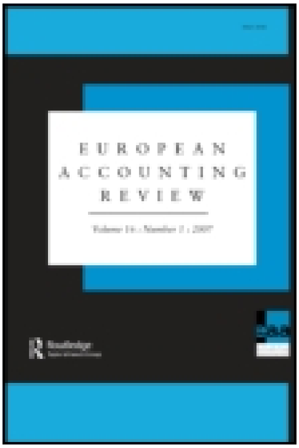

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Predicting Corporate Failure: Empirical Evidence for the UK

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ABSTRACT *The main purpose of this study is to examine the incremental information content of operating cash flows in predicting financial distress and thus develop reliable failure prediction models for UK public industrial firms. Neural networks and logit methodology were employed to a dataset of fifty-one matched pairs of failed and non-failed UK public industrial firms over the period 1988–97. The final models are validated using an out-of-sample-period* ex-ante *test and the Lachenbruch jackknife procedure. The results indicate that a parsimonious model that includes three financial variables, a cash flow, a profitability and a financial leverage variable, yielded an overall correct classification accuracy of 83% one year prior to the failure. In summary, our models can be used to assist investors, creditors, managers, auditors and regulatory agencies in the UK to predict the probability of business failure.*

1. Introduction

One of the most significant threats for many businesses today, despite their size and the nature of their operations, is insolvency. Extant evidence shows that in the past two decades business failures have occurred at higher rates than at any time since the early 1930s. It is also interesting to note that during the 1980s certain sectors of the UK economy, such as small industrial businesses in depressed areas, experienced failure rates as high as 50% over a five-year period (Rees, 1995).

The factors that lead businesses to failure vary. Many economists attribute the phenomenon to high interest rates, recession-squeezed profits and heavy debt burdens. Furthermore, industry-specific characteristics, such as government

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regulation and the nature of operations, can contribute to a firm's financial distress. Studies of patterns of business failure in the UK, US, Canada and Australia found that small, private and newly founded companies with ineffective control procedures and poor cash flow planning are more vulnerable to financial distress than large well-established public firms.

The economic cost of business failures is significant; evidence shows that the market value of the distressed firms declines substantially prior to their ultimate collapse (Warner, 1977; Charalambous *et al.*, 2000). Hence, the suppliers of capital, investors and creditors, as well as management and employees, are severely affected by business failures. The auditors also face the threat of a potential lawsuit if they fail to provide early warning signals about failing firms through the issuance of qualified audit opinions (Zavgren, 1983; Jones, 1987; Boritz, 1991; Laitinen and Kankaanpaa, 1999).

Indeed, the need for reliable empirical models that predict corporate failure promptly and accurately is imperative to enable the parties concerned to take either preventive or corrective action. Although a substantial volume of failure prediction studies has been published worldwide since Beaver's (1966) pioneering work, research interest has declined in the past few years. The majority of current UK failure prediction studies employ multiple discriminant analysis (MDA). However, despite the popularity of the MDA technique in constructing failure classification models, questions were raised regarding the restrictive statistical requirements imposed by the models (Ohlson, 1980). Also, the researchers did not examine the usefulness of operating cash flow information in explaining financial distress, despite the increased interest in cash flow reporting in the UK during the past decade (Accounting Standards Board FRS1, 1991/1996; Charitou and Vafeas, 1998).

Thus, the main objectives of this study are to develop reliable failure prediction models for UK public industrial firms using a more recent dataset, and to explore the incremental information content of operating cash flows in explaining and predicting financial collapse. Logit analysis and neural networks (NNs) are used to develop alternative prediction models and several cash flow-based financial ratios are tested in order to examine whether they have the potential to provide warning signals over more conventional, accrual-based variables.

The present study differs from prior UK failure studies in the following respects. First, the usefulness of operating cash flows in predicting corporate failure is examined. Second, neural networks are used to predict financial distress. Third, there is a methodological refinement of prior UK studies by using a more recent sample of failed and non-failed firms. Fourth, an out-of-sample-period *ex-ante* test as well as the Lachenbruch jackknife procedure are used to validate the classification results.

The dataset consists of fifty-one matched pairs of failed and healthy UK public industrial firms over the period 1988–97. Logistic regression analysis and neural networks are used to develop bankruptcy prediction models for one, two and three years prior to the event. The models are validated by means of a future-dated holdout sample and the Lachenbruch jackknife procedure. The results indicate that a parsimonious model, which includes two accrual-based financial ratios, representing the gearing and the profitability position of a firm, and an operating cash flow variable, can yield an overall correct classification accuracy of 83% one year prior to failure. The statistical significance of the operating cash flow variable in the final models contrasts the findings of many prior insolvency prediction studies.

The study proceeds as follows. Section 2 provides a brief literature review and the motivation for the study; the research design is presented in section 3; the empirical results are presented and analysed in section 4; conclusions are presented in section 5.

2. Literature Review and Motivation for the Study

The UK is considered a major worldwide economic market. The London Stock Exchange has a huge daily volume of transactions, competing with other major international stock exchanges, such as the New York, NASDAQ, Tokyo and Toronto stock exchanges. Researchers contend that the UK provides a financial environment 'ideal' for the successful development of statistical models that could facilitate the assessment of company solvency and performance (Taffler, 1984).

However, a substantial volume of the corporate failure literature has mainly employed US data to extend Beaver's (1966) early univariate approach and Altman's (1968) subsequent linear multiple discriminant analysis model.[1] The extensions include among others: (a) the assignment of prior probability membership classes (Deakin, 1972); (b) the use of a more appropriate quadratic classifier (Altman *et al.*, 1977); (c) the use of cash flow-based models (Casey and Bartczak, 1985); (d) the use of quarterly information (Baldwin and Glezen, 1992); and (e) the use of current cost information (Aly *et al.*, 1992). Even though the aforementioned studies provided high classification accuracy, they were criticized because MDA models are based on certain assumptions that are frequently violated in the context of failure prediction.[2]

Because of the well-documented limitations of the linear discriminant analysis approach, Ohlson (1980) employed logistic regression to predict company failure, a technique that avoids some of the problems of the MDA approach.[3] Since then, logistic regression has been extensively used for the development of bankruptcy models. Extensions to Ohlson's study include, among others, the following: (a) the investigation of the effect of industry-related ratios on the likelihood of corporate failure (Platt and Platt, 1990); (b) the attempt to discriminate between firms in financial distress and failed firms (Gilbert *et al.*, 1990); (c) the development of industry-specific models (Platt *et al.*, 1994); and (d) the adoption of a multinomial logit approach to reduce misclassification error by adding, to the outcome space used to predict bankruptcy, a 'weak' state of financial distress (Johnsen and Melicher, 1994).

Table 1 presents the main features of the major US bankruptcy-related studies. Specifically, features such as the technique used, the period studied, the matching procedure, years prior to failure tested, the estimation sample as well as the validation methods are presented for each study.

The popularity of the early MDA studies in the US had a substantial influence on subsequent British failure prediction studies. Several MDA models were developed in the UK during the 1970s and the 1980s and, despite the major statistical advancements that occurred in this area in the years that followed, MDA still remains the most popular and most widely used failure prediction technique in the UK. The best-known UK applications of linear discriminant analysis are the models developed by Taffler (Morris, 1997).[4]

Peel *et al.* (1986) were among the first to apply logit analysis in the UK. In an attempt to refine the 'classic' financial ratio-based failure model, they added a number of non-conventional ratios and variables. Keasey and Watson (1987) applied a similar framework in order to predict small company failure. Subsequently, Peel and Peel (1988) and Keasey *et al.* (1990) examined whether it is possible to discriminate simultaneously between healthy and failing firms for a number of reporting periods prior to failure, by applying multi-logit models. Lennox (1999) demonstrated that the industry sector, company size and the economic cycle have important effects on the likelihood of corporate failure, which is expected to increase when the company in question is unprofitable, is highly leveraged and it has liquidity problems.

Table 2 presents the main features of the major UK bankruptcy-related studies. Specifically, features such as the technique used, the period studied, the matching procedure, years prior to failure tested, the estimation sample as well as the validation methods are presented for each study.

In addition to the aforementioned statistical models, an alternative simulation approach, neural networks (NN), has emerged in recent years. NNs have been applied extensively to an increasingly wide variety of business areas, including financial forecasting, credit analysis, bond ratings, bankruptcy prediction and fraud detection. NNs are computer systems that take their inspiration from known facts about how the brain works and they can be 'trained' to solve certain problems or identify specific patterns. Empirical evidence to date using the NN methodology shows that it can provide at least as good results as those produced by the more traditional statistical methods, such as discriminant analysis and conditional probability models (Coats and Fant, 1993; Wilson and Sharda, 1994; Charalambous *et al.*, 2000). Although the neural network approach has been applied extensively in the US, research on bankruptcy prediction using neural networks has been very limited in the UK.

The majority of researchers who conducted failure prediction studies admit that one of the major reasons that organizations fail is their inability to repay their debt and interest obligations, i.e. lack of sufficient cash flows from operating activities. None the less, very few researchers examined the role of operating cash flows in predicting the probability of default. One of the first studies to examine

Table 1. Main features of representative US failure prediction studies

Researcher(s) (year of publication)	Features					
	Technique(s) used	Period studied	Matching by:*	YPTF used	Estimation sample: F/NF	Validation sample: F/NF
Beaver (1966)	Univariate	1954–64	Industry, Asset size	5	79/79	Yes
Beaver (1968)	Univariate	1954–64	Industry, Asset size	5	51/62	No
Altman (1968)	MDA	1946–65	Industry, Asset size	5	33/33	25/66
Deakin (1972)	Univariate, MDA	1964–70	Industry, Asset size (univ. only)	5	32/32	11/23
Edmister (1972)	Zero–one regression	1954–69	Small businesses	3	42/42	No
Blum (1974)	MDA	1954–68	Industry, Sales, No. of employees	8	115/115	Yes
Elam (1975)	Univariate, MDA	1966–72	Industry, Sales	5	48/48	No
Wilcox (1973, 1976)	Linear gambler's-ruin score	1955–75	Industry, Asset size	5	52/52	Yes
Diamond (1976)	MDA	1970–75	Industry, Asset size	3	75/75	Jackknife method
Altman *et al.* (1977)	MDA	1962–75	Industry	5	53/58	Yes
Deakin (1977)	MDA	1964–71	No	2	63/80	Compustat 1971 file
Dambolena and Khoury (1980)	MDA	1969–75	Industry	5	46/46	Jackknife method
Ohlson (1980)	Logit	1970–76	No	3	105/2058	No
Zavgren (1982)	Logit	1972–78	Industry, Asset size	5	45/45	No
Casey and Bartczak (1985)	MDA, Logit	1971–82	Industry	5	60/230	Yes
Gentry *et al.* (1985)	Logit	1970–81	Industry, Sales, Asset size	3	33/33	23/23
Gentry *et al.* (1987)	Probit	1970–81	Industry, Asset size	3	33/33	23/23

(*continued*)

Table 1. *Continued*

	Features					
Researcher(s) (year of publication)	Technique(s) used	Period studied	Matching by:*	YPTF used	Estimation sample: F/NF	Validation sample: F/NF
Platt and Platt (1990)	Logit	1972–87	Industry, Asset size	1	57/57	Jackknife, 34/34
Gilbert *et al.* (1990)	Logit	1974–83	No	1	52/208	24/96
Tennyson *et al.* (1990)	Logit	1978–80	Industry, Asset size	2	23/23	No
Baldwin and Glezen (1992)	MDA	1977–83	Industry, Asset size	Up to six quarters	40/40	Jackknife method
Aly *et al.* (1992)	MDA, Logit	1979–87	Industry, Asset size, Internal acctg methods	3	26/26	No
Ward (1994)	Logit	1988–89	Industry	3	14/37 (MOG no.) 89/245 (control)	Jackknife method
Johnsen and Melicher (1994)	Multinomial logit	1970–83	No	1	112/255**/ 293	No
Platt *et al.* (1994)	Logit	1982–88	Oil and gas industry	1	35/89	No
Wilson and Sharda (1994)	MDA, NNs	1975–82	Industry	1	50:50 (%) 80:20 (%) 90:10 (%)	50:50 (%) 80:20 (%) 90:10 (%)
Boritz *et al.* (1995)	Logit, NNs	1971–84	No	1	41/4099	21/2049
Barniv *et al.* (2002)	Ordered logit	1980–92	–	–	49 (acquired) 119 (emerged) 69 (liquidated)	123 (1987–91) Jackknife method

* All studies matched their sample companies (failed/non-failed) by fiscal year.

** Financially weak firms, MOG = Mining, oil and gas firms.

MDA = Multivariate discriminant analysis; NNs = Neural networks; F = Failed; NF = Non-failed; YPTF = Years examined prior to failure.

Table 2. Main features of representative UK failure prediction studies

	Features					
Researcher(s) (year of publication)	Technique(s) used	Period studied	Matching by:*	YPTF used	Estimation sample: F/NF	Validation sample: F/NF
Lis (1972, cited in Taffler, 1982)	MDA	1964–72	Year, Industry, Asset size	1	30/30	No
Taffler (1974, cited in Taffler, 1982)	MDA	1968–73	No	4	23/61	33/00
Taffler (1977, cited in Taffler, 1983)	MDA	1969–76	Industry, Asset size	1	46/46	Yes
Taffler (1984)	MDA	1978–81	No	1	39/56	Jackknife method
El Hennawy and Morris (1983)	MDA	1960–68 1969–71	No	5	22/22	22/22 9/9
Keasey and Watson (1986)	MDA	1974–80	Year, Industry	3	25/30	8/39
Peel *et al.* (1986)	Logit	1971–84	No	1	34/44	12/12
Keasey and Watson (1987)	Logit	1970–83	Year	3	73/73	10/10
Peel and Peel (1988)	Logit, Multilogit	1978–82	No	3	35/44	12/15
Keasey *et al.* (1990)	Logit, Multilogit	1976–84	Year, Industry, Net assets	5	40/40	12/12
Keasey and McGuinness (1990)	Logit	1976–84	Year, Industry, Net assets	5	43/43	15/15
Piesse and Wood (1992)	MDA	1973–86	Year, Industry (motor components)	5	No model development	3/24
Morris (1997)	Univariate Logit NNs	1973–83	Year, Industry	5 10 5	111/111 75/75 61/61	21/0
Wilson *et al.* (1995)	NNs, Logit	1972–79	Year	1	40/32*/40	Jackknife method
Lennox (1999)	MDA Probit Logit	1987–94	No	4	Varies with fiscal year	33/3288

* Distressed acquired firms.

MDA = Multivariate discriminant analysis; NNs = Neural networks; F = Failed; NF = Non-failed; YPTF = Years examined prior to failure.

the incremental information content of operating cash flow variables in predicting bankruptcy was the study by Casey and Bartczak (1985). They concluded that cash flow variables do not provide incremental predictive power over accrual-based ratios. In contrast, Gentry *et al.* (1987) demonstrated that cash-based funds flow ratios could serve as a viable alternative to accrual accounting financial ratios when trying to establish the financial health of a firm. Gilbert *et al.* (1990) investigated the discriminating ability of cash flow variables, concluding that they can significantly add to the explanatory power of insolvency prediction models. Ward (1994) argued that the usefulness of cash flow information is industry specific and his empirical results suggested that cash flow variables might be better predictors of corporate failure in the mining and oil and gas industries.

Bernard and Stober (1989) also argue that operating cash flows rather than accrual earnings are expected to play an important role in predicting the probability of default, as cash flows provide a direct link to the liquidity ability of the organization to repay its debt and interest obligations. On the other hand, accrual earnings represent only indirect links to expected cash flows, since accruals are subject to arbitrary allocations and manipulation by managers.

It is indeed a fact that the majority of the bankruptcy-related studies thus far have emphasized more either the method used (i.e. MDA, logit, neural networks) or the financial variables that should be used for predicting purposes. Very few researchers make reference to a specific theory that might explain why a certain number of businesses might be expected to fail, despite the fact that such theories have been discussed in the broad business literature, e.g. disequilibrium models, financial models, management theory, agency theory and option theory (Morris, 1997; Charitou and Trigeorgis, 2003). The reasons that urge failure researchers to ignore these normative theories vary: some of the models derived from such theories are essentially descriptive, many others are not really operational in an economic context since they make unrealistic assumptions, while some of them were found to yield similar or even inferior results from the so-called ‘ad hoc’ financial ratio models (Morris, 1997).

Whilst normative theories attempt to explain by deductive reasoning why a certain proportion of businesses might be expected to fail, positive theories attempt to explain by inductive reasoning why in practice they do fail. These theories are usually supported by empirical results. Although the majority of bankruptcy studies were conducted in line with the positivistic paradigm, very few researchers clearly identified an underlying theory. Instead, they chose to select the potential predictor variables based on their intuition, popularity and predictive success in previous similar studies. However, the weakness that relates to the lack of theoretical analysis is mitigated to some extent by validating the model against a holdout sample from a future time period. This approach was followed in designing the present study.

As has already been discussed, the main motivation for this study is the limited research in the insolvency prediction area during the past decade in the UK, and in particular, the lack of research examining the usefulness of operating cash flow information when assessing the financial position of UK companies. The following question, however, can justifiably be raised: why not use a model developed from US financial data to predict a UK company failure? There exists evidence that: (a) there are significant financial reporting differences between the two countries (Nobes and Parker, 1999), and (b) the UK and US also have different insolvency codes (Franks *et al.*, 1996).

As far as UK research in corporate insolvency prediction is concerned, evidence shows that such research was undertaken mainly in the 1980s and early 1990s.[5] It can thus be argued that the models developed in those studies may not be currently applicable, given that various economic changes have occurred in the UK since then. This study employs a more recent UK dataset to develop and test a number of alternative insolvency classification models. In addition, since the majority of the existing UK failure classification models were based on the MDA approach, a method that was shown to suffer from certain limitations, the research is extended by applying more contemporary approaches; namely, logit analysis and the neural network methodology.

Furthermore, because organizations cannot survive without generating cash from their normal everyday operating activities, several operating cash flow-related ratios are constructed in order to evaluate their usefulness in predicting corporate failure.[6] As presented above, prior US studies provided some evidence that these variables may add to the explanatory power of insolvency prediction models (Gentry *et al.*, 1987; Gilbert *et al.*, 1990; Ward, 1994). In contrast, an examination of the existing UK failure literature reveals that operating cash flow variables have not been used in UK insolvency models, despite the fact that there has been increasing interest in cash flow reporting in the UK in the past decade (Accounting Standards Board FRS1, 1991/1996; Charitou and Vafeas, 1998).

3. Methodology

In this section the following issues are discussed: (a) the dataset, (b) the selection of the predictor variables, and (c) the statistical models applied.

Dataset

The majority of bankruptcy prediction studies defined failure legalistically. The main reason for a legal definition is that it provides an objective criterion that allows researchers to easily classify the population of firms being examined. The legal definition of failure is also adopted in this study. According to the UK Insolvency Act of 1986, 'a company is said to be insolvent if it either does not have enough assets to cover its debts (i.e. the value of assets is less than the amount of the liabilities), or it is unable to pay its debts as they fall due'. Once a company has become insolvent, the Act provides five courses of action: administration, company voluntary arrangement (CVA), receivership, liquidation and dissolution.

The companies that comprised the failed sample group for the study followed the three most common routes, i.e. administration, receivership and liquidation. They were identified from the Wall Street Journal Index (Europe) and the UK Bankruptcy & Insolvency Website. For a failed company to be included in the sample, it had to satisfy the following criteria: (a) the company's shares must have been publicly traded, i.e. the company was a public limited one (plc) according to the UK Companies Act of 1985; (b) the company must have been classified as industrial: utilities, banks and other financial institutions were excluded from the dataset, since firms in these industries are structurally different and their financial reporting practices generally preclude combining them with non-financial firms in models using financial ratios (Gilbert *et al.*, 1990); (c) the company must have failed between the ten-year period from 1988 to 1997; and (d) it must have had at least three years of full financial statement data prior to its formal failure year.

The application of the above criteria resulted in a sample of fifty-one failed companies. Table 3 presents a list of the company names. For each company, the formal year of failure, the US Standard Industrial Classification Code (SIC), the total asset size, expressed in US dollars, and the nature of the failure, are also presented.

The financial statement information for the failed companies was collected from the Global Vantage database, the Worldscope European Disclosure database and the Silverplatter (UK Corporations) database. The Global Vantage database was also used to obtain a control sample of healthy companies from the same time period. The company names of the healthy group are also shown in Table 3.

Consistent with the majority of prior insolvency prediction studies, the healthy companies were chosen to match with the failed companies in terms of industry classification and total asset size. The main reason for matched pairing the companies when developing bankruptcy models is to isolate key factors which distinguish otherwise similar firms (Morris, 1997).[7]

The final dataset was subsequently split into two sub-samples. The first sub-sample was used for estimating (training) the prediction models and included companies that failed between 1988 and 1994. The validation (testing or forecasting) sub-sample was comprised of companies that failed during the three-year period, 1995–97. Each sub-sample also included the respective matched healthy companies.

Selection of Predictor Variables

The study employs a relatively large number of financial ratios, proved to be successful in predicting bankruptcy in prior studies. Table 4 presents these ratios along with their definitions.

The first step in identifying the most significant variables was to perform a univariate logistic regression for each ratio in turn.[8] In addition, the forward

Table 3. Sample of UK failed and healthy companies over the period 1988–97

	Failed companies				Healthy companies		
Company name	Failure year	SIC	Asset size*	F**	Non-bankrupt firms	SIC	Asset size*
Sound Diffusion	1988	7359	251,966	R	Staveley Industries plc	7349	270,569
Eagle Trust	1989	3500	249,622	L	Ransomes plc	3524	216,720
Fairbriar plc	1991	1531	146,845	A	Galliford plc	1521	154,598
Turriff Corp. plc	1991	1520	99,678	R	Cala plc	1520	138,033
Stormgard plc	1991	2760/80	43,252	R	Haynes Publishing Group plc	2741	26,467
Maxwell Communication	1991	2721	6,336,532	A	Reed International plc	2700	4,647,267
Astra Holdings plc	1992	3480	152,356	R	McLeod Russell Holdings plc	3479	117,931
Ward Holdings (group) plc	1992	1531	147,446	A	St Modwen Properties plc	1531	177,469
Willaire Group plc	1992	3585	35,725	A	Psion plc	3570	42,717
Graham Wood plc	1992	1629	47,241	R	Bailey (Ch.) plc	1600	45,119
West Industries plc	1992	1520/40	29,198	R	Wiggins Group plc	1531	33,444
Harland Simon plc	1992	7379	94,889	R	Kalamazoo plc	7370	68,130
Cabra Estates plc	1992	2590	234,550	L	Spring Ram Corp. plc	2510	272,908
Barrett (Henry) plc	1992	1791	128,454	R	Eleco Holdings plc	1700	83,723
Sale Tilney plc	1992	5140	86,855	R	Sidney C. Banks plc	5150	93,131
Lilley plc	1993	1629	331,191	R	Gleeson (M. J.) Group plc	1629	225,285
Speyhawk plc	1993	1541	443,659	R	Tilbury Douglas plc	1540	462,199
Dunkeld Group plc	1993	2339	14,092	R	Honeysuckle Group plc	2339	8,651
McLaughlin & Harvey plc	1993	1520/40	41,414	R	London & Clydeside Holdings	1520	47,573
Ferranti International plc	1993	3812	392,738	R	Meggitt plc	3823	382,244
Resort Hotels plc	1994	7011	105,827	R	Savoy Hotel plc	7011	175,786
Bimec	1994	4961	56,762	R	Bournemouth Water plc	4940	33,597
Scottish Heritable Trust plc	1994	2273	83,253	R	Sirdar plc	2273	90,232
Melville Group plc	1994	8900	41,719	R	Hawtal Whiting Holdings plc	8711	43,839
Airborne Group plc	1994	3720/28	9,685	R	Ipeco Holdings plc	3728	38,288
Pentos plc	1995	5940	260,947	R	Brown (N.) Group plc	5961	226,880

(*continued*)

Table 3. *Continued*

	Failed companies				Healthy companies		
Company name	Failure year	SIC	Asset size*	F**	Non-bankrupt firms	SIC	Asset size*
Union International plc	1995	2000	596,945	R	Greene King plc	2082	561,958
Buckingham International	1995	7011	184,917	R	Friendly Hotels plc	7011	186,344
Louis Newmark plc	1995	3540	26,037	R	Garton Engineering plc	3540	26,446
Enterprise Computer Holdings	1995	7370	13,810	R	Instem plc	7371	13,199
Reject Shop plc	1995	5710	22,952	R	World of Leather	5712	17,422
Automagic Holdings plc	1995	5900	6,761	R	Rosebys plc	5990	40,965
Donelon Tyson plc	1995	1622	76,577	R	Jarvis plc	1700	62,901
Bullers plc	1995	3990	2,648	R	Soundtracs	3679	6,591
Cellular Telecom Holdings plc	1995	5900	7,765	L	Elys (Wimbledon) plc	5990	18,287
De Morgan Group plc	1996	4380	1,228	L	Seacon Holdings plc	4400	29,204
D. Y. Davies plc	1996	8712	6,178	R	Aukett Associates plc	8712	5,012
Heritage plc	1996	5023	12,166	R	Glenchewton plc	5023	19,140
Campari International plc	1996	3949	28,574	L	Hornby Group	3940	34,571
Colorvision plc	1996	5731	37,813	R	Eclipse Blinds plc	5714	39,795
Minstergate plc	1996	3714	50,869	L	Brasway plc	3714	47,926
GRI Group plc	1996	3670/79	2,123	L	LPA Industries plc	3643	9,211
NSM plc	1997	1220	340,643	A	Hardy Oil & Gas plc	1311	553,669
Millwall Holdings plc	1997	7999	29,827	A	Allied Leisure plc	7933	49,607
Virtuality Group plc	1997	7371	17,566	A	Barbour Index plc	7375	22,830
Kendell plc	1997	8712	6,603	R	YRM plc	8711	6,570
Wakebourne plc	1997	7370	17,589	R	Trace Computers plc	7370	11,837
Helene plc	1997	2330	94,317	R	Waterglade Int'l Holding	2300	93,501
Lister & Co. plc	1997	2231	32,360	A	Colefax and Fowler Group plc	2260	33,697
Yorkshire Food Group plc	1997	2034	172,035	R	Thorntons plc	2060	104,084
Brent Walker Group plc	1997	7999	865,062	R	First Leisure Corp. plc	7900	665,527

* Asset size is expressed in US $ ('000).

** Nature of failure: A = administration; R = receivership; L = liquidation.

Table 4. List of financial ratios tested in the present study. (For each ratio, the variable name and definition are presented; moreover, the ratios are broken down into their major categories)

Category	Variable name	Variable definition
Financial leverage	*REAT*	Retained Earnings/Total Assets
	SEQAT	Shareholders' Equity/Total Assets
	SEQDT	Shareholders' Equity/Total Debt
	SEQTL	Shareholders' Equity/Total Liabilities
	TLAT	Total Liabilities/Total Assets
	TLNW	Total Liabilities/Net Worth
Operating cash flow	*CFFOAT*	Cash Flow from Operations/Total Assets
	CFFOLCT	Cash Flow from Operations/Current Liabilities
	CFFONW	Cash Flow from Operations/Net Worth
	CFFOSALE	Cash Flow from Operations/Sales
	CFFOTL	Cash Flow from Operations/Total Liabilities
	RECTCFFO	Debtors/Cash Flow from Operations
Liquidity	*ACTAT*	Current Assets/Total Assets
	ACTLCT	Current Assets/Current Liabilities
	LCTACT	Current Liabilities/Current Assets
	LCTAT	Current Liabilities/Total Assets
	LCTNW	Current Liabilities/Net Worth
	LCTTL	Current Liabilities/Total Liabilities
	QAAT	Quick Assets/Total Assets
	QALCT	Quick Assets/Current Liabilities
	WCAT	Working Capital/Total Assets
Profitability	*CHIB*	$(IB_t - IB_{t-1})/(\|IB_t\| + \|IB_{t-1}\|)$ Change in *IB*
	EBITAT	Earnings Before Interest & Taxes/Total Assets
	EBITLCT	Earnings Before Interest & Taxes/Current Liabilities
	EBITPPEN	Earnings Before Interest & Taxes/Fixed Assets
	EBITSEQ	Earnings Before Interest & Taxes/Shareholders' Equity
	EBITTL	Earnings Before Interest & Taxes/Total Liabilities
	IBPPENT	Income Before Extraordinary Items/Fixed Assets
	IBSALE	Income Before Extraordinary Items/Sales
	IBTL	Income Before Extraordinary Items/Total Liabilities
	ROA	Income Before Extraordinary Items/Total Assets
	ROE	Income Before Extraordinary Items/Shareholders' Equity
	WCFOAT	Working Capital from Operations/Total Assets
	WCFONW	Working Capital from Operations/Net Worth
	WCFOSALE	Working Capital from Operations/Sales
Activity	*ACTSALE*	Current Assets/Sales
	INVTSALE	Stocks/Sales
	NWSALE	Net Worth/Sales
	QASALE	Quick Assets/Sales
	SALEACT	Sales/Current Assets
	SALEAT	Sales/Total Assets
	SALEPPEN	Sales/Fixed Assets
Market	*MKVALDT*	Market Value of Equity/Total Debt
	MKVALSEQ	Market Value of Equity/Shareholders' Equity

Net Worth = Total Assets − Total Liabilities; Working Capital = Current Assets − Current Liabilities; Working Capital from Operations (*WCFO*) = Income Before Extraordinary Items (*IB*) + Depreciation; Cash Flow from Operations (*CFFO*) = *IB* + Depreciation ± Change in Working Capital; *IB* = Income Before Extraordinary Items.

selection and backward elimination methods, both available in SPSS, were applied, and the incremental information content of the operating cash flow variables over accrual-based ratios was examined using a formal statistical test. More information regarding the selection of the predictor variables is provided in section 4 below.

The Logit Model

The logit model utilizes the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable (Dielman, 1996). In the context of failure prediction, the technique weighs the financial ratios and creates a score for each company in order to be classified as either failed or healthy. The function in logit analysis is called the logistic function and can be written as follows:

$$
\begin{aligned}
P_{jt}(Y=1) &= 1/(1+e^{-z}) \\
&= 1/\{1+\exp[-(\beta_0+\beta_1 X_{1,jt}+\beta_2 X_{2,jt}+\cdots+\beta_n X_{n,jt})]\}
\end{aligned}
$$

where

$$
\begin{aligned}
P_{jt}(Y=1) &= \text{probability of failure for entity } j \text{ at the end of year } t; \\
\exp &= \text{exponential function;} \\
\beta_1, \beta_2, \ldots, \beta_n &= \text{slope coefficients;} \\
X_1, X_2, \ldots, X_n &= \text{explanatory variables.}
\end{aligned}
$$

The critical value used for classifying companies between the two groups (i.e. the cutoff probability), was left to the default value of 0.50, which assumes an equal probability of group membership. Two important issues influenced this decision. The first reason was to achieve consistency between the estimation and validation samples, which included equal observations of failed and non-failed companies. The use of the critical value to minimize the classification errors would have probably resulted in sample-specific results, overstating the power of the prediction models. Jones (1987) states that adjusting the probability cutoff provides a means of incorporating the costs of misclassification. However, these costs are likely to differ across user groups. As the models developed in this study are intended for general application by a wide range of user groups, no attempt was made to include the costs of misclassification in the analysis. This is consistent with a number of previous bankruptcy studies (e.g. Keasey and Watson, 1986; Gilbert *et al.*, 1990).

Neural Networks

To validate and complement the prediction performance of the logit model, feedforward neural network models with a conjugate gradient training algorithm were employed.[9] A feedforward artificial neural network consists of a set of input nodes that constitute the input layer, one or more hidden layers of neurons, and an output layer of neurons (Tam and Kiang, 1992; Boritz *et al.*, 1995; O'Leary, 1998; Charalambous *et al.*, 2000). Figure 1 shows the neural network architecture applied in this study. The network consists of three layers: the input layer, the hidden layer, with a number of hidden neurons, and the output layer with a single neuron. The hidden layer uses the hyperbolic tangent sigmoid activation function $f_H(\cdot)$, while the output layer uses the log-sigmoid activation function $f_0(\cdot)$. The neurons in any layer of the network are connected to all neurons in the previous layer.

The model of a single neuron is similar to that of the logistic model. A set of n-input signals $x_0, x_1, x_2, \ldots, x_n$ ($x_0 \equiv 1$) are applied to a corresponding set of weights (multipliers) $w_0, w_1, w_2, \ldots, w_n$. The weighted signals are then summed to produce z, which is applied to the activation function to produce the output y. In mathematical terms, the performance of a neuron is described by the following pair of equations:

$$z = \sum_{j=0}^{n} w_j x_j \qquad y = f(z)$$

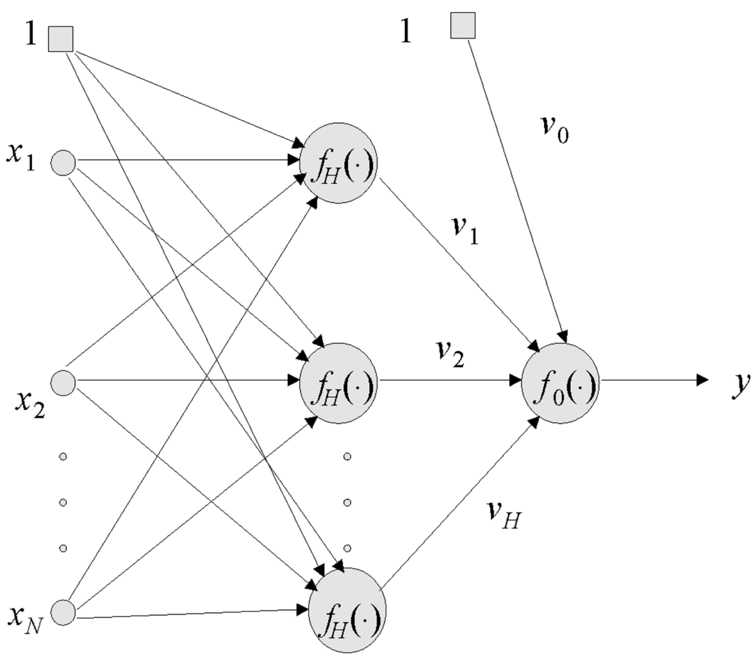


Figure 1. Architecture of a single layer feedforward neural network.

Two basic types of activation function may be identified. One is the hard-limiter function, described by:

$$f(z) = 1 \quad \text{if } z \geq 0$$
$$f(z) = 0 \quad \text{otherwise}$$

The second is the sigmoid function, which is defined as a strictly increasing function that exhibits smoothness and asymptotic properties. An example of the sigmoid function is the logistic function:

$$f(z) = \frac{1}{1 + e^{-\beta z}}$$

where β is the slope parameter.

The logit model is a special case of a neural network model that consists of a single neuron, with the logistic activation function having $\beta = 1$. Since the hard-limiter function is non-differentiable, the logistic function, which is differentiable, is most widely used in practice, usually with $\beta = 1$.

Consider a neural network with a single output unit and n-input signals. The network tries to correctly classify the m-input samples by minimizing the least squares error function:

$$S(W) = \frac{1}{2}\sum_{k=1}^{m} (y_k - d_k)^2$$

where

y_k = the output of the network corresponding to the kth input sample $x^{(k)}$;
W = the weight vector, whose elements are the weights of the network.

In this work, the conjugate gradient algorithm (Charalambous, 1992) was used to minimize $S(W)$.

4. Empirical Results

This section discusses the following: (a) descriptive statistics, (b) univariate logit analysis, (c) estimation of the multivariate logit models, (d) validation of the logit models, (e) application of Altman's (1968) variables, (f) neural network results, and (g) comparison of the validation results.

Descriptive Statistics

An important initial step is the identification of any possible differences between the two groups of companies. To achieve this, several main descriptive statistics were calculated (i.e. mean, median, standard deviation, minimum and maximum).

Figure 2 presents the median of three representative financial ratios over the three-year period prior to the failure event. First, it can be clearly observed that the medians of all three ratios differ significantly between the two groups of companies. Second, the medians of the *CFFOTL* (cash flows from operations to total liabilities) and *EBITTL* (earnings before interest and taxes to total liabilities) ratios for the bankrupt group reveal a decreasing trend as the year of failure approaches, whereas the medians of the healthy companies do not follow any specific pattern. These observations confirm the findings of previous failure research, which indicated that the cash flow and profitability measures are inversely correlated to the probability of company failure. Finally, the median of the financial leverage variable, *TLTA* (total liabilities to total assets), increases for the failed company sub-sample as the failure year approaches, whereas it remains relatively stable over the three-year period for the healthy company sub-sample. Again, this observation is consistent with the findings of previous failure studies, i.e. that financial leverage is positively related to the probability of failure.

Univariate Logit Analysis

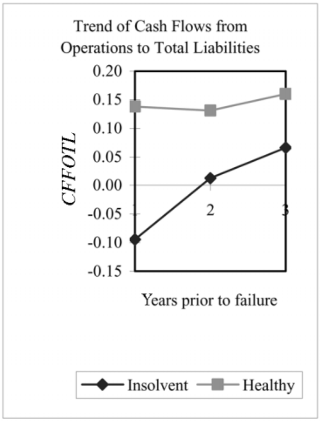
The objective of the univariate logistic regression analysis was to evaluate the predictive ability of the individual variables. Data for the last year prior to failure for the failed companies and the latest financial data for the healthy companies were used for this purpose. Table 5 shows the financial ratios that were found statistically significant in univariate analysis.

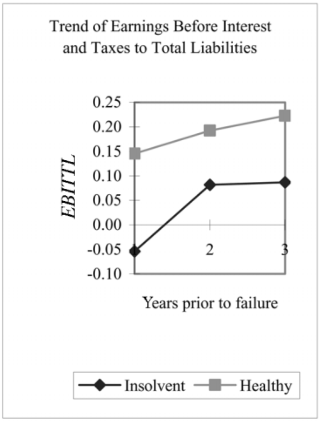
Results indicate that a number of financial leverage, operating cash flow, liquidity, profitability and activity ratios are good univariate predictors of business failure. Several financial ratios demonstrate very high classification ability, ranging from 80% to 90%. Financial leverage variables provide the highest univariate classification accuracy. Specifically, the retained earnings to total assets (*REAT*) and the shareholders' equity to total assets (*SEQAT*) ratios achieve a nearly 90% overall correct classification in the first year prior to failure. These findings suggest that financial leverage variables possess a strong discriminatory power, consistent with the argument that one of the major reasons of company failure is their inability to meet their heavy debt burdens.

Relatively high overall classification accuracy is also produced by profitability ratios. The earnings before interest and taxes to total liabilities (*EBITTL*) ratio provides the highest classification rate, while the rest of the profitability ratios follow closely. Moreover, the operating cash flow to total liabilities (*CFFOTL*) ratio yields a high classification accuracy of 69% and it is statistically significant at the 5% level. The operating cash flow to current liabilities (*CFFOLCT*) ratio is significant at the 10% level and classifies correctly 67% of the observations. The fact that operating cash flow ratios have a good univariate predictive ability suggests that they have the potential to add significantly to the explanatory power of a multivariate model.

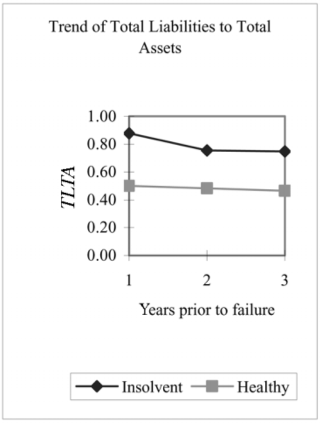
CFFOTL		
*YPTF**	*Insolvent*	*Healthy*
1	-0.09	0.14
2	0.01	0.13
3	0.07	0.16

EBITTL		
*YPTF**	*Insolvent*	*Healthy*
1	-0.05	0.15
2	0.08	0.19
3	0.09	0.22





TLAT		
*YPTF**	*Insolvent*	*Healthy*
1	0.88	0.50
2	0.76	0.48
3	0.75	0.47



**YPTF* = years examined prior to failure; *TLAT* = total liabilities to total assets; *EBITTL* = earnings before interest and taxes to total liabilities; *CFFOTL* = cash flows from operations to total liabilities.

Figure 2. Median trend of representative financial ratios.

Table 5. Univariate analysis results. (The ratios presented are the ones found significant in univariate analysis. The ratio name, the beta coefficient and its respective *p*-value along with the overall correct classification percentage are presented for each ratio; variable definitions are presented in Table 4)

Category	Variable	Coefficient	*p*-value	Over. classification
Financial leverage	*REAT*	−09.2851	0.0033	89.58%
	SEQAT	−10.6758	0.0005	87.50%
	SEQTL	−05.0041	0.0007	83.33%
	TLAT	10.0174	0.0005	83.33%
	SEQDT	−02.0774	0.0050	80.43%
Operating cash flow	*CFFOTL*	−03.1978	0.0208	68.75%
	CFFOLCT	−00.8457	0.0977	66.67%
Liquidity	*LCTACT*	02.6859	0.0066	77.08%
	ACTLCT	−00.9829	0.0634	75.00%
	WCAT	−04.1806	0.0051	72.92%
	LCTAT	04.5645	0.0021	70.83%
	QALCT	−01.3220	0.0812	70.83%
Profitability	*EBITTL*	−15.1326	0.0013	85.42%
	IBPPENT	−01.2750	0.0297	83.33%
	EBITLCT	−06.4062	0.0023	83.33%
	EBITAT	−13.6184	0.0067	81.25%
	ROA	−15.1833	0.0028	81.25%
	IBSALE	−12.9225	0.0047	81.25%
	IBTL	−14.7356	0.0011	81.25%
	WCFOAT	−14.2587	0.0028	81.25%
	WCFOSALE	−12.9784	0.0053	81.25%
	EBITPPEN	−01.7565	0.0137	77.08%
	CHIB	−01.1894	0.0309	70.83%
Activity	*NWSALE*	−02.1077	0.0149	79.17%
Market	*MKVALDT*	−01.1018	0.0145	81.82%
	MKVALSEQ	−00.9101	0.0334	60.00%

It should be stressed that statistically significant variables in a univariate model may not necessarily enter in a multivariate model, due to the presence of some other key variables in the multivariate model, which may prevent the particular variable from displaying incremental information content. Univariate analysis is none the less considered a useful tool for the identification of the potential predictor variables that will ultimately become part of a multivariate model.

Estimation of the Multivariate Logistic Regression Model

In order to find the best combination of financial variables for predicting company failure, we employ stepwise logistic regression analysis. The SPSS statistical package provides two variations of this method: the forward selection and backward elimination techniques. These techniques are considered particularly useful since they select variables based on a formal test, called the likelihood ratio test, and they avoid the multicollinearity problems that may arise with the inclusion of a number of highly correlated variables in a multivariate model (Dielman, 1996).

The forward selection procedure was first applied on the most recent set of financial data of the companies comprising the estimation sample, in order to select the combination of accrual-based financial ratios that would yield the highest prediction accuracy. The resulting multivariate model included a financial leverage variable, total liabilities to total assets (*TLAT*), and a profitability variable, earnings before interest and taxes to total liabilities (*EBITTL*). The backward elimination procedure resulted in the same set of financial ratios.

The second step was to test if either of the two operating cash flow variables found to be significant in the univariate analysis, i.e. cash flows from operations to total liabilities (*CFFOTL*) and cash flows from operations to current liabilities (*CFFOLCT*), significantly adds to the explanatory power of the accrual-based prediction model. This was achieved by performing a likelihood ratio test (Pampel, 2000). Only the former variable, cash flows from operations to total liabilities (*CFFOTL*) was found to convey incremental information content. The respective likelihood ratio test for the *CFFOTL* variable is presented below:

$$H_0\colon \beta_3 = 0$$
$$H_1\colon \beta_3 \neq 0$$

where β_3 is the coefficient of the operating cash flow variable (*CFFOTL*).

$$\begin{aligned}&[-2\log \text{likelihood (baseline model)}] - [-2\log \text{likelihood (full model)}]\\ &\quad = 21.704 - 14.661 = 7.043\end{aligned}$$

where

baseline model = prediction model without the *CFFOTL* variable;
full model = prediction model with the *CFFOTL* variable.

With one degree of freedom, which is the difference between the numbers of parameters in the two models, the critical χ^2 value at the 1% level of significance equals 6.6349. Consequently, the null hypothesis is rejected, confirming the proposition that operating cash flow considerations are significant when evaluating a company's probability of failure.

Panel A of Table 6 presents the multivariate logistic regression results for the first, second and third year prior to failure for the estimation sample, which covers the years from 1988 to 1994. The predictor variables that entered the final

Table 6. Multivariate models: estimation results. (Results on the first line represent the beta coefficient of each variable, whereas the *p*-value of each coefficient is presented in parentheses on the second line)

Model	Year	*TLAT*		*EBITTL*		*CFFOTL*	Constant	Type I error	Type II error	Overall correct	Goodman–Kruskal γ	Likelihood ratio	Nagelkerke adj. R^2
Panel A	1	12.3826		−20.9691		−3.0174	−7.1786	8.33%	4.17%	93.75%	0.992	51.881	88.10%
Logit		(0.0131)		(0.0239)		(0.0834)	(0.0211)				(0.000)	(0.0000)	
Model I	2	6.9859		−4.7569		1.4902	−3.6868	18.18%	13.64%	84.09%	0.932	20.190	49.10%
(1988–94)		(0.0221)		(0.1828)		(0.3133)	(0.0963)				(0.000)	(0.0002)	
	3	5.7730		−4.1952		1.7874	−2.7864	33.33%	27.78%	69.44%	0.677	12.7080	39.70%
		(0.0661)		(0.2526)		(0.3377)	(0.2355)				(0.011)	(0.0053)	
Panel B	1							0.00%	8.33%	95.83%			
Neural	2							13.64%	18.18%	84.09%			
Networks	3							22.22%	27.77%	75.00%			
(1988–94)													
Panel C	1	4.6861		−1.9967		−0.9315	−3.2626	15.56%	13.33%	85.56%	0.945	42.787	50.40%
Logit		(0.0007)		(0.2238)		(0.2238)	(0.0011)				(0.000)	(0.0000)	
Model II	2	3.0307		−0.6982		0.2575	−1.9015	32.56%	20.93%	73.26%	0.773	14.022	20.10%
(jackknife		(0.0084)		(0.5380)		(0.7463)	(0.0142)				(0.000)	(0.0029)	
method)	3	5.0734		−0.5805		1.2962	−3.1762	30.00%	30.00%	70.00%	0.690	19.042	28.20%
(1988–97)		(0.0024)		(0.6827)		(0.1847)	(0.0054)				(0.000)	(0.0003)	
		WCAT	*REAT*	*EBITAT*	*MKVALDT*	*SALEAT*	Constant						
Panel D	1	4.3826	−8.2896	−18.3134	−1.6611	1.0026	1.7461	8.33%	4.17%	93.75%	0.992	49.595	85.90%
Altman (1968)		(0.4289)	(0.1578)	(0.1655)	(0.0379)	(0.2139)	(0.2335)				(0.000)	(0.0000)	
Variable Set	2	3.3037	−15.2635	6.1010	−0.0166	0.1166	1.2203	18.18%	22.73%	79.55%	0.877	25.713	59.00%
(1988–94)		(0.2221)	(0.0073)	(0.3377)	(0.5868)	(0.8077)	(0.1829)				(0.000)	(0.0001)	
	3	4.4476	−22.2139	10.6120	−0.0337	0.3368	1.7476	16.66%	22.22%	80.56%	0.892	22.500	62.00%
		(0.2226)	(0.0128)	(0.2661)	(0.4992)	(0.6041)	(0.1632)				(0.000)	(0.0004)	

TLAT = total liabilities to total assets; *EBITTL* = earnings before interest and taxes to total liabilities; *CFFOTL* = cash flows from operations to total liabilities; *WCAT* = working capital to total assets; *REAT* = retained earnings to total assets; *EBITAT* = earnings before interest and taxes to total assets; *MKVALDT* = market value of equity to total debt; *SALEAT* = sales to total assets.

multivariate model are: cash flows from operations to total liabilities (*CFFOTL*), earnings before interest and taxes to total liabilities (*EBITTL*), and total liabilities to total assets (*TLAT*). Interestingly, this is a parsimonious model that includes only three variables, which represent the main categories of financial ratios, i.e. operating cash flow, profitability and financial leverage. Consistent with prior expectations and past empirical evidence, the debt ratio (*TLAT*) is positively associated with the probability of failure, whereas the profitability (*EBITTL*) and the operating cash flow (*CFFOTL*) ratios are negatively related to the failure probability. Moreover, in line with the univariate analysis results, the debt ratio (*TLAT*) appears to be the most significant variable in the multivariate model.

The overall correct classification of the model for the first year prior to bankruptcy is 94%. The type I and II error rates are 8% and 4%, respectively.[10] Multivariate results for the logit model two years prior to bankruptcy show that the model correctly classifies 84% of the sample companies. The type I and II error rates are 18% and 14%, respectively. Finally, as expected, multivariate logit results three years prior to bankruptcy indicate that, overall, the classification accuracy of the model drops to 70%. Again, as expected, the type I and II error rates increase to 33% and 28%, respectively.

Panel A of Table 6 also presents the likelihood ratio test statistics for the yearly multivariate logit models along with their respective significant levels. The likelihood ratio statistic tests whether the null model, i.e. the model that only includes the constant term, fits the data as well as the full (final) model. In other words, it tests whether the set of variables included in the final model explains a significant portion of the variability in the data. In all three models, the test is significant at the 1% level, indicating that the three-variable set adds significantly to the explanatory power of the model.

To assess the concordance between the observed and predicted groups of companies, Goodman–Kruskal's γ-coefficient of association was calculated (Goodman and Kruskal, 1954). This is a symmetric measure of association for observations measured on an ordinal scale. The measure ranges from -1 to $+1$ and it is calculated as follows:

$$\gamma = \frac{n_s - n_d}{n_s + n_d}$$

where

n_s = the number of concordant (agreeing) pairs of observations;
n_d = the number of discordant (deviant) pairs of observations.

Results indicate that the coefficient is close to 1, i.e. 0.99 and 0.93, for the first two years prior to failure, respectively, and 0.68 for the third year. The *p*-values indicate significance at the 1% level, suggesting that the models classify correctly a relatively large number of the sample companies between the two groups, i.e. failed and non-failed.[11]

However, in order to test for overfitting and to check how robust a model's discriminatory power is, the model should be tested either by using the Lachenbruch jackknife procedure or by using a holdout sample of companies, either randomly selected from the same time period as the data from which the model was derived, or better still, from a future-dated time period (Morris, 1997). A discussion of the model validation follows.

Validation of the Logit Model

Validation tests examine the ability of the classification models to predict failure among a new set of companies. Prior studies used various validation methods, including (a) an out-of-sample-period *ex-ante* test (forecast test), and (b) the Lachenbruch jackknife procedure. These methods are also applied in the present study.

Forecast validation test. The external validity of the multivariate logit model discussed in the previous section is tested using an out-of-sample-period *ex-ante* test.[12] The validation sample consists of companies that failed during the three-year period, 1995–97, and their matched healthy companies.

Table 7 presents the validation results of the logit model. The overall correct classification results for one, two and three years prior to failure are 81%, 74% and 73%, respectively. Goodman–Kruskal's γ-statistic also yields high values (0.90, 0.79 and 0.82, respectively), all statistically significant at the 1% level, indicating a strong association between the observed and predicted groups of companies. It is interesting to note that in all three years tested, the type I error

Table 7. Comparative validation test results for the period 1995–97

	Year	Logit forecast	NNs forecast	Jackknife validation	Altman forecast
Overall correct	1	80.95%	83.33%	82.22%	82.50%
	2	73.81%	76.19%	72.09%	62.50%
	3	72.92%	75.00%	70.00%	68.00%
Type I error	1	14.29%	9.52%	17.78%	10.00%
	2	19.05%	23.81%	34.89%	15.00%
	3	13.04%	18.18%	30.00%	16.00%
Type II error	1	23.81%	23.81%	17.78%	25.00%
	2	33.33%	23.81%	20.93%	60.00%
	3	40.00%	31.82%	30.00%	48.00%
Goodman–Kruskal γ	1	0.901 (0.000)		0.911 (0.000)	0.929 (0.000)
	2	0.789 (0.000)		0.752 (0.000)	0.581 (0.065)
	3	0.818 (0.000)		0.690 (0.000)	0.701 (0.004)

rates are much lower than the type II error rates. Specifically, the average type I error rate is about 15%, whereas the average type II error rate is 32%.

To summarize, the forecast validation test indicates that a parsimonious logit model that includes three financial ratios (a financial leverage, a profitability and an operating cash flow ratio) can yield relatively high classification results when used to predict the probability of financial distress for UK companies. Another merit of the model is that it produces much lower type I errors than type II errors. The type I error is typically considered more costly than the type II error. Specifically, Altman *et al.* (1977) estimated type I error rates to be thirty-five times as costly as type II error rates.

The above results differ from prior UK evidence in the following respects. First, prior UK studies did not find operating cash flows to be an important variable in predicting the probability of default. Second, the majority of prior UK studies did not use the forecasting approach in validating their model results.

Lachenbruch jackknife procedure. A statistical technique widely used in the literature for the validation of bankruptcy prediction models is the Lachenbruch jackknife procedure. The technique is considered particularly useful to researchers who deal with relatively small sample sizes, since the entire sample can be used to derive the parameters and a model is then constructed using $n - 1$ observations. The model is then used to predict the remaining observation. The process is repeated n times and the misclassified observations are used to estimate the misclassification rate. According to Lachenbruch (1975), the method gives an almost unbiased estimate of the misclassification rate so that the statistical overfitting problem will be accounted for.

The entire sample of companies covering the ten-year period from 1988 to 1997 was used to apply the jackknife procedure.[13] Table 7 presents the resulting classification rates along with the Goodman–Kruskal γ-statistic. The overall correct predictions one, two and three years prior to bankruptcy are 82%, 72% and 70%, respectively. These results do not differ much from the forecast classification rates of the first logit model (i.e. Logit Model I).

Application of Altman's (1968) Variables

The bankruptcy prediction model developed by Altman (1968) has been commonly applied in finance and accounting research. Furthermore, it has been used extensively by both academics and practitioners as a standard of comparison for subsequent failure studies (Coats and Fant, 1993; Wilson and Sharda, 1994).

Five ratios are included in Altman's (1968) model: (a) working capital to total assets, a liquidity indicator; (b) retained earnings to total assets, which is considered as a rough indicator of a firm's age; (c) earnings before interest and taxes to total assets, a measure of the true productivity of the firm's assets; (d) market value of equity to book value of total debt, which shows how much the firm's assets can decline in value before the liabilities exceed the assets and the firm becomes insolvent; and (e) sales to total assets, which illustrates the sales-generating ability of the firm's assets and can therefore be used as a measure of management's capability to deal with competitive conditions (Altman, 1968).

The aim here was to examine whether the five-variable set developed by Altman can be used to predict the probability of bankruptcy in UK companies. Altman, however, tested the predictive ability of the variables by means of linear discriminant analysis. To avoid the limitations of this technique, the present study uses logistic regression analysis.

Panel D of Table 6 presents the estimation results and the relevant test statistics for the Altman model. Results indicate that only the market variable (*MKVALDT*) and the retained earnings to assets total (*REAT*) ratio are statistically significant in at least one year. The classification rates for the first year are similar to the classification rates of the first logit model. These rates are inferior (superior) for the second (third) year. Results also show that the type I error is lower than the type II error rate in the last two years. Consistent with the results of the two logit models, Goodman–Kruskal's γ-statistic is statistically significant in all three years and the likelihood ratio test statistics indicate that the model explains a significant portion of the variability in the estimation dataset.

The external validity of the Altman model was also examined using the future-dated holdout sample for the period 1995–97, used to validate Logit Model I. Table 7 presents the resulting classification rates. The results in the first year prior to failure are comparable to the logit model results but they are inferior in the second and third years. Specifically, the overall correct classification rate is 83% for the first years before failure, but it declines substantially in the second and third years (63% and 68%, respectively). The deterioration of the model's predictive ability is also evident from the low values of the Goodman–Kruskal γ-statistic. In summary, empirical evidence suggests that the logit model developed in the study provides superior results to those results derived from the Altman model.

Neural Networks (NNs)

Panel B of Table 6 presents the neural network estimation results for the three years prior to failure. The results indicate that they provide higher overall classification rates for the first and third years than Logit Model I (96% vs 94% and 75% vs 70%, respectively). The classification rate for the second year remains the same. Interestingly, NNs also reduce significantly the type I errors for all three years before the failure event, yielding no such error in the first year. The type II error rate, however, increases in the first and second years, but remains the same in the third year (28%).

Table 8 shows the final weights of the training phase of the feedforward neural networks for all three years prior to bankruptcy. Annotation H represents the number of neurons included in the hidden layer of the network. The last column for W and V corresponds to the threshold weights.

To assess the *ex-ante* predictive power of the neural network models, intertemporal validation was performed using the future-dated dataset for the period 1995–97. The resulting classification rates of the models are presented in Table 7 under the 'NNs forecast' heading. As anticipated, the overall classification rates for the first two years are significantly lower than those achieved with the training dataset. The correct classification percentage, however, remains the same in the third year (75%). Moreover, in all three years, the overall classification rates of the NN models are slightly higher than the respective classification rates produced by Logit Model I.

Comparison of Validation Results

This section compares the validation results (overall correct classification, type I and type II error rates) of the four different models developed in the study. These results are presented in Table 7.

As far as the overall correct classification is concerned, results in Table 7 indicate that the neural network model provides the highest percentage in all

Table 8. Final weights of the neural network estimation phase (annotation H represents the number of neurons included in the hidden layer of the network and the last column for W and V corresponds to the threshold weights)

One year prior to failure (H = 3)

$$W = \begin{bmatrix} 1.4814 & -0.3801 & -0.8137 & 1.1996 \\ -0.1320 & -0.7775 & 0.1995 & 0.0936 \\ 2.5014 & -0.9571 & -2.2542 & 0.9307 \end{bmatrix}$$

$$V = [3.5061 \quad -0.4310 \quad 2.9191 \quad -0.5978]$$

Two years prior to failure (H = 3)

$$W = \begin{bmatrix} 1.8475 & -0.3744 & -0.0107 & 2.3532 \\ 0.1365 & 1.2945 & -0.0070 & 0.3834 \\ -0.3909 & -0.7778 & 0.2135 & -0.0430 \end{bmatrix}$$

$$V = [3.6470 \quad -2.6004 \quad -4.4305 \quad -2.7393]$$

Three years prior to failure (H = 3)

$$W = \begin{bmatrix} -0.4197 & -0.1198 & 0.0149 & 0.1147 \\ 0.0759 & -0.0439 & -0.6055 & 1.0340 \\ -0.0161 & 0.0256 & -0.0853 & -0.2000 \end{bmatrix}$$

$$V = [-2.0148 \quad 1.0271 \quad 0.1891 \quad -0.3978]$$

three years tested, closely followed by the forecasting test results of Logit Model I and the jackknife validation of Logit Model II. Although Logit Model II yields a slightly higher prediction rate in the first year prior to bankruptcy, its classification ability declines in the other two years and it is outperformed by Logit Model I. Since the jackknife procedure is a cross-validation test that provides *ex-post* discrimination, without giving indications of the model's *ex-ante* predictive power, it can be argued that the first logit model provides superior results.[14] Regarding the Altman model, the five-variable set seems to achieve a satisfactory overall classification rate when applied to a future-dated holdout sample for the first year prior to failure, but its performance declines substantially in the second and third years prior to failure.

Moreover, since the type I error is arguably more costly than the type II error, researchers consider models to be superior if they minimize type I error rates. Table 7 shows that the Altman (1968) variable set yields the lowest type I error percentage in the first two years prior to failure. Nonetheless, type II error rates are extremely high (59% on average) and therefore this model may not be considered reliable for practical application purposes. Results in Table 7 and in Figure 3 also reveal that the forecasting test of Logit Model I provides the lowest type I error rates (on average 15% in all three years tested).

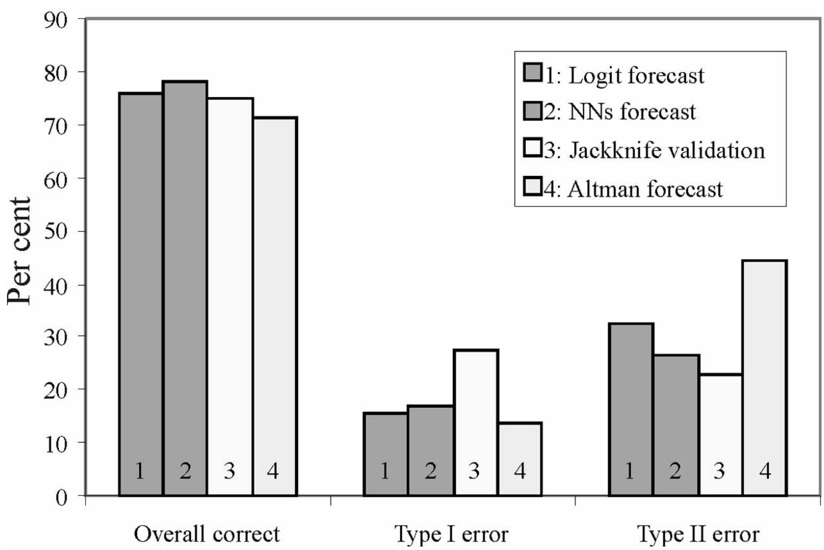


Figure 3. Average classification rates over the three years tested for validation samples. (Models presented include logit forecasting model, neural networks, jackknife validation method and the Altman forecasting model; results include the overall correct validation rate, as well as the type I and type II error rates.)

In summary, comparing the validation results of the different failure prediction models developed in the study, we can conclude that the Logit Model I and the NN model results are considered the most reliable for predicting UK corporate failure. One of the arguments in favour of these models is that, in spite of the fact that they were tested against an intertemporal sample, they still yield high overall prediction rates with relatively low type I error rates.

5. Summary and Conclusions

The primary objectives of this study were to develop failure prediction models for UK public industrial firms using a recent company sample, via logit analysis and the neural network (NN) methodology, and also to explore the incremental information content of operating cash flows in predicting the probability of business failure.

Although many researchers developed failure prediction models using a variety of statistical techniques, they have mainly used US company data. In the UK, several failure prediction studies were conducted in the 1970s and 1980s, using linear discriminant analysis, but they ignored the potential incremental explanatory power of operating cash flow-based variables in assessing a firm's financial status. Therefore, we were motivated to develop corporate failure prediction models using recent UK company data and to examine the usefulness of operating cash flows.

The dataset consists of fifty-one matched pairs of bankrupt and healthy UK public industrial firms. The bankrupt companies failed between the years 1988 and 1997. A parsimonious logit model with three financial ratios, a financial leverage, a profitability and an operating cash flow, was built. The variable set was subsequently used to develop an alternative bankruptcy prediction model using feedforward neural networks. An intertemporal test was performed to validate the two models. A second logit model was also constructed using the entire sample of companies and it was then validated using the Lachenbruch jackknife technique. All three models yielded high classification results one, two and three years prior to bankruptcy.

Nevertheless, it has been argued that the first logit model and the NN model are superior, as their overall *ex-ante* predictive ability is comparatively high and they result in low type I error rates. NNs achieved the highest overall classification rates for all three years prior to insolvency, with an average classification rate of 78% (see Figure 3). The logit model, although it achieved overall a lower correct classification (average of 76%), produced slightly lower type I error rates (average of 16% vs 17% for the NNs). Hence, it is argued that the two models can be viable alternatives for bankruptcy prediction in practical applications.

Furthermore, the predictive ability of the Altman model was also examined for our UK dataset but it did not perform that well compared to the other models tested, and thus it may not be that appropriate for predicting UK business failure. Moreover, contrary to prior studies, the results indicate that operating cash flows possess discriminatory power when it comes to predicting UK company failure.

In summary, this study extends prior studies in the following respects. First, the usefulness of operating cash flow-based variables to predict corporate failure was examined. Second, it methodologically refines prior UK studies by using a more recent company sample. Third, it employs logistic regression to develop a classification model and it uses an out-of-sample-period *ex-ante* test, as well as the Lachenbruch jackknife procedure, to validate the results. Fourth, it uses neural network methodology to predict the probability of business failure.

However, the main limitation of the present study and almost all previous failure prediction studies is the lack of a sound theoretical framework to guide the selection of variables with the best potential to discriminate corporate bankruptcy. Thus, the need for a sound economic theory of corporate failure still remains.

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Notes

1. For an in-depth review of the corporate failure-related literature see Zavgren (1983), Taffler (1984), Jones (1987), Keasey and Watson (1991), Allen and Chung (1998) and Laitinen and Kankaanpaa (1999).
2. The multiple discriminant approach (MDA) is based on the following main assumptions: (a) the independent variables are multivariate normal, and (b) the covariance matrices of the two groups (failed and non-failed) are equivalent.
3. Logistic regression has the following advantages over MDA models (Ohlson, 1980; Mensah, 1984): (a) no assumptions need to be made regarding prior probabilities of failure and the distribution of predictor variables, (b) the use of such models permits an assessment of the significance of the individual independent variables included in the model, and (c) the models calculate the weight which each coefficient contributes to the overall prediction of failure or non-failure and produce a probability score, which makes the results more accurate.
4. Taffler is one of the most prominent insolvency researchers in the UK. He developed a number of failure prediction models for the UK corporate sector, which have

performed well in terms of classification accuracy and they have become widely accepted tools for practical financial analysis in the UK.

5. For a review of the failure-related literature undertaken prior to the mid-1980s, see Taffler (1984).
6. The cash flow from the operations variable was defined as operating earnings plus non-cash expenses/revenues (non-current accruals) plus changes in working capital except for changes in cash and cash equivalents (current accruals). This definition of cash flows differs from the traditional one, which approximates cash flows by adding only depreciation to earnings (Laitinen, 1994). The traditional measure was shown in prior studies to be a measure of profitability (Ali and Pope, 1995).
7. Jones (1987) states the advantages of matching: 'Bankrupt firms are often disproportionately small and concentrated in certain failing industries. If non-bankrupt firms were drawn at random, there would probably be substantial differences between the two groups in terms of size and industry. The result is that the model attempting to discriminate between failing and healthy firms may actually be distinguishing between large and small firms, or between railroads and other industrials'.
8. Statistical analysis was performed with the SPSS (version 8.0) statistical package.
9. The neural network analysis was performed using the Matlab programming language.
10. Type I error is the misclassification of a failed firm as non-failed and the type II error is the misclassification of a non-failed firm as failed.
11. Nagelkerke's adjusted R^2 for each model is also shown in Table 6. The measure is an improvement of Cox–Snell's $R^2 = 1 - \exp(-\text{model } L^2/N)$, where L^2 is the model χ^2, which is the direct counterpart to the global F-test in linear regression analysis. N is the number of observations.
12. As Jones (1987) comments, if a holdout sample is obtained from a later period, one can test for both overfitting and a violation of the stationarity assumption. The stationarity assumption implies that the relationship between the independent variables and the dependent variable will hold over time. However, only a small number of researchers tested their models on a sample obtained from a later period (e.g. Peel and Peel, 1988; Platt and Platt, 1990; Charalambous *et al.*, 2000).
13. Panel C of Table 6 presents the estimation results of the logit model developed using the entire sample of companies (1988–97) and which, for convenience, is referred to as Logit Model II. To achieve consistency with the first logit model (referred to as Logit Model I), the same explanatory variables were used. The overall estimation results of Logit Model II for the first two years before the failure are much lower than the respective results of Logit Model I (86% and 73% vs 94% and 84%). Both models provide equal classification rates for the third year.
14. Cross-validation means verification using a time-coincident holdout sample.

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