COMPASS — A BANK LENDING ADVISER EXPERT SYSTEM

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ABSTRACT

The increasing complexity of the financial world, and high levels of losses in the late 1980s and early 1990s, have led the banking sector to question the effectiveness of traditional techniques used to assess the risks inherent in commercial loans — that is, commercial risk. This paper describes the problems associated with theoretical models developed to detect future business failure, namely their emphasis on financial data and their consequent inability to represent the reality of the process of assessing bank commercial risk. It then outlines the development and structure of COMPASS, the Bank of Scotland's lending adviser expert system which has succeeded in capturing and modelling the inherent risk of the Bank of Scotland's lending process.

INTRODUCTION

A survey published in 1993 (*The Economist*) highlighted a general failure by banks to address risk on commercial lending effectively, and a misplaced faith in traditional financial data analysis that blindly accepted the book value placed on assets, irrespective, for example, of the economic situation or outlook. It also cited examples of increased risks and losses resulting from the failure of banks to apply a defined or consistent lending policy. These included:

- A $450 million loss incurred by the Bank of New England in the fourth quarter of 1990 as a result of bad loans

- Barclay's Bank's £240 million 1992 bad debt provision against a £422 million loan to one property development company
- Barclay's Bank's £2.6 billion 1992 overall bad debt provision
- National Westminster Bank's £1.9 billion 1992 overall bad debt provision
- Germany's BfG Bank's $700 million 1992 loss, which resulted mainly from doubtful debt provisions on foreign loans

Irish banks have also suffered from high level of losses on loans (Boland, 1992):

- Allied Irish Banks suffered an increase in losses from £4.9 million to £47 million in the year to 31 March 1992 on its UK operations as a result of increased bad debt charges; non-performing loans to the UK small business sector had increased 65 per cent over the previous year (Coone, 1992a).
- In the year to 31 March 1991, Bank of Ireland lost £60 million and then another £76.6 million in the following year as a result of bad loans incurred through its subsidiary, the First New Hampshire Bank (which had cost $370 million to acquire in 1988, and against which nearly $300 million had then been written off for bad loans by 31 March 1992) (Boland, 1992; Coone, 1992b).

In response to an increasingly complex business environment and to the rising level of loan default, the banks have recognised the need to address risk on commercial lending proactively. A bank loan officer considers many quantitative and qualitative factors when evaluating a loan application. Knowledge of the applicant and details of the business plan are necessary in order to analyse the viability of the application. This risk analysis, which incorporates financial data, is then considered in the context of the sector in which the company operates and the economic climate. The bank's exposure to risk can then be assessed from an analysis of the security available from the underlying assets. The decision reached by the loan officer will be the result of the above analysis, together with the officer's expertise, built up over time through experience of the process.

The use of information technology in the complex environment of loan evaluation is intuitively appealing. However, in practice, the banks have found that application of information technology is a difficult goal to achieve, partly because of a tendency to rely on traditional data mining techniques that use mainly quantitative financial data; and partly because of a lack of success in incorporating qualitative factors into the analysis. This paper considers the alternative theoretical approaches available when assessing commercial risk. It then reports upon the successful development of an expert system — a system that emulates the decision process of an expert, in this case the bank loan officer — that has succeeded in assessing commercial risk.

COMMERCIAL RISK

In the context of this paper, 'commercial risk' refers to the possibility that a bank will suffer a loss as a result of a borrower failing to maintain and/or repay funds lent — that is, whether a loss would occur were a borrower to default on a loan. Clearly, there are two steps to this process:

- Will a borrower fail?
- Would it be unable to meet its debt to the lender?

Banks wishing to assess the likelihood of this occurring are, effectively, assessing whether the borrower is likely to fail during the term of the loan. While loan default would often precede company failure, it is a key indicator and characteristic of many company failures. Consequently, the various theoretical models developed to detect future business failure are directly relevant to the banks' desire to assess commercial risk. Were these models good predictors of failure, and hence of a possibility of commercial risk, the banks could base their commercial risk assessment systems upon them.

FAILURE PREDICTION MODELS

Arising from the ratio analysis-based work of Ramser and Foster (1931) and others over the ensuing 30 years, numerous univariate and multivariate bankruptcy prediction models have been derived, including the *z-scores* models of Altman (1968) and Taffler (1983), and others by Beaver (1966), Deakin (1972), Edmister (1972), Altman et al. (1977), Moyer (1977) and Robertson (1983). In the context of banking, examples include

Orgler (1970) and Altman et al. (1974) who developed models to predict bank loans that would be identified as 'at risk' by loan officers, and to predict bank loans that had repayment problems, respectively. The theoretical papers describing these models built on the basis of financial ratios generally propose that they can be relatively effective in predicting failure.

However, research has found that *discriminant analysis*-based models are theoretically flawed in a manner that reduces the likelihood that they could be generally effective at predicting failure. For example, Back et al. (1995) report that failing firms violate the need for 'normality' in the variables used in these *discriminant analysis* models, and that multi-collinearity among the independent variables is often a serious problem. The effect of this is that while companies could still be classified as more likely to fail, the ability to predict failure is diminished. Other approaches to corporate failure prediction that address these issues have been pursued over the past 20 years, two of the most prominent being *logistic regression analysis* and *neural networks*.

Logistic regression analysis (Ohlson, 1980) uses the same variable selection methods as *discriminant analysis* and similarly weights the independent variables to arrive at a failure probability, or *z-score*. However, it does not assume multivariate normality, thereby overcoming that weakness of the *discriminant analysis* models. Although found to be a better model for predictive purposes, like *discriminant analysis* it also depends upon financial ratios for its underlying data.

Neural networks employ artificial intelligence techniques to identify relationships between the variables based on an analysis of large volumes of data. The technique assigns the weights to apply to the variables and has been found to be the most effective of the three approaches at failure prediction (Back et al., 1995). It has also been found to be particularly suited to situations where there is non-linearity between variables (Curram and Mingers, 1994), such as would be anticipated between the independent variables and the dependent variable (failure).

Whether any of these approaches would be suitable as the basis for commercial risk assessment systems depends on the validity of the underlying data upon which they all rely — the financial ratios — and there is an old and growing body of literature that suggests that such a basis is inappropriate. Paton (1928) and Wright (1956) are just two of many that have cast doubt upon their usefulness. It is not surprising, therefore, to discover that many authors have indicated considerable scepticism as to whether a ratio-analysis-based model is useful outside the context in which it has been constructed. For example, Samuels et al. (1990, pp. 61–2) state:

> There are many theoretical problems with [a ratio-analysis-based approach]. There are also problems with . . . accounting data. . . . use of this approach [may result in] 'self-fulfilling prophecies' . . . [and] . . . it is necessary to make assumptions in preparing a set of financial accounts. All attempts to value a company must be estimated, whether based on measuring asset values or based on expected future cash flows.

In a bank-lending context, Hartvigsen (1992) critically assessed the literature in this area and concluded that these models had been subject to 'oversell'. He referred to the inability of multiple discriminant analysis to assess the significance of any variable independently of other variables in the model and to problems identified elsewhere (Eisenbeis, 1977) that arise when attempting to apply statistical models to the decision process.

In addition, he reiterated the often-mentioned need to consider the nature of the operating environment when assessing corporate stability; and drew attention to Fulmer et al.'s (1984) conclusion that the deciding factor in a bank loan decision rests upon the bank loan officer's assessment of the overall situation, not simply on a group of financial ratios.

Hartvigsen concluded that there is no overall accepted theory on how to evaluate the results of ratio analysis, never mind the actual ratios to use; and that, as a result, it takes many years of experience to build up the heuristic knowledge necessary to take ratio results and apply them appropriately in the assessment of a loan application. It is this heuristic knowledge or 'expertise' that commercial risk assessment expert systems seek to encapsulate.

Just as bank lending experts do not rely on financial ratio analysis for lending decisions, neither do other classes of experts similarly interested in forecasting company performance. For example, in their study of financial analysts, Birts et al. (1993) found that the analysts used ratios, not to determine company health, but to find anomalies and inconsistencies in the data gathered. Qualitative factors — the management, the environment, the company's external profile, information from sources within the company — were highly valued, and played a major role in the overall assessment. Clearly, this is a very different form of input compared to that used by the various failure prediction models and approaches.

In conclusion, the various failure prediction models have all tended to use financial ratios as the underlying data upon which the model they adopted was run. While it could be argued that *neural networks* models are more likely to be better at predicting failure than *logistic regression analysis* models, and that they, in turn, are likely to be better than *multivariate discriminant analysis* models, they all suffer from the narrowness of any model that relies mainly on quantitative data that (a) is of doubtful accuracy, and (b) only represents a portion of the information an expert would use if asked to assess the likelihood of a company failing. That is, none of these models effectively simulates what occurs in practice and, as such, they cannot be assumed to be sufficient as the basis for bank commercial risk assessment systems. This view is clearly supported by the experiences of the banks in the late 1980s/early 1990s when, despite using quantitative data mining models to support lending decisions, they incurred massive losses on commercial lending (*The Economist*, 1993).

COMMERCIAL RISK ASSESSMENT SYSTEMS

Commercial risk assessment systems need to move away from a ratio-analysis-based focus on failure prediction towards a more qualitative approach. By doing so, they should be better placed to emulate the reality of commercial risk assessment, and be more effective as a result. However, that is only the first stage in the two-stage assessment process. If a potential risk of failure is predicted, commercial risk will still only exist where the lender is unable to recover the amount owed because adequate security is not in place. To assess this aspect of commercial risk, the 'true' value of the borrower's underlying assets is required in order that appropriate assets can be secured against the loan, thereby ensuring repayment should failure occur.

It is this combination of qualitative information and 'true' asset values that was missing from the commercial risk assessment decision-support systems adopted by the banks in the mid-1980s and early 1990s. For smaller amounts, it would have been left to the loan officers responsible to apply the output of the bank's system (if any) to their knowledge of the borrower's circumstances, and take the decision on whether or not to lend.

In the case of larger amounts, as would often be the case with commercial loans, someone specialising in these loans, based perhaps at the bank's head office, would take both the output from the bank's commercial risk assessment system (if any), and the opinion of the bank branch-based loan officer, and make the decision on whether or not to lend. How the decision was taken would vary from individual to individual; the level of awareness of the environment within which the borrower operated would depend upon the experience of the loan officer(s) involved; 'true' asset values, if sought, would depend on the judgment of the loan officer(s) and would not be included in any financial ratio analysis undertaken. The approach adopted, while often underpinned by financial ratio analysis, was highly subjective, and consequently inconsistent; and, as demonstrated by the major bank losses incurred on loans, the level of security assigned was frequently inadequate.

The banks were increasingly aware that they needed to develop computer-based commercial risk assessment systems that incorporated qualitative as well as quantitative information. However, they found that although ratio analysis can be performed using spreadsheets and statistical packages, the interpretation and application of qualitative information requires a form of expertise that can only be encapsulated in a computer program through the use of artificial intelligence. Attempts by the banks in the late 1980s and early 1990s to develop expert systems capable of doing so were neither generally successful, nor very close to encapsulating the extent of expertise required. Even when major software companies including IBM and Microsoft became involved, the attempts to develop suitable systems generally failed.

Friedman (1989), for example, reported that credit analysis and risk analysis software systems were beginning to emerge in the US. These systems were variously credited with speeding up the assessment pro-cess and ensuring consistency — both factors that assist in risk minimisation. However, although these were commercial products, none was generally

adopted by the banks, many of whom (for example, Banker's Trust, Citicorp) took to developing their own systems instead.

The expert systems that were developed and used by the banks tended to address only part of the risks inherent in loan facility approval. They generally emphasised the financial data and their characteristics, and continued to leave the assessment of qualitative information largely to the loan officer (see, for example, Butera et al., 1990; Hartvigsen, 1990).

This lack of success in automating the qualitative aspect of the loan assessment process was not caused by problems of lack of acceptance of expert system technology in the banks. They have been using expert systems for a number of years and across the range of traditional banking activities (Feigenbaum et al., 1988; Lecot, 1988; Butera et al., 1990; Klein and Methlie, 1990; Chorofas and Steinman, 1991; Harris, 1992). Rather, it appears that it may have resulted from inappropriate methods of acquiring and encoding the expertise necessary to construct a suitable expert system for this task (Sangster, 1995).

Nevertheless, after many years of effort, there are now two generic expert systems-based models being adopted by banks, which appear to be capable of achieving the appropriate level of quantitative and qualitative-based analysis: LENDING ADVISER, whose users include UK and Canadian banks; and COMPASS, developed for the Bank of Scotland but now also being used and/or field-tested by other UK, Irish, and a number of overseas banks. LENDING ADVISER was intended to be a generic product and is the most successful of the output from the many efforts, dating from the late 1980s, of software houses to create a program capable of assessing commercial risk that could be used across the banking sector.

In contrast, COMPASS was developed for a specific bank by its senior lending officer in conjunction with a psychologist. The role of the lending officer was to provide the expertise that was to be encapsulated in the expert system. The psychologist, who was an expert neither in accounting nor in banking, played the role of 'knowledge engineer' — he retrieved and expressed the knowledge and expertise of his co-developer in a form that enabled it to be incorporated into COMPASS.

The development process started after a chance conversation between the two developers, both of whom had previously been involved separately in

attempts to develop expert systems for other tasks. The psychologist was not and never has been an employee of the bank; and they started on the project in their own time and unbeknown to the bank. Only once they had developed a pilot version of the system did the bank become aware of it and support its development. It was by complete chance that one of them was a psychologist, but it proved extremely fortuitous as his professional expertise was ideally suited to the complex task of eliciting knowledge.

The model took seven years to complete at a cost of approximately £1.5 million. It had been anticipated at the outset that the system would take about six months to complete. It took longer because of difficulties in eliciting expertise — the expert found it difficult to articulate his thought processes — and because it was quite easy to over-engineer the system, by making it more complex than it was possible to encode with the software. When this was found to have occurred, work on the affected area was abandoned and restarted from a more informed perspective, resulting in significant additional time costs. Occasionally, others were brought in to fine-tune some of the knowledge. However, this was never particularly successful. Some were so enthusiastic that it became over-complicated. Others had no sense of ownership/loyalty to the project, which led to their dropping their input when something else came along. However, the developers viewed all these difficulties as having ultimately been of positive benefit to the project, enabling greater awareness of the nature of the loan assessment process and resulting in a robust and very effective expert system.

COMPASS is applied in the case of all loan applications in excess of £250,000, and the bank has suffered no losses on new loans of that magnitude since the system was introduced in 1994. In fact, it is believed to have more than recouped all the costs of its development during the testing phase alone. Such has been the improvement in the bank's control over commercial risk arising from the use of COMPASS, that in mid-1995 all commercial loans with an outstanding balance in excess of £10,000 were appraised using the system. Loans assessed as being at risk could then be identified and steps taken to redefine their terms in order to minimise the risk that they held for the bank.

As part of the development agreement, the company formed to prepare and write the COMPASS software, Rackwick Ltd., is allowed to market the product to any other interested party, irrespective of where they operate.

The adoption of a modular approach has the benefit of permitting removal from COMPASS of the data and information specific to the Bank of Scotland, thereby leaving a generic shell that can be adopted by any bank in any market to perform similar assessments on their loan portfolios and loan applications. The system is written in C++ and runs on both Windows and OS/2 platforms, ensuring compatibility with the vast majority of computer systems worldwide.

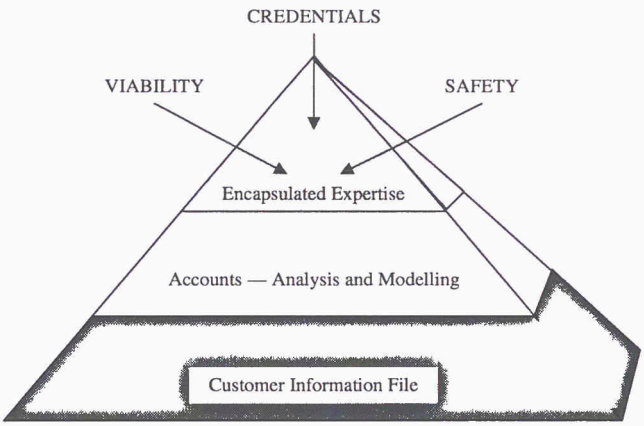
THE COMPASS MODEL

Where COMPASS differs from the traditional spreadsheet-model-based data-mining/what-if analysis decision support systems used by many banks for the assessment of commercial risk can be seen in **Figures 1** and **2**. The bottom two layers shown in **Figure 1** comprise the data typically used by these other systems — the Customer Information File at the base level, which holds information on the customers and on existing agreements with the customers; and the Accounts level, which deals with all analysis and modelling of the data.

COMPASS differs from these traditional banking decision support systems in that it has a third layer containing encapsulated loan officer expertise, which seeks the relevant knowledge from the loan officer conducting the assessment, applies it to the ratios and other relevant information held, and makes recommendations concerning the lending proposal. At the same time, it differs from other loan assessment expert systems — for example, KABAL (Hartvigsen, 1990) and PARMENIDE (Butera et al., 1990) — in that, while they encapsulate some of the relevant expertise, COMPASS encapsulates it all.

Thus the financial ratios at the heart of the various failure prediction models are only a small part of the process and information used by the COMPASS model. Furthermore, the financial ratios calculated by COMPASS are based on the asset values discounted to 'true' values, thereby minimising the risks to the bank both by improving the quality of the financial analysis and by virtually ensuring that adequate security is obtained for any advance made.

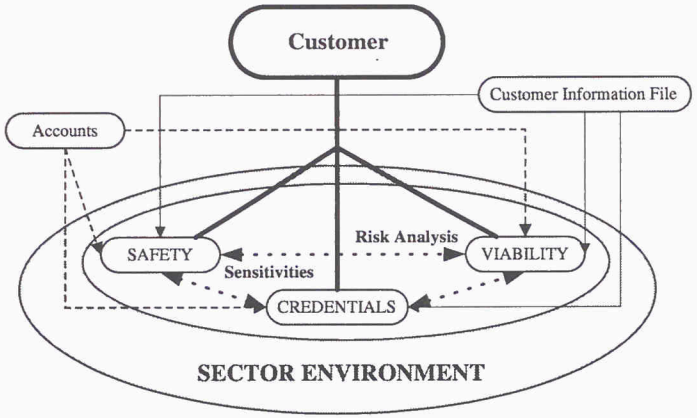
Figure 1: The COMPASS Model



However, only a part of COMPASS is presented in **Figure 1**. The overall structure can be seen in **Figure 2**. COMPASS is based on the underlying premise that the main lending process takes place away from the financial data — that the traditional spreadsheet modelling-based facility used in many banks is only a supporting factor in the overall lending decision process. Much of that process is based on other factors and it is these other factors that have been incorporated into separate modules within COMPASS.

Three key modules — VIABILITY (the potential of the customer to attain and support the proposed activity), SAFETY (the assessment of the means by which the loan facility may be recouped), and CREDENTIALS (how well the customer is known to the Bank, including qualitative factors such as its management style) — interact with an accounts module (containing seven years' data — three years' historic, the current year and a three-year projection) within a two-dimensional (on-site loan officer and Head Office) control environment (module). Concurrently, customer-specific data (held in a Customer Information File) is filtered and assessed against environmental-specific data concerning the sector (industrial, geographical, market) in which the customer operates.

Figure 2: The COMPASS Modules



Effectively, quantitative and qualitative customer-specific information is filtered by COMPASS in the context of the environment in which the customer operates, values are adjusted accordingly, and the resulting recommendations are presented in context to the loan officer who may explain the recommendations to the customer in a relevant and informative way. To assist this process, at the end of each COMPASS consultation, a report is produced containing recommendations to the bank loan officer on the customer's request for lending. The entire consultation process takes between five minutes and half-an-hour.

CONCLUSIONS

Expert systems like COMPASS demonstrate the importance of operating beyond the quantitative world of the theoretical *discriminant analysis*, *logistic regression*, and *neural networks* failure-prediction models when considering commercial risk. These models neither represent the reality of how failure prediction is undertaken in the 'real' world, nor address how to prevent risk of loss when the prediction proves to be incorrect — when a company fails that was not expected to fail. This is not surprising for these models were developed in order to determine whether any ratio or group of ratios could be a good indicator of financial distress, rather than to find a model that would accurately predict failure.

Their use as the core of a bank's commercial risk assessment system would be inappropriate. At best they can aid the decision-making process when interpreted in the context of the environment of the company concerned. At worst, they can be misleading, being based on data that are themselves flawed and subjective and open to significant manipulation, if not in amount, in description and in classification.

COMPASS uses seven years of data to enable trends to be detected and cash flows to be identified, and adjusts the underlying value of assets to their 'true' values before undertaking any financial ratio analysis. It then considers many other qualitative factors together with the financial data in the same manner as a highly experienced lending expert would, looks for signs of impending failure, advises the lending officer of them, and then determines whether the underlying assets make the granting of a loan appropriate. As a result, loans are granted to companies that would not otherwise be granted the facility, loan applications that may have otherwise escaped identification as 'high risk' are detected, and both bank and customer are made more aware of the 'true' position of the customer in relation to potential failure.

As illustrated by the heavy losses on lending incurred by the banks in the late 1980s and early 1990s, the banking environment had become too complex for the loan officer plus quantitative decision-support tool approach. Only by producing a computer-based system that incorporated qualitative information was it possible to create a system capable of protecting banks from commercial risk on bank lending. To date, COMPASS has consistently prevented losses on commercial lending, unlike the financial ratio-based models developed over the previous 30 years.

While it is certainly a very successful system, it is too early to suggest that the adoption of expert systems based on the development strategy and design of COMPASS would be a panacea for the banks. However, it does suggest that other banks should be looking to adopt COMPASS, at least on a trial basis, to assess whether the success achieved by the Bank of Scotland is truly transferable to another financial institution. A number of banks are currently doing so, and their experiences shall be the subject of future research.

REFERENCES

Altman, E.I. (1968). 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *Journal of Finance*, Vol. 23, No. 4, pp. 589–609.

Altman, E.I., Margaine, M., Schlosser, M. and Vernimmen, P. (1974). 'Financial and Statistical Analysis for Commercial Loan Evaluation: A French Experience', *Journal of Financial and Quantitative Analysis*, Vol. 9, No. 2, pp. 195–211.

Altman, E.I., Haldeman, R.G. and Narayanan, P. (1977). 'Zeta Analysis: A New Model to Identify Bankruptcy Risk of Corporations', *Journal of Banking and Finance*, Vol. 1, No. 1, pp. 29–54.

Back, B., Laitinen, T., Sere, K. and van Wezel, M. (1995). 'Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis, and Genetic Algorithms', *Paper presented at the European Accounting Association Conference*, Birmingham, UK, May.

Beaver, W.H. (1966). 'Financial Ratios as Predictors of Failure', *Journal of Accounting Research*, No. 4 (supplement), pp. 71–111.

Birts, A., McAulay, L. and King, M. (1993). 'Financial Analysis and Expert Systems', *Journal of Information Technology*, No. 8, pp. 184–94.

Boland, V. (1992). 'Survey of European Finance and Investment, Ireland (2)', *The Financial Times*, 10 July, p. 30.

Butera, G., Frascari, E. and Iacona, G. (1990). 'Parmenide: An Expert System for Assessing the Credit of Industrial Clients', *International Journal of Expert Systems*, Vol. 3, No. 1, pp. 73–85.

Chorafas, D.N. and Steinmann, H. (1991). *Expert Systems in Banking*, Basingstoke: Macmillan.

Coone, T. (1992a). 'UK Company News: Heavy UK Losses Peg Allied Irish Banks' Rise', *The Financial Times*, 14 May, p. 22.

Coone, T. (1992b). 'UK Company News: Bank of Ireland Jumps to £77m but Suffers Higher Tax Charge', *The Financial Times*, 15 May, p. 26.

Curram, S.P. and Mingers, J. (1994). 'Neural Networks, Decision Tree Induction and Discriminant Analysis: An Empirical Comparison', *Journal of the Operational Research Society*, Vol. 45, No. 4, pp. 440–50.

Deakin, E.B. (1972). 'A Discriminant Analysis of Predictors of Business Failure', *Journal of Accounting Research*, Vol. 10, No. 1, pp. 167–79.

Edmister, R.O. (1972). 'An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction', *Journal of Financial and Quantitative Analysis*, Vol. 7, No. 2, pp. 1477–93.

Eisenbeis, R.A. (1977). 'Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics', *Journal of Finance*, Vol. 32, No. 3, pp. 875–900.

Feigenbaum, E., McCorduck, P. and Nii, H.P. (1988). *The Rise of the Expert Company*, Basingstoke: Macmillan, pp. 119–22.

Fulmer, J.G., Moon, J.E., Gavin, T.A. and Erwin, J.M. (1984). 'A Bankruptcy Classification Model for Small Firms', *Journal of Commercial Bank Lending*, July, pp. 25–37.

Friedman, R. (1989). 'Credit Analysis Automation', *United States Banker*, Vol. 98, No. 6, p. 58.

Harris, M.D. (1992). 'Natural Language in Banking', *Intelligent Systems in Accounting, Finance and Management*, Vol. 1, No. 1, pp. 65–73.

Hartvigsen, G. (1990). 'KABAL: A Knowledge-Based System for Financial Analysis in Banking', *Expert Systems for Information Management*, Vol. 3, No. 3, pp. 213–31.

Hartvigsen, G. (1992). 'Limitations of Knowledge-Based Systems for Financial Analysis in Banking', *Expert Systems with Applications*, Vol. 4, No. 1, pp. 19–32.

Klein, M. and Methlie, L. (1990). *Expert Systems: A Decision Support Approach*, Wokingham: Addison-Wesley.

Lecot, K. (1988). 'Using Expert Systems in Banking: The Case of Fraud Detection and Prevention', *Expert Systems Review*, Vol. 1, No. 3, pp. 17–20.

Moyer, R.C. (1977). 'Forecasting Financial Failure: A Re-examination', *Financial Management*, Vol. 6, No. 1, pp. 11–17.

Ohlson, J. (1980). 'Financial Ratios and the Probabilistic Prediction of Bankruptcy', *Journal of Accounting Research*, Spring, pp. 109–131.

Orgler, Y.E. (1970). 'A Credit Scoring Model for Commercial Loans', *Journal of Money, Credit, and Banking*, Vol. 2, No. 4, pp. 435–45.

Paton, W.A. (1928). 'Limitations of Financial and Operating Ratios', *The Accounting Review*, Vol. 3, No. 3, pp. 252–60.

Ramser, J. and Foster, L. (1931). 'A Demonstration of Ratio Analysis', *Bulletin No. 40*, Urbana, IL: University of Illinois, Bureau of Business Research.

Robertson, J. (1983). 'Company Failure: Measuring Changes in Financial Health through Ratio Analysis', *Management Accounting* (UK), November, pp. 24–8.

Samuels, J.M., Wilkes, F.M. and Brayshaw, R.E. (1990). *Management of Company Finance* (5th edition), London: Chapman and Hall.

Sangster, A. (1995). 'The Bank of Scotland's *COMPASS* — The Future of Bank Lending?', *Expert Systems with Applications*, Vol. 9, No. 4, pp. 457–68.

Taffler, R.J. (1983). 'The Z-score Approach to Measuring Company Solvency', *The Accountant's Magazine*, March, pp. 91–6.

The Economist (1993). 'Banking: New Tricks to Learn', *The Economist*, No. 7806, 10 April, Survey.

Wright, F.K. (1956). 'An Examination of the Working Capital Ratio', *The Australian Accountant*, March, pp. 101–7.