text{WC/TA} + 3.07\text{EBIT/TA} + 0.66\text{EBT/CL} + 0.4\text{S/TA}$

If $Z < 0.862$; then the firm falls into the B category; otherwise, it is OB

Fulmer: $\text{H} = -6.075 + 5.528\text{RE/TA} + 0.212\text{S/TA} + 0.073\text{EBT/Eq} + 1.27\text{CF/TL} - 0.12\text{TL/TA} + 2.335\text{CL/TA} + 0.575\log\text{TgA} + 1.083\text{WC/TL} + 0.894\log\text{EBIT/I}$

If $H < 0$, then the firm falls into the B category; otherwise, it is OB

Our predictive models, C7 and C13, follow the same procedure as Fulmer to arrive at the estimated probabilities. For each co-op, sum the products composed of the variables included in the respective model times the appropriate coefficients from Table 2. If the sum is below 0, then the firm falls into the B category; otherwise, it is considered as OB. The process of arriving at a critical cutting score of zero arises from its computation (e.g. Hair et al. 1998) as the average of the centroids of each discriminant group (.761, −.633, for B and OB co-ops, respectively from the C13 model; .761, −.617, for B and OB co-ops, respectively from the C7 model), weighted by the relative importance of each group in the sample (30/67 and 37/67 for B and OB co-ops, respectively). Then, the comparison between the predictions and the actual realizations easily leads to the computation of *AR%*. An alternate way of assessing the quality of the BP is the early-warning approach. It uses past data (for 2000 and 1999, in this study) and the DMA coefficients of the two BP models of Table 2 to estimate the 2001 bankruptcy probabilities. Then, it computes the accuracy rates of these predictions using (1).

The results of this exercise appear in Table 3. With respect to the BP models, both, C7 and C13, are clearly superior in overall accuracy (*AR%* = 77.63% for C13 and 76.13 for C7) to Springate (70.15%) and especially to Fulmer (59.70%). It is also clear that this dominance arises primarily from *W*2 and *R*1, and to a lesser extent, from *W*1 and *R*2. Hence, C7 and C13 are particularly efficient in forecasting the success of active firms (*R*1) and in avoiding the mistake of predicting the failure of active firms (*W*2). Finally, Table 3 contains the accuracy results for the holdout sample that SPSS constructs for cross-validation purposes. The evidence is quite encouraging, since the values are quite similar to those obtained from the actual data, especially for C7. The dominance on *W*2 and *R*1 is still there and they are significantly different from those of Springate and Fulmer, computed with the actual data.

For the early-warning models, the picture is slightly less clear. C7 comes out ahead of C13 on the overall accuracy criterion for the 2-year

Table 3 – Accuracy rates

		W1	W2	R1	R2	AR%	Sample size
1-year	Springate	19.40	10.45	44.78	25.37	70.15	
	Fulmer	20.90	19.40	35.82	23.88	59.70	
	C13 – Actual	19.39	2.98	52.24	25.39	**77.63**	
	C13 – Holdout	23.87	8.94	46.28	20.91	67.19	67
	C7 – Actual	19.39	4.47	50.75	25.39	76.13	
	C7 – Holdout	22.39	4.47	50.75	22.39	73.14	
2-year	Springate	16.42	19.40	35.82	28.36	64.18	
	Fulmer	20.00	20.00	35.56	24.44	60.00	
	C13	23.90	10.40	44.80	20.90	65.70	45
	C7	28.89	4.44	51.11	15.56	**66.67**	
3-year	Springate	20.90	16.42	38.81	23.88	62.69	67
	Fulmer	30.00	12.50	30.00	27.50	57.50	
	C13	25.00	10.00	32.50	32.50	**65.00**	40
	C7	27.50	10.00	32.50	30.00	62.50	

case (66.67% vs. 65.70%) but behind for its 3-year counterpart (62.50% vs. 65.00) and both are substantially superior to Fulmer. Further, both C13 and C7 also dominate Springate in overall accuracy (with the exception of C7 for 3-year), even if the differences are much smaller. C13 and C7 are also the worst performers for $W1$ and $R2$ in 2-year, by being the most likely of the four to predict ahead the success of future B firm ($W1$) and least likely to predict ahead the failure of an eventual OB co-op ($R2$). As in the 1-year case, both C13 and C7 continue being ahead on $R1$ and especially on $W2$. In addition, observe the lower sample size for some 2-year (n = 45) and 3-year (n = 40) cases. This is due to the difficulty, alluded to earlier, in obtaining cash-flow data.

Finally, observe that, from results not shown here, other methods of assessing overall fit, such as the proportional chance criterion or Press's Q (Hair et al. 1998), for the actual and the holdout samples, attest to the high accuracy of C13 and C7 in classifying the various co-ops into their appropriate B or OB grouping.

5 Some concluding comments

The current Springate prediction formula reported an average accuracy rate of 85 per cent and the current Fulmer formula an accuracy rate of 92 per cent when applied to IOFs one year prior to failure (www.bankruptcyaction.com/insolart1.htm). The results of Table 3 indicate that these prediction rates are considerably lower, 70.15 per cent and 59.7 per cent respectively, when applied to agricultural co-operatives. Adding the Altman variable to this set of variables did not improve the prediction accuracy. This justifies testing the basic hypothesis of section 2, namely that the differences in organizational structure and goals between co-ops and IOFs require each firm type to have its own BP coefficients. As a result, the accuracy rate of the BP for agricultural co-ops has risen approximately 10 percentage points. The saliency of this conclusion is compounded by the fact that, quite often, a co-op is the community's main tool for economic and social development. Hence, forecasting the financial strength of these co-ops cannot only be a helpful tool to prevent their potential bankruptcy but also a tool to help on developing specific financial assistance programs.

In addition, both the extended C13 and the reduced C7 models provided similar levels of prediction accuracy. This lack of dominance has a simple explanation. The purpose of this paper is to develop a predictor rather than a casual model. For the former, multicolinearity is not necessarily an issue. Hence, C13 and C7 can be used interchangeably as bankruptcy predictors, even if, in the interest of parsimony, the smaller, C7, may be preferable.

Of special importance is the evidence from the early-warning models. They provide a first indication of the advisability to carry out further dynamic analysis in an effort to identify, as early in time as possible, warning signals of potential financial problems in the future. Data problems render such undertaking quite hazardous, but future efforts in that direction are certainly justified. These models also question somewhat the dominance of C13 and C7, because, from the point of view of community development efforts to prevent co-op failure, the ability to forecast ahead a potential failure is of paramount importance and the high values in C13 and C7 for W1 (23.90 per cent and 28.89 per cent, for 2-year, respectively) are particularly worrisome.

Another worthwhile area for future research is the introduction of non-financial variables into the model. The data problems associated with this effort are known worldwide. Public availability of co-op data is mostly restricted to that information that the law requires to disclose. That is mostly financial, as is the case in the agricultural sector. Finally, other cooperative sectors such as credit unions where regulations require more in depth disclosure of information point the way towards other avenues for further research. Two recent examples in this area are the four-country comparison of credit unions by Sibbald et al. (2002) and the Grifell-Tatjé and Lovell (2004) study on the variations in cooperative dividends.

Further research may be useful on the question of the range and type of firms that may be appropriate to select, when developing specific bankruptcy predictor models. For example, our universe of interest consists of firms belonging to a specific industry type, agriculture, and to a specific ownership configuration, cooperatives. The alternate models, Springate and Fulmer, include IOFs of a wide variety of industry types. The problem of interest here is whether the improvement in prediction accuracy achieved is due to one or to both characteristics. Our answer here is, of necessity, clear: either one or both, the type of organization and of industry. To be able to differentiate between these answers is an empirical issue that would require a rather formidable data set, related to a wide variety of firms of various types, with an appropriate control sample. Such an undertaking falls outside the scope of this paper.

Finally, a similar difficulty arises when assessing whether the type of variables used in the existing methodology is appropriate to all industries or whether alternate sets of financial key elements, more representative of the industry or of the organization type in question, should be considered. As the references in the paper clearly attest, rationales for the selection of this type of variables abound and the extant literature includes studies carried out worldwide and based upon practically all industry types. Besides, attempting to resolve this issue would require a similar type of massive computational effort needed to deal with the problem posed on the last paragraph. Such an effort also falls outside the scope of this paper. Nevertheless, the study of these and other issues justify additional research.

REFERENCES

ALTMAN E.I., 1968, 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy', *Journal of Finance*, 23(2), 589–609.

ALTMAN E.I. and HALDEMAN R., 1995, 'Corporate credit scoring models: approaches and tests for successful implementation', *Journal of Commercial Bank Lending*, 77(9), 10–22.

ALTMAN E.I. and NARAYANAN P., 1997, 'An international survey of business failure classification models', *Financial Markets, Institutions and Instruments*, 6(2), 1–57.

ANTHONY R., HAWKINS D. and MERCHANT K., 1999, *Accounting, Text and Cases*, 10th Ed., New York: McGraw-Hill.

BEAVER W.H., 1966, ‘Financial ratios as predictors of failure’, *Journal of Accounting Research*, Supplement, 71–11.

BOND L., CLÉMENT M., COURNOYER M. and DUPONT G., 1999, *Survival Rate of Co-operatives in Québec*, Co-operative Secretariat of the Government of Canada and Québec Industrie et Commerce.

CYBINSKI P., 2000, ‘The path to failure: where are bankruptcy studies now’, *Journal of Business and Management*, 7(1), 11–39.

CYBINSKI P., 2001, ‘Description, explanation, prediction – the evolution of bankruptcy studies’, *Managerial Finance*, 27(4), 29–44.

FAIRBAIRN, B., 2003, ‘Three strategic concepts for the guidance of co-operatives: linkage, transparency and cognition’, Centre for the Study of Co-operatives, University of Saskatchewan (http://coop-studies.usak.ca).

FULMER J.G. JR., MOON J.E., GAVIN T.A. and ERWIN M.J., 1984, ‘A bankruptcy classification model for small firms’, *Journal of Commercial Bank Lending*, 66(11), 25–37.

FULMER J.G. JR., MOON J.E., GAVIN T.A. and ERWIN M.J., 1985, ‘More on bankruptcy model’, *Journal of Commercial Bank Lending*, 67(3), 60–61.

GRIFELL-TATJÉ E. and LOVELL C.A.K., 2004, ‘Decomposing the dividend’, *The Journal of Comparative Economics*, 32(3), 500–518.

HAIR J.F., ANDERSON R.E., TATHAM R.L. and BLACK W.C., 1998, *Multivariate Data Analysis*, Englewood Cliffs, N.J.: Prentice Hall.

HART O. and MOORE J., 1998, *Cooperatives vs. Outside Ownership*, National Bureau of Economic Research Working Paper 6421 (www.nber.org).

LIND D., MARCHAL W., MASON R., GUPTA S., KABADI S. and SINGH J., 2003, *Techniques in Business and Economics*, First Canadian Edition, Toronto: McGraw-Hill Ryerson.

LINDSAY D.H. and CAMPBELL A., 1996, ‘A chaos approach to bankruptcy prediction’, *Journal of Applied Business Research*, 12(4), 1–9.

PLATT H.D. and PLATT M.B., 1990, ‘Development of a class of stable predictive variables: the case of bankruptcy prediction’, *Journal of Business Finance & Accounting*, 17(1), 31–51.

PLATT H.D. and PLATT M.B., 1991, ‘A note on the use of industry-relative ratios in bankruptcy prediction’, *Journal of Banking and Finance*, 15(4), 1183–1194.

PLATT H.D. and PLATT M.B., 2002, 'Predicting corporate financial distress: reflections on choice-based sample bias', *Journal of Economics and Finance*, 26(2), 184–198.

PLATT H.D., PLATT M.B. and YANG R., 2000, 'Probabilistic neural networks in bankruptcy prediction', *Journal of Business Research*, 44(2): 67–74.

SANDS E.A., 1980, Business Failure Prediction and the Efficient Market Hypothesis, Unpublished M.B.A. Research Project, Simon Fraser University, Canada.

SANDS E.A., SPRINGATE G.L.V. and VAR T., 1983, 'Predicting business failures', *CGA Magazine*, 24–27.

SPRINGATE G.L.V., 1978, Predicting the Possibility of Failure in a Canadian Firm, Unpublished M.B.A. Research Project, Simon Fraser University, Canada.

SIBBALD, A., FERGUSON, C. and McKILLOP, D., 2002, 'An examination of key factors of influence in the development process of credit union industries', *Annals of Public and Cooperative Economics*, 73(3): 399–428.

SPEAR, R., 2000, 'The co-operative advantage', *Annals of Public and Cooperative Economics*, 83(4), 507–523.

TYLER S., 2001, 'Forecasting bankruptcy more accurately: a simple hazard model', *Journal of Business*, 74(1), 101–124.

UNDP, 2003, *Human Development Report 2002* (http://hdr.undp.org).

Prédiction de l'insolvabilité: L'exemple des coopératives agricoles au New Brunswick

Dû au rôle essentiel que jouent les coopératives dans l'économie canadienne, le but premier de cet article est de développer des méthodes pour prévoir leur probabilité d'insolvabilité. Cependant, les firmes 'd'investisseurs-propriétaires' composent l'unité de base de l'analyse de la plupart des prédicteurs de faillite utilisés au Canada. Il s'agit de décider si les éléments fondamentaux qui distinguent ces firmes des coopératives justifient la dérivation de formules spécifiques pour la prédiction de faillite, exclusives à chaque type d'organisation d'affaires. A cet effet, ce travail évalue l'efficacité des prédicteurs courants et suggère un prédicteur amélioré pour les coopératives agricoles.

Zahlungsunfähigkeit voraussagen: Das Beispiel der landwirtschaftlichen Genossenschaften in New Brunswick

Wenn man es als gegeben ansieht, dass die genossenschaftliche Bewegung eine wesentliche Rolle in der Kanadischen Wirtschaft spielt, dann ist das hauptsächliche Ziel dieses Artikels die Entwicklung von Methoden zur Voraussagung der Wahrscheinlichkeit von Zahlungsunfähigkeit. Wir haben die Eigentümerfirma als Basis unserer Analyse benutzt wie die meist benutzten Konkurs Indikatoren in Kanada für eine voraus zusehende Zahlungsunfähigkeit. Die Frage ist, ob die wesentlichen elementaren Eigenschaften welche die Eigentümerfirma von einer Genossenschaftliche Gesellschaft unterscheiden es nötig machen, spezielle den Konkurs voraussagende Erkenntnisse exklusiv für die beiden Firmentypen zu haben. Zu diesem Zweck unterscheidet diese Analyse die Effektivität dieser zur Zeit benutzten Prediktoren und schlägt verbesserte Prediktoren für landwirtschaftliche Betriebe vor.

Predicción de insolvencia: El ejemplo de las cooperativas en New Brunswick

Dado el papel tan esencial que desempeñan las Cooperativas en la economía canadiense, el objetivo primario de este trabajo es desarrollar métodos para prever su probabilidad de insolvencia. Los predictores de quiebra más populares usados en Canadá, sin embargo, están basados principalmente en el análisis de firmas corporativas. La duda planteada a investigar es si los importantes elementos subyacentes, que diferencian las corporaciones de las cooperativas, justifican fórmulas nuevas de predicción de quiebra específicas para cada tipo de estructura comercial. Con ese fin, este trabajo evalúa la eficacia de los predictores mas utilizados y permite inferir la necesidad de un nuevo método mejor acoplado a las características de las Cooperativas agrícolas.