Predicting corporate bankruptcy: where we stand?

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Abstract

Purpose – *The incidence of important bankruptcy cases has led to a growing interest in corporate bankruptcy prediction models since the 1960s. Several past reviews of this literature are now either out-of-date or too narrowly focused. They do not provide a complete comparison of the many different approaches towards bankruptcy prediction and have also failed to provide a solution to the problem of model choice in empirical application. Seeks to address this issue.*

Design/methodology/approach – *Through an extensive literature review, this study provides a comprehensive analysis of the methodologies and empirical findings from these models in their applications across ten different countries.*

Findings – *The predictive accuracies of different models seem to be generally comparable, although artificially intelligent expert system models perform marginally better than statistical and theoretical models. Individually, the use of multiple discriminant analysis (MDA) and logit models dominates the research. Given that financial ratios have been dominant in most research to date, it may be worthwhile increasing the variety of explanatory variables to include corporate governance structures and management practices while developing the research model. Similarly, evidence from past research suggests that small sample size, in such studies, should not impede future research but it may lead researchers away from methodologies where large samples are critically necessary.*

Originality/value – *It is hoped that this study will be the most comprehensive to-date review of the literature in the field. The study also provides a unique ranking system, the first ever of its kind, to solve the problem of model choice in empirical application of bankruptcy prediction models.*

Keywords *Bankruptcy, Corporate finances, Financial analysis*
Paper type *Case study*

1. Introduction

Prediction of bankruptcy is of increasing importance to corporate governance. Global economies have become cautious of the risks involved in corporate liability, especially after the demise of giant organizations like WorldCom and Enron, and one of the major aims of the Basel II regulations is now to minimize credit risk. Many different models have been used to predict corporate bankruptcy. These methods all have their particular strengths and weaknesses, and choosing between them for empirical application is not straightforward.

There have been several reviews of this literature but these are now either out-of-date (Scott, 1981; Zavgren, 1983; Altman, 1984; Jones, 1987) or too narrowly focused. Zavgren (1983); Altman (1984); and Keasey and Watson (1991) focus exclusively on statistical models while Jones (1987) and Dimitras *et al.* (1996) do not give full coverage of theoretical models. Zhang *et al.* (1999) restrict their review to empirical applications of neural networks models while Crouhy *et al.* (2000) cover only the most important theoretic current credit risk models. Overall, Morris (1998) provides the most comprehensive review to date of bankruptcy prediction models but does not discuss important artificially intelligent expert system (AIES) models.

None of these studies provides a complete comparison of the many different approaches towards bankruptcy prediction. The studies have also failed to provide a solution to the problem of model choice in empirical applications. Furthermore, there have been important theoretical developments since Morris, 1998. There is therefore a place for an up-to-date comparative review. This paper provides such a review, clarifying the problem of model choice in empirical prediction of corporate bankruptcy and suggesting some directions for future research. The analysis is based on a sample taken from 89 published empirical investigations[1] that were collected from a search of more than 180 sources and grouped in a framework of three broad categories: statistical models, AIES models and theoretical models. It is found that the three classes of models have comparable predictive power. Individually, however, some of the statistical models seem to dominate other models.

The paper is organized as follows: model methodology and a brief critique is presented in Section 2; model applications are discussed in Section 3; conclusions and recommendations for further research are proposed in Section 4.

2. Methodology of corporate bankruptcy prediction

Our discussion is based on three model categories, in which the models are further grouped by their main investigative purpose. These categories and their main features are presented in Table I.

Classical statistical models include both univariate and multivariate analysis, of which later are more commonly used. Table II outlines main characteristics of different types of statistical models.

Expert systems (ES) in artificial intelligence and problem solving (AI) have evolved to serve essentially the same functions as knowledge in human intelligence and reasoning. Much AI research has focused on the role of knowledge acquisition in ES, with particular emphasis on ''machine learning'' under varying conditions of ''supervision''. In the language of AI, a system that ''learns'' is one that improves its problem-solving performance as a function of previous experience, and ''machine learning'' methods have been successfully applied in a variety of problem-solving contexts including bankruptcy prediction. Table III outlines major features of the more commonly used AIES models.

Unlike the statistical and AIES models, which focus on firms' symptoms of failure, the theoretic models (presented in Table IV) determine causes of bankruptcy.

A careful analysis of various methods of corporate bankruptcy prediction leaves the impression that there is little to choose between them. The advance of information technology since the 1980s has motivated the development of technology-driven models as

Table I Categories of prediction models

Model category	*Main features*
Statistical models	Focus on symptoms of failure Drawn mainly from company accounts Could be univariate or multivariate (more common) in nature Follow classical standard modelling procedures
Artificially intelligent expert system models (AIES)	Focus on symptoms of failure Drawn mainly from company accounts Usually, multivariate in nature Result of technological advancement and informational development Heavily depend on computer technology
Theoretical models	Focus on qualitative causes of failure Drawn mainly from information that could satisfy the theoretical argument of firm failure proposed by the theory Multivariate in nature Usually employ a statistical technique to provide a quantitative support to the theoretical argument

Table II Different types of statistical prediction models

Models	*Main features*
Univariate (see Altman, 1993; Morris, 1998)	Traditionally focused on financial ratio analysis Underlying rationale: if financial ratios exhibit significant differences across the failing and non-failing firms then they can be used as predictive variables
Multiple discriminant analysis (MDA) (see Klecka, 1981; Altman, 1993; Morris, 1998)	MDA model is a linear combination (a bankruptcy score) of certain discriminatory variables Bankruptcy score is used to classify firms into bankrupt and non-bankrupt groups according to their individual characteristics
Linear probability model (LPM) (see Maddala, 1983; Theodossiou, 1991; Gujarati, 1998; Morris, 1998)	LPM expresses the probability of failure or success of a firm as a dichotomous dependent variable that is a linear function of a vector of explanatory variables Boundary values are obtained to distinguish between failing and non-failing firms
Logit model (see Maddala, 1983; Theodossiou, 1991; Gujarati, 1998; Morris, 1998)	Like LPM, Logit also expresses the probability of failure of a firm as a dichotomous dependent variable that is a function of a vector of explanatory variables The dichotomous dependent variable of a logit model, however, is the logarithm of the odds (probability) that an event (fail/not-fail) will occur Such a transformation of LPM is accomplished by replacing the LPM distribution with a logistic cumulative distribution function In application to bankruptcy, a probability of 0.5 implies an equal chance of company failure or non-failure. Therefore, where 0 indicates bankruptcy, the closer the estimate is to 1 the less the chance of the firm becoming bankrupt
Probit model (see Maddala, 1983; Theodossiou, 1991; Gujarati, 1998; Morris, 1998)	It is possible to substitute the normal cumulative distribution function, rather than logistic, to obtain the probit model Rest of the interpretations remain same as for the logit model
Cumulative sums (CUSUM) procedures (see Page, 1954; Healy, 1987; Kahya and Theodossiou, 1999)	CUSUM procedures are among the most powerful tools for detecting a shift in a distribution from one state to another In the case of bankruptcy prediction, the time series behaviour of the attribute variables for each of the failed and non-failed firms is estimated by a finite order VAR model The procedure, then, optimally determines the starting-point of the shift and provides a signal about the firm's deteriorating state as soon as possible thereafter The overall performance of the firm at any given point in time is assessed by a cumulative (dynamic) time-series performance score (a CUSUM score) As long as a firm's time-series performance scores are positive and greater than a specific sensitivity parameter, the CUSUM score is set to zero, indicating no change in the firm's financial condition. A negative score signals a change in the firm's condition
Partial adjustment processes (see Laitinen and Laitinen, 1998; Gujarati, 1998)	Partial adjustment models are a theoretic rationale of famous Koyck approach to estimate distributed-lag models Application of these models in bankruptcy prediction can best be explained by using cash management behaviour of the firms as an example, which refers to the management of cash by the firm from inflow to outflow, with failure being defined as the inability of the firm to pay financial obligations as they mature Elasticities of cash balances with respect to the motive factors will be smaller in absolute magnitude for a failing firm than for a similar healthy firm Also, the adjustment rate for a failing firm will exceed the rate for a healthy firm

Table III Different types of AIES models

Model	*Main features*
Recursively partitioned decision trees (an inductive learning model) (see Friedman, 1977; Pompe and Feelders, 1997)	It is a form of supervised learning in which a program learns by generalising from examples (thereby mimicking the behaviour of many human experts) This kind of learning is exploited by decision tree procedures that use recursive partitioning decision rules to transform a ''training'' sample of data In bankruptcy classification the training sample is recursively partitioned into a decision tree in which the final nodes contain firms of only one type, bankrupt or healthy
Case-based reasoning (CBR) models (see Kolodner, 1993)	CBR solves a new classification problem with the help of similar previously solved cases CBR programs can be applied directly to bankruptcy prediction by application of its typical four-stage procedure of (1) identification of a new problem, (2) retrieval of solved cases from a ''case library'', (3) adaptation of solved cases to provide a solution to the new problem, and (4) evaluation of the suggested solution and storage in the case library for future use
Neural networks (NN) (see Salchenberger *et al.*, 1992; Coats and Fant, 1993; Yang *et al.*, 1999)	Neural networks perform classification tasks in a way intended to emulate brain processes The ''neurons'' are nodes with weighted interconnections that are organized in layers. Each node in the input layer is a processing element that receives a variety of input signals from source objects (information about firms, in the case of bankruptcy prediction) and converts them into a single output signal. The latter is either: accepted as a classifying decision; or re-transmitted as an input signal to other nodes (possibly including itself) Signal processing continues until a classifying decision is reached (with some probability, the firm will fail) that satisfies pre-specified criteria
Genetic algorithms (GA) (see Shin and Lee, 2002; Varetto, 1998)	Based on the idea of genetic inheritance and Darwinian theory of natural evolution (survival of the fittest), GAs work as a stochastic search technique to find an optimal solution to a given problem from a large number of solutions GAs execute this search process in three phases: genetic representation and initialisation, selection, and genetic operation (crossover and mutation). The process continues until the actual population converges towards increasingly homogeneous strings In order to solve a classification problem like bankruptcy, researchers extract a set of rules or conditions using GAs. These conditions are associated with certain cut-off points. Based on these conditions, the model would predict whether or not a firm is likely to go bankrupt
Rough sets model (see Pawlak, 1982; Ziarko, 1993; Dimitras *et al.* 1999)	The aim of rough sets theory is to classify objects using imprecise information In a rough sets model, knowledge about the objects is presented in an information table that, in effect, works like a decision table containing sets of condition and decision attributes that is used to derive the decision rules of the model by inductive learning principles. Every new object (for example, a firm) can then be classified (healthy or in financial distress) by matching their characteristics with the set of derived rules

alternatives to classical statistical models. However, virtually all of the current models depend on a statistical heritage, one way or another. AIES models, for example, generally exploit both univariate and multivariate statistical techniques and may be considered as automated offspring of the statistical approach, albeit more sophisticated. Similarly, theoretical models are often developed by employing an appropriate available statistical technique rather than by building directly on theoretical principles.

Table IV Different types of theoretical models

Model	*Main features*
Balance sheet decomposition measures (BSDM)/entropy theory (see Theil, 1969; Lev, 1973; Booth, 1983)	One way of identifying financial distress is to examine changes in the structure of balance-sheets, under the argument that firms try to maintain equilibrium in their financial structure If a firm's financial statements reflect significant changes in the composition of assets and liabilities on its balance-sheet it is more likely that it is incapable of maintaining the equilibrium state. If these changes are likely to become uncontrollable in future, one can foresee financial distress in these firms
Gambler's ruin theory (see Scott, 1981; Morris, 1998)	In this approach, the firm can be thought of as a gambler playing repeatedly with some probability of loss, continuing to operate until its net worth goes to zero (bankruptcy) With an assumed initial amount of cash, in any given period, there is a net positive probability that firm's cash flows will be consistently negative over a run of periods, ultimately leading to bankruptcy
Cash Management Theory (see Aziz *et al.*, 1988) Laitinen and Laitinen, 1998)	Short-term management of corporate cash balances is a major concern of every firm An imbalance between cash inflows and outflows would mean failure of cash management function of the firm, persistence of which may cause financial distress to the firm and, hence, bankruptcy
Credit risk theories (including JP Morgan's CreditMetrics, Moody's KMV model (see Black and Scholes, 1973; Merton, 1973), CSFB's CreditRisk + (see Crédit Suisse, 1997), and KcKinsey's CreditPortfolio View (see Wilson, 1997a, b, 1998)	Credit risk theories are linked to the Basel I and Basel II accords and mostly refer to financial firms Credit risk is the risk that any borrower/counterparty will default, for whatever reason. Following the Basel II guidelines, a number of recent attempts have been made to develop internal assessment models of credit risk. These models and their risk predictions thereof are based on economic theories of corporate finance and are collectively referred as credit risk theories. For example: JP Morgan's CreditMetrics and Moody's KMV models rely on option pricing theory[a], whereby default is endogenously related to capital structure and the firm may default on its obligations if the value of its assets falls below a critical level (determined by the credit risk model) CSFB's CreditRisk+ follows a framework of actuarial science in order to derive the loss distribution of a bond/loan portfolio where the default is assumed to follow an exogenous Poisson process. Model captures the essential characteristics of credit default events and allows explicit calculation of a full loss distribution for a portfolio of credit exposures McKinsey's CreditPortfolio View model uses a macro-economic approach to risk measurement. Credit cycles follow business cycles closely, with the probability of default being a function of variables such as the unemployment rate, interest rates, growth rate, government expenses, foreign exchange rates, and aggregate savings, so that a worsening economy should be followed by an increase in the incidence of downgraded security rating and default

Note: [a] An option is a financial claim that gives the holder a right to buy (call option) or sell (put option) an underlying asset in the future at a pre-determined exercise price. Merton (1974) recognised that the model could be applied as a pricing theory for corporate liabilities in general. Option pricing as a valuation model for investment under uncertainty, ''real options'', has been developed by Dixit and Pindyck (1994)

Given the general importance of statistical techniques in corporate bankruptcy prediction, it is natural for purely statistical models to be in frequent use. Their performance, however, is questionable. MDA, logit and probit models all suffer in one way or another from restrictive assumptions (and actually differ little in their predictive performance, as will be seen in Section 4 of this paper). The frequent empirical violation of the LPM assumptions and the lack of large time series data sets required for CUSUM and partial adjustment models makes it unlikely that any of these models will be of great practical value.

No matter what the relative conceptual appeal (or otherwise) of statistical, AIES and theoretical models, their relative usefulness is ultimately an empirical question. Since there have been many empirical applications of these models to the case of corporate bankruptcy prediction, a review of the empirical results is both necessary and challenging. This is the aim of the next section of this paper.

3. Applications of corporate bankruptcy prediction models

The exercise in this paper consists of the analysis of results from 46 articles (43 articles, one technical report and two discussion papers) reporting 89 empirical studies of corporate bankruptcy prediction. Table V reports critical information from these studies, including the best predictive accuracy rates of each model (rounded to the nearest whole figure), one year before failure. Abbreviations used in Table V are defined in the Appendix. The analysis and findings presented next are drawn from the information contained in Table V.

Traditionally, bankruptcy prediction studies have used financial ratios to predict failure in firms. It can be seen from Table V that more than 60 per cent of the studies used financial ratios (measuring liquidity, solvency, leverage, profitability, asset composition, firm size, and growth etc.) as the only explanatory variables, about 7 per cent used cash flow information while the remaining 33 per cent employed a mix of financial ratios and other variables (including macroeconomic, industry-specific, location, and other firm-specific variables). These findings reveal a marked reliance on information from company accounts, making only marginal use of other information. However, considering corporate governance structures and management practices is expected to enrich understanding of corporate failure.

Conventionally, the predictive value of empirical results is considerably increased by the use of holdout samples. (part of the data is used to estimate the model and part is set aside to assess the performance of the estimated model, giving a stronger test of predictive validity.) However, only 46 per cent of the reviewed studies used such a sample to verify their predictive claims. This trend needs to be discouraged in the interest of stronger test of predictive validity.

Corporate bankruptcy prediction is inherently vulnerable to problems arising from small samples (happily, most firms with publicly available data do not go bankrupt). The sample sizes reported in Table V range from 32 to 35,287 firms, with samples of less than 100 firms used in about 42 per cent of the reviewed studies. Small sample size appears to be an inevitable limitation and, hence, may not hamper future research in this area.

With regard to the samples of firms used, almost all of the cited studies analysed data from public limited companies – presumably because bankruptcy is more common in such firms and because there is relatively easy access to the required data. Around 43 per cent of the studies used data from mixed-industry firms and about 25 per cent from manufacturing firms (including a few retail and mining firms) respectively. The limitations imposed by small sample sizes and the past trend in favour of mix industry, suggest that it may prove useful for future research to work with mix industry sample.

A major focus of this section is to examine the methodologies used in recent bankruptcy prediction studies. Figure 1 uses information from Table V and indicates that statistical models were used in 64 per cent of the cited studies, followed by AIES and theoretic models with respective shares of 25 per cent and 11 per cent. This is in line with expectations, as the use of AIES models for bankruptcy prediction is relatively new.

Figure 2 (also drawn from Table V) shows that more than 30 per cent studies used MDA model for bankruptcy prediction, while another 21 per cent preferred the logit model. Together these account for 77 per cent of all the statistical models used. Within the AIES group of models, neural networks rank first with 9 per cent share followed by recursive partitioning. Entropy theory (BSDM) was most popular among the theoretic models, although it accounted for only 4.5 per cent of the whole sample of studies. These results suggest that MDA has been the dominant model of choice in past.

Figure 3 summarises the average overall predictive accuracies (rounded to nearest whole number) of these models, one year before actual bankruptcy. The actual figures are given in

Table V Summary of previous research attributes and findings

No.	Author and year	Model	OPA (%)	Type I (%)	Type II (%)	ES	TS	Ind. Var.	Country	Years	Firm type
1	Altman (1968)	MDA	95	6	3	66	25	FR	USA	46-65	Manufac. Ind. (ltd.)
2	Altman *et al.* (1977)	MDA	92.8	3.77	10.34	111	111	FR	USA	64-74	Manf. and retail (ltd.)
3	Altman *et al.* (1994)	MDA	NA	13.6	9.7	1212	450	FR	Italy	85-92	Industrial (ltd.)
4	Altman *et al.* (1994)	NN	NA	13.8	10.6	1212	450	FR	Italy	85-92	Industrial (ltd.)
5	Aziz *et al.* (1988)	MDA	88.8	NA	NA	98	NA	CF	USA	71-82	Mix. Ind. (ltd.)
6	Aziz *et al.* (1988)	Logit	91.8	14.3	2.1	98	NA	CF	USA	71-82	Mix. Ind. (ltd.)
7	Aziz *et al.* (1988)	BSDM	91.8	NA	NA	98	NA	CF	USA	71-82	Mix. Ind. (ltd.)
8	Back *et al.* (1996)	MDA	85.14	13.51	16.22	74	NA	FR	Finland	86-89	Mix. Ind. (ltd.)
9	Back *et al.* (1996)	Logit	96.49	13.51	13.51	74	NA	FR	Finland	86-89	Mix. Ind. (ltd.)
10	Back *et al.* (1996)	NN	97.3	5.26	0	74	NA	FR	Finland	86-89	Mix. Ind. (ltd.)
11	Back *et al.* (1996)	GA	97.3	5.26	0	74	NA	FR	Finland	86-89	Mix. Ind. (ltd.)
12	Beynon and Peel (2001)	MDA	78.3	16.7	26.7	60	30	Mix	UK	NA	Manufac. Ind. (ltd.)
13	Beynon and Peel (2001)	Logit	80	16.7	23.3	60	30	Mix	UK	NA	Manufac. Ind. (ltd.)
14	Beynon and Peel (2001)	RPA	93.3	10	3.3	60	30	Mix	UK	NA	Manufac. Ind. (ltd.)
15	Beynon and Peel (2001)	RS	91.7	13.3	3.3	60	30	Mix	UK	NA	Manufac. Ind. (ltd.)
16	Booth (1983)	MDA	85	18	12	44	26	Mix	Australia	64-79	Mix. Ind. (ltd.)
17	Booth (1983)	BSDM	85	18	12	44	26	Mix	Australia	64-79	Mix. Ind. (ltd.)
18	Brockman and Turtle (2003)	MDA	74.5	NA	NA	NA	NA	Mix	USA	89-98	Mix. Ind. (ltd.)
19	Brockman and Turtle (2003)	Logit	85	NA	NA	NA	NA	Mix	USA	89-98	Mix. Ind. (ltd.)
20	Brockman and Turtle (2003)	Credit	85	NA	NA	NA	NA	Mix	USA	89-98	Mix. Ind. (ltd.)
21	Casey and Bartczak (1984)	Univariate	75	10	27	290	NA	CF	USA	71-82	Mix. Ind. (ltd.)
22	Casey and Bartczak (1984)	MDA	86	17	13	290	NA	FR	USA	71-82	Mix. Ind. (ltd.)
23	Casey and Bartczak (1984)	Cash	75	10	27	290	NA	CF	USA	71-82	Mix. Ind. (ltd.)
24	Coats and Fant (1993)	MDA	87.9	36.2	0	282	NA	FR	USA	70-89	Mix. Ind. (ltd.)
25	Coats and Fant (1993)	NN	95	10.6	2.1	282	NA	FR	USA	70-89	Mix. Ind. (ltd.)
26	Dimitras *et al.* (1999)	MDA	90	12.5	7.5	80	38	FR	Greece	86-93	Mix. Ind. (ltd.)
27	Dimitras *et al.* (1999)	Logit	90	7.5	12.5	80	38	FR	Greece	86-93	Mix. Ind. (ltd.)
28	Dimitras *et al.* (1999)	RS	97.5	2.5	2.5	80	38	FR	Greece	86-93	Mix. Ind. (ltd.)
29	El Hennawy and Morris (1983)	MDA	97.72	4.55	0	44	44	Mix	UK	60-71	Mix. Ind. (ltd.)
30	Foreman (2002)	Logit	97.4	14.29	0	77	14	FR	USA	1999	Telecom. Ind.
31	Frydman *et al.* (1985)	MDA	74	9	17	200	NA	FR	USA	71-81	Mix. Ind. (ltd.)
32	Frydman *et al.* (1985)	RPA	89	9	2	200	NA	FR	USA	71-81	Mix. Ind. (ltd.)
33	Gombola *et al.* (1987)	MDA	89	NA	NA	77	NA	FR	USA	70-82	Manf. and retail (ltd.)
34	Gombola *et al.* (1987)	BSDM	89	NA	NA	77	NA	FR	USA	70-82	Manf. and retail (ltd.)
35	Jo *et al.* (1997)	MDA	82.22	NA	NA	542	NA	Mix	Korea	91-93	Mix. Ind. (ltd.)
36	Jo *et al.* (1997)	NN	83.79	NA	NA	542	NA	Mix	Korea	91-93	Mix. Ind. (ltd.)
37	Jo *et al.* (1997)	CBR	81.52	NA	NA	542	NA	Mix	Korea	91-93	Mix. Ind. (ltd.)
38	Kahya and Theodossiou (1999)	MDA	77.8	31	17	189	NA	FR	USA	74-91	Manf. and retail (ltd.)
39	Kahya and Theodossiou (1999)	Logit	77.2	33	16	189	NA	FR	USA	74-91	Manf. and retail (ltd.)
40	Kahya and Theodossiou (1999)	CUSUM	82.5	18	17	189	NA	FR	USA	74-91	Manf. and retail (ltd.)
41	Keasey and McGuinness (1990)	Logit	86	14	14	86	30	FR	UK	76-84	Mix. Ind. (ltd.)
42	Laitinen and Laitinen (1998)	Logit	80.49	17.07	21.95	82	NA	Mix	Finland	86-91	Industrial (ltd.)
43	Laitinen and Laitinen (1998)	Par Adj.	80.49	17.07	21.95	82	NA	Mix	Finland	86-91	Industrial (ltd.)
44	Laitinen and Laitinen (1998)	Cash	58.54	41.46	41.46	82	NA	CF	Finland	86-91	Industrial (ltd.)

(*Continued*)

Table V

No.	Author and year	Model	OPA (%)	Type I (%)	Type II (%)	ES	TS	Ind. Var.	Country	Years	Firm type
45	Lin and Piesse (2001)	Univariate	79.22	28.12	2.22	77	NA	FR	UK	85-94	Mix. Ind. (ltd.)
46	Lin and Piesse (2001)	Logit	87	12.5	8.89	77	NA	FR	UK	85-94	Mix. Ind. (ltd.)
47	McGurr and DeVaney (1998)	MDA	74.1	NA	NA	112	NA	Mix	USA	89-93	Retail firms (ltd.)
48	McGurr and DeVaney (1998)	Logit	67.2	NA	NA	112	NA	Mix	USA	89-93	Retail firms (ltd.)
49	McGurr and DeVaney (1998)	Cash	68.43	NA	NA	112	NA	Mix	USA	89-93	Retail firms (ltd.)
50	McKee and Lensberg (2002)	GA	82.6	6.8	10.3	291	NA	FR	USA	91-97	Mix. Ind. (ltd.)
51	McKee and Lensberg (2002)	RS	82.6	6.8	10.3	291	NA	FR	USA	91-97	Mix. Ind. (ltd.)
52	Messier and Hansen (1988)	RPA	100	NA	NA	32	16	FR	USA	75-76	NA
53	Meyer and Pifer (1970)	LPM	80	3	0	60	18	FR	USA	48-65	Banks
54	Moyer (1977)	MDA	90.48	5	14	54	NA	Mix	USA	65-75	NA
55	Moyer (1977)	BSDM	85.19	11	18	54	NA	Mix	USA	65-75	NA
56	Neophytou *et al.* (2001)	Univariate	90	NA	NA	102	52	FR	UK	88-94	Industrial (ltd.)
57	Neophytou *et al.* (2001)	Logit	93.75	8.33	4.17	102	52	FR	UK	88-94	Industrial (ltd.)
58	Neophytou *et al.* (2001)	MDA	93.75	NA	NA	102	52	FR	UK	88-94	Industrial (ltd.)
59	Neophytou *et al.* (2001)	NN	95.83	NA	NA	102	52	FR	UK	88-94	Industrial (ltd.)
60	Park and Han (2002)	CBR	84.52	NA	NA	2144	NA	Mix	Korea	95-98	Mix. Ind. (ltd.)
61	Piesse and Wood (1992)	MDA	NA	25	34	48	48	FR	UK	73-86	Motor Compnts. (ltd.)
62	Platt and Platt (1990)	Logit	90	7	14	171	68	Mix	USA	72-86	Mix. Ind. (ltd.)
63	Pompe and Feelders (1997)	MDA	70	NA	NA	288	288	FR	Belgium	88-94	Constn. ind. (ltd)
64	Pompe and Feelders (1997)	RPA	70	NA	NA	288	288	FR	Belgium	88-94	Constn. ind. (ltd)
65	Pompe and Feelders (1997)	NN	73	NA	NA	288	288	FR	Belgium	88-94	Constn. ind. (ltd)
66	Salchenberger *et al.* (1992)	Logit	93.5	10	3	200	404	FR	USA	86-87	S and loan Association
67	Salchenberger *et al.* (1992)	NN	97	4	2	200	404	FR	USA	86-87	S and loan Association
68	Shin and Lee (2002)	GA	79.7	NA	NA	476	52	FR	Korea	95-97	Manufac. Ind. (ltd.)
69	Skogsvik (1990)	Probit	84	NA	NA	379	NA	FR	Sweden	66-80	Mining and Manfc.
70	Stone and Rasp (1991)	LPM	70.4	NA	NA	108	108	FR	USA	NA	NA
71	Stone and Rasp (1991)	Logit	72.3	NA	NA	108	108	FR	USA	NA	NA
72	Sung *et al.* (1999)	MDA	82.1	31	10.2	152	NA	FR	Korea	91-97	Manf. and retail (ltd.)
73	Sung *et al.*, 1999	RPA	83.3	27.6	10	152	NA	FR	Korea	91-97	Manf. and retail (ltd.)
74	Taffler (1982)	MDA	90.7	12.12	0	43	NA	FR	UK	68-73	Mix. Ind. (ltd.)
75	Taffler (1983)	MDA	97.8	4.3	0	92	46	FR	UK	69-76	Manufac. Ind. (ltd.)
76	Taffler and Tisshaw (1977)	MDA	98.9	2.17	0	92	NA	FR	UK	69-76	Manufac. Ind. (ltd.)
77	Theodossiou (1991)	LPM	92.7	NA	NA	363	138	FR	Greece	80-84	Manufac. Ind. (ltd.)
78	Theodossiou (1991)	Logit	94.5	NA	NA	363	138	FR	Greece	80-84	Manufac. Ind. (ltd.)
79	Theodossiou (1991)	Probit	93.7	NA	NA	363	138	FR	Greece	80-84	Manufac. Ind. (ltd.)
80	Theodossiou (1993)	MDA	84.6	34	9	259	NA	FR	USA	67-86	Manf. and retail (ltd.)
81	Theodossiou (1993)	CUSUM	84.9	15	15	259	NA	FR	USA	67-86	Manf. and retail (ltd.)
82	Varetto (1998)	GA	95	6	4	3840	898	Mix	Italy	NA	Mix. Ind. (ltd.)
83	Ward (1994)	Logit	92	NA	NA	227	158	Mix	USA	84-88	Non-Fin. Firms
84	Westgaard and Wijst (2001)	Logit	97.3	22.73	2.11	35287	35287	Mix	Norway	95-99	Mix. Ind. (ltd.)
85	Westgaard and Wijst (2001)	Credit	97.3	22.73	2.11	35287	35287	Mix	Norway	95-99	Mix. Ind. (ltd.)
86	Wilcox (1973)	Gamb.	94	NA	NA	82	NA	FR	USA	49-71	Mix. Ind. (ltd.)
87	Yang *et al.* (1999)	MDA	71	12	33	122	NA	FR	USA	84-89	Oil and Gas
88	Yang *et al.* (1999)	NN	74	50	20	122	NA	FR	USA	84-89	Oil and Gas
89	Zavgren (1985)	Logit	82	NA	NA	90	32	FR	USA	72-88	Mix. Ind. (ltd.)

Figure 1 Proportion of model categories employed by past studies

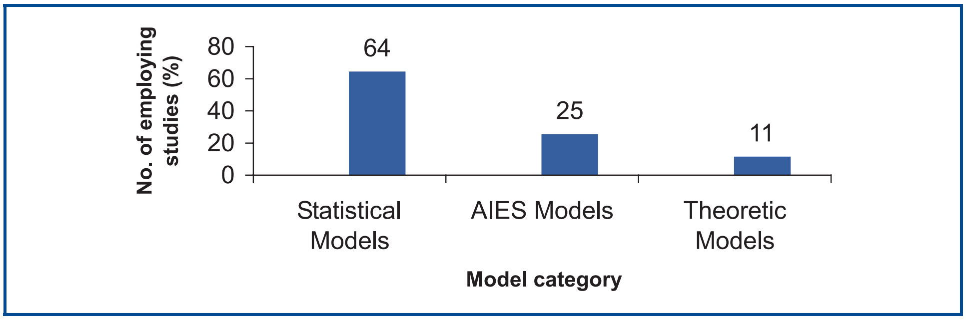


Figure 2 Proportion of model employed by past studies

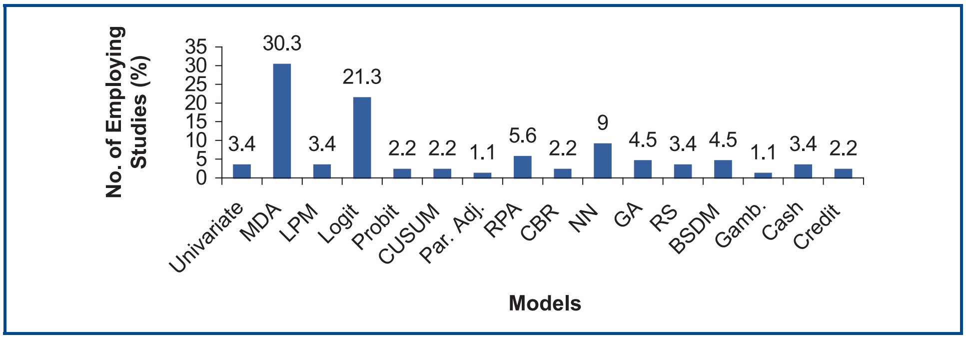


Figure 3 Individual model predictive accuracies

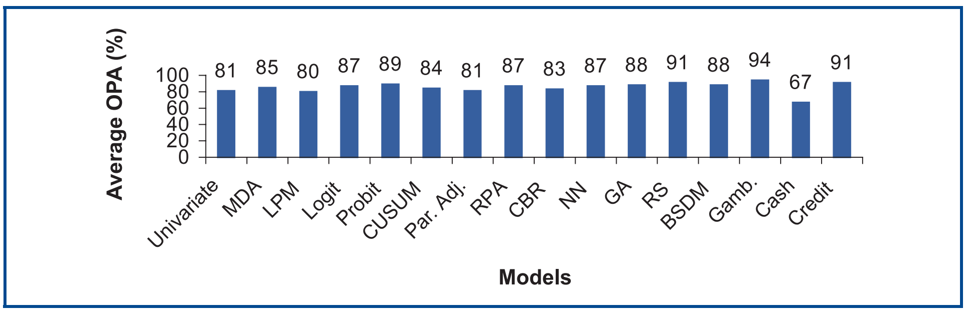


Table VI. The most striking observation here is the collective average accuracy of more than 85 per cent in bankruptcy prediction. Individually, the Gambler's Ruin model seems to perform best, with an accuracy rate of 94 per cent, but accounts for only about 1 per cent of all the cited studies. Rough sets, credit risk, Probit models, and genetic algorithms also predict very accurately, but again account for only small fractions of the total. Hence, they all invite for further applications to establish more reliable rankings. Table VI presents rather a better measure of relative performance, whereby each individual model is ranked according to its adjusted standard deviation. This ranking suggests that the performance of MDA and Logit models (with lower adjusted standard deviations of 0.34 and 0.47, respectively) may be more reliable. BSDM, a theoretical approach, stands third in this ranking, followed by CUSUM and NN. A note of caution should be introduced here. A one-year prediction horizon for bankruptcy is not long, and it seems likely that accuracy rates would reduce sharply for longer horizons.

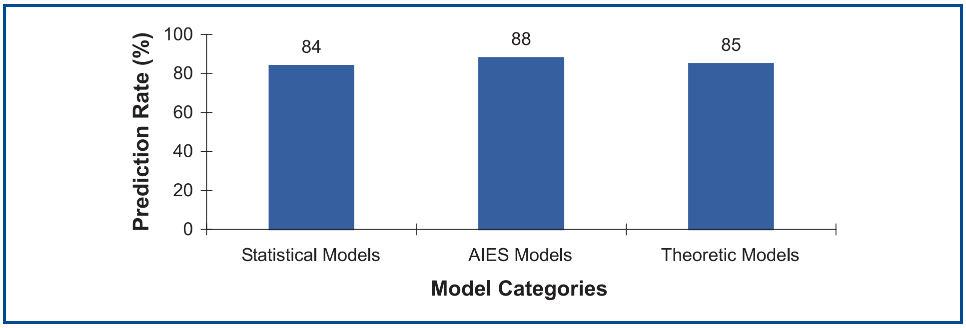
While MDA and Logit models are the methods of popular choice in bankruptcy prediction, it is not evident that this popularity is entirely warranted by their relative accuracy. Figure 4 suggests that the AIES approach actually provides the best overall accuracy rates, at 88 per cent,

Table VI Summary statistics (individual models)

Model type	*Number of applications in past studies (f)*	*Geometric mean of % prediction rates (X)*	*fX*	*Weighted variance (WV), using GM*	*Weighted standard deviation (WSD), using GM*	*Adjusted standard deviation (WSD/f)*	*Ranks (using WSD/f)*
Univariate	3	81.0918	243.2754	86.02245	9.274829	3.09161	9
MDA	25	85.13469	2128.367	74.09812	8.608027	0.344321	1
LPM	3	80.45573	241.3672	162.9942	12.76692	4.255639	11
Logit	19	86.6655	1646.645	78.9162	8.883479	0.467552	2
Probit	2	88.85944	177.7189	74.8978	8.654352	4.327176	12
CUSUM	2	83.99405	167.9881	6.331802	2.516307	1.258154	4
Par. Adj.	1	81	81	NA	NA	NA	NA
RPA	5	86.37933	431.8966	131.4196	11.46384	2.292768	7
CBR	2	83.48653	166.9731	12.2752	3.503598	1.751799	6
NN	7	87.39402	611.7582	126.1244	11.23051	1.604359	5
GA	4	88.44349	353.7739	86.57967	9.30482	2.326205	8
RS	3	90.78846	272.3654	102.8432	10.14116	3.380387	10
BSDM	4	87.70087	350.8035	18.5042	4.301651	1.075413	3
Gamb.	1	94	94	NA	NA	NA	NA
Cash	3	67.01017	201.0305	557.8339	23.61851	7.872836	14
Credit	2	90.80198	181.604	133.1242	11.53795	5.768973	13
Total	86	1363.206	7350.567				

Note: Grand mean (GM) $= \Sigma fX/\Sigma f = 7350.567/86 = 85.4717 \approx 85$

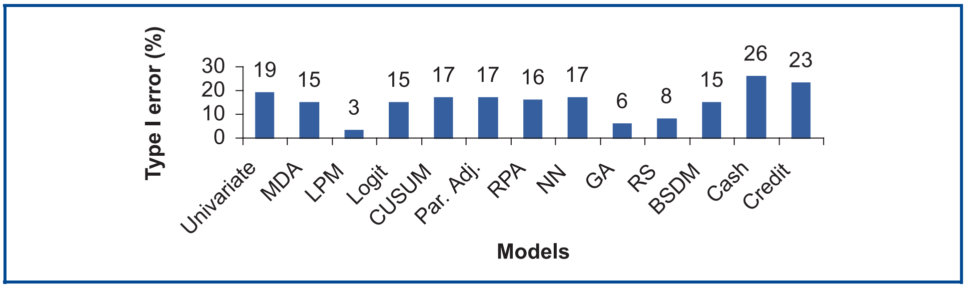
Figure 4 Overall predictive accuracies of different approaches



followed by theoretical and statistical approaches. The performance of all groups is in fact very similar. These results indicate that future research might benefit from greater use of AIES models, particularly if the models could be developed so as to overcome their major weaknesses.

It is both interesting and important to assess predictive power by the misclassification rates for each model – the number of failed firms that are classified as non-failed (type I error) – since such misclassification can be very costly to lenders. Figure 5 presents the average type I error rates of the models used in the studies cited here. Although the lowest error is observed in case of LPM, it ranks only 11th in Table VI. Similarly, lower rankings of GA and RS in Table VI decrease the importance of their lesser error rates in Figure 5. The three top-ranked models of Table VI (MDA, Logit, and BSDM) show error rates of 15 per cent each, reassuring their significance as useful prediction models. CUSUM and neural networks models (4th and 5th, respectively in Table VI) are also comparable with a 17 per cent error rate. The cash management model seems to produce the highest error rate at 26 per cent, followed by credit risk models at 23 per cent. It is no surprise, as these two assume the lowest ranks in Table VI, also. Overall, using type I error as a criterion for model evaluation, MDA, Logit, CUSUM (Statistical models); NN (AIES model); or BSDM (theoretic model) may be the most reliable methods of bankruptcy prediction.

Figure 5 Type I errors of the models



Classifying non-failed firms as failed is a Type II error. This may have less costly real-world consequences than Type I error, but it is still important to classify healthy firms as healthy. Figure 6 reports Type II error rates of the cited models. There appears to be considerably greater variability than for Type I error rates. The cash management model again shows the highest average misclassification rate (35 per cent) while MDA and Logit models are again marginally comparable with 12 and 10 per cent error rates, respectively. Performance of BSDM and CUSUM is slightly poorer this time, but neural networks perform much better than MDA and Logit models with an average error rate of only 6 per cent. Low misclassification rates are also observed for credit risk, genetic algorithm and rough sets models, while a zero rate was achieved by LPM. However, all these models suffer from lower ranking in Table VI and cannot reasonably be assessed as more reliable than MDA, Logit, BSDM, CUSUM and NN models with respect to Type II error rates.Table VII considers if there are any differences in predictive accuracies across different countries. As common in almost all fields of research, US data set has been used most extensively in applications of bankruptcy prediction. Table VII ranks ten countries (used in our sample) according to their adjusted standard deviations. US data set proves to be the most reliable and stands first. UK and Australia follow next. Table VII also reports an average of 86 per cent correct prediction rate (GM) for all the countries, which is a noticeable observation as the average correct prediction rate (GM) reported in Table VI for different models is also 85 per cent. Such a finding may invite us to hypothesize that the predictive power of individual models is independent of the data set being used. In other words, almost all the methods of corporate bankruptcy prediction (particularly, MDA, Logit, BSDM, CUSUM, and NN) are capable of providing consistent accuracy rates using any data set, provided the data has been drawn from reliable and dependable sources. Future research may well be able to test the trueness of such a hypothesis.

As a final observation, Table V includes studies published between 1968 and 2003. Despite a dedicated effort of more than 35 years, there is apparently still no academic consensus as to the most useful method for predicting corporate bankruptcy. The major finding of this paper, that the various approaches are broadly comparable, may indicate that consensus is not necessarily important. However when choosing between models is desired, rankings of Table VI may serve as an appropriate guide.

Figure 6 Type II errors of the models

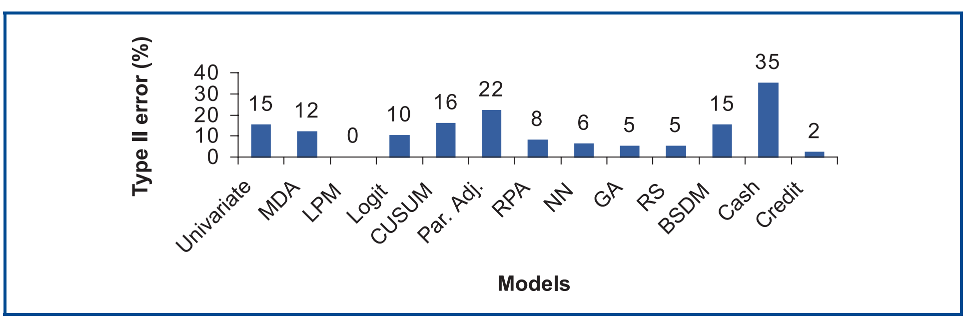


Table VII Summary statistics (individual countries)							
Country	*Number of studies in past using data sets of the country (f)*	*Geometric mean of % prediction rates (X)*	*fX*	*Weighted variance (WV), using GM*	*Weighted standard deviation (WSD), using GM*	*Adjusted standard deviation (WSD/f)*	*Ranks (using WSD/f)*
USA	42	83.46237	3505.419	79.61621	8.922792	0.212447	1
UK	16	90.01561	1440.25	64.19431	8.012135	0.500758	2
Finland	7	85.94285	601.5999	204.6199	14.30454	2.043506	6
Korea	7	82.43658	577.0561	34.45165	5.869553	0.838508	4
Greece	6	93.03009	558.1806	72.98208	8.542955	1.423826	5
Italy	3	95	285	NA	NA	NA	NA
Belgium	3	70.98604	212.9581	328.0096	18.11104	6.037012	7
Australia	2	85	170	1.036278	1.017977	0.508989	3
Norway	2	97.3	194.6	268.2012	16.37685	8.188425	8
Sweden	1	84	84	NA	NA	NA	NA
Total	89	867.1735	7629.064				

Note: Grand mean (GM) $= \Sigma fX/\Sigma f = 7629.064/89 = 85.71982 \approx 86$

4. Conclusion and recommendations

The motivation for empirical research in corporate bankruptcy prediction is clear – the early detection of financial distress and the use of corrective measures (such as changes in corporate governance) are preferable to protection under bankruptcy law. This study has provided a critical analysis of a large number of empirical studies of corporate bankruptcy prediction, based variously on statistical, AIES and theoretical models. It appears that there is still substantial disagreement over the most suitable methodology and substantial scope for model development. Various other conclusions are given below.

The review shows that statistical techniques (MDA and Logit models in particular) have been most frequently used, that the AIES approach is relatively new and that theoretical models are relatively uncommon. While predictive accuracy was observed to be generally good across all models, the review also suggests that AIES and theoretical models have slightly better average predictive accuracy than statistical models, although this measured superior performance is based on a smaller number of studies (with larger adjusted standard deviations, except in the case of NN and BSDM). On the other hand, the consistently high predictive accuracy of MDA and Logit models and their low Type I and II error rates were achieved in a relatively large number of studies (with smaller adjusted standard deviations), suggesting that these models may provide overall the most reliable methods of bankruptcy prediction. These conclusions must be tempered by the low incidence of holdout samples (not used for model validation in about half of the studies reviewed) and by the relatively short one-year prediction horizon. These considerations suggest that the reported predictive power of the models may be biased upwards.

Some areas for model development are suggested by this review. It is evident that much past research has employed relatively small samples of firms. This inherent difficulty should not impede future research but it may lead researchers away from methodologies where large samples are critically necessary. It may also be worthwhile to include corporate governance structure in addition to financial ratios that have been dominant in most research to date.

Note

1. Some published papers use several methods and thus count as more than one empirical investigation (an approach used by Dimitras *et al.*, 1996). A complete reference list is available on request

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Appendix. List of abbreviations used in the study

BSDM	Balance sheet decomposition measure (entropy theory).
Cash	Cash management theory.
CBR	Case-based reasoning.
CF	Cash flow.
Const.	Construction.
Credit	Credit risk theories (including ''option pricing'' and ''macro-economic'' theories.
CUSUM	Cumulative sums model (time series).
ES	Estimation sample.
FR	Financial ratios.
GA	Genetic algorithms.
Gamb.	Gambler's ruin theory.
Ind.	Industry.
Ind. Var.	Independent variables.
LPM	Linear probability model.
Manf.	Manufacturing.
MDA	Multiple discriminant analysis.
NA	Not available.
NN	Neural networks.
Non-Fin.	Non-financial.
OPA	Overall predictive accuracy.
Par. Adj.	Partial adjustment model (time series).
RPA	Recursive partitioning (decision tree) analysis.
RS	Rough sets model.
S and Loan	Saving and loan.
Telecom.	Telecommunications.
TS	Test (or holdout) sample.
Type I	Type I error of classifying failed firms as non-failed.
Type II	Type II error of classifying non-failed firms as failed.

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