

9 Financial Modelling

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INTRODUCTION

Recognition of an optimum combination of financial and non-financial indicators which best measures current performance, or is capable of explaining or predicting future levels of performance, remains an area of current concern. The balanced scorecard provides the basis for a partial solution, through alternative measures and assumed relationships. But few of these internal relationships have been shown to exist empirically, making the prediction of outcomes from implemented strategies difficult to achieve. We need to be able to appraise our own performance, and that of our customers, suppliers and competitors, and we need to be able to make predictions about future performance, at least in the short term. The methods discussed in earlier chapters have identified techniques for tactical decision-making, and to support the analysis of product and customer profitability and of project viability. To date we have ignored the financial modelling and forecasting methods which are fundamental to budgeting and investment appraisal. This chapter looks at modelling methods to see how we can match methods with data availability, in order to explain and predict returns as well as evaluating risk.

FORECASTING METHODS

These methods might be classified according to the nature of the data available:

- quantitative – i.e., numerical (financial or non-financial), continuous or categorical;
- qualitative – i.e., non-numerical, descriptive, or narrative. Scales may sometimes be introduced to quantify what would otherwise be qualitative variables.

For both data types different forecasting methods might be employed, depending on whether the data are:

- time series data, where trend data are available for several variables across a number of successive time periods;
- cross-section data, where data are collected at a single point of time for several variables across a number of different cases.

With time series data we attempt to forecast values for future time periods, by making projections based on the components of the data. With cross-section data we attempt to forecast values for new cases outside the sample under consideration, based on what we have learned from the existing sample. We may also be able to ‘explain’ changes in forecasts in a way that makes it possible for us to instigate strategies which cause the forecast target to move in the desired direction. The primary methods available for different purposes might be categorized as follows, with methods of increasing sophistication corresponding with the quantitative data available:

- Delphi methods – popular in market research and often involving focus groups to gauge opinion and specify rankings or preferences;
- heuristic methods – essentially loose guidelines or rules of thumb used for decision-making in instances of uncertainty;
- probabilistic simulation – the specification of a range of ‘possible’ outcomes, together with associated probabilities, so that the alternatives may be modelled to simulate alternative scenarios.

All three of these methods start with very little in the way of hard data, though quantification might be introduced by attaching numbers to the alternatives and conducting detailed sensitivity analyses to test the robustness of the assumptions. The Derrick’s Ice Cream (Chapter 5) and Casual Fashions (this chapter) case studies provide examples of the development of analysis, forecasting and strategies based on ‘soft’ data of this nature. The remaining methods require good quality numerical data, often a lot of it:

- time series methods (e.g., moving averages, exponential smoothing, Box-Jenkins) to identify systematic patterns in historical data and extrapolate forwards;
- causal methods (e.g., regression analysis for continuous data; discriminant analysis or logistic regression, where the dependent variables are categorical) to specify explanatory relationships and predict the effect of changes in the component variables.

DELPHI METHODS

Delphi assessment is a group process involving a panel of ‘experts’ who attempt to forecast future outcomes in situations where there is no direct knowledge, or at least a great deal of uncertainty. It is an intuitive procedure which relies on the subjective probabilities that participants attach to the likelihood of future events; it is also iterative in nature, so that individual opinion can be modified by the influence of other group members. The Delphi method attempts to generate collective expert opinion by making two substitutions: expert judgement for direct knowledge, and group for individual. Linstone and Turoff (2002: 223) note a significant convergence of responses for almost all forecast statements within three rounds of the process, and considerable stability of opinion thereafter.

However, Linstone (2002: 561) highlights the potential problems arising in the selection of ‘expert group’ participants:

- The differences in planning horizons for such a group may be wildly different from that for a more representative group; we expect loss of forecast accuracy when the time horizon expands for any group, but such variation needs to be controlled.
- The preferences expressed in an artificial planning session may differ from those in a real-life scenario, so that different approaches to risk taking, for example, are exhibited.
- The subjective probability basis of the technique makes it susceptible to the problems associated with heuristic devices, detailed in the next section.
- Poor selection of participants may lead to poor interaction and misleading outcomes; this is especially so with like-minded individuals not subject to differing opinions at either end of the spectrum.
- Groups are commonly over-pessimistic when making long-term forecasts, and over-optimistic when making short-term forecasts. This is complicated by individual traits of optimism/pessimism, though fortunately there is a great deal of consistency in individual behaviour in this regard.
- The process can be subject to deliberate deception if an assertive and articulate individual is able to disrupt the final outcomes through misleading and unrepresentative feedback.

However, despite these drawbacks, in some situations we may have no realistic alternative for generating any reasonable indication of likely future outcomes.

HEURISTIC METHODS

In practice, such heuristics may resemble trial and error, but are often ‘rules of thumb’ or standard operating procedures based on a wealth of knowledge and experience. For example, Thorngate (1980) provides examples of optimum decisions using decision-making heuristics, and Ashton (1976) demonstrates the robust nature of simple linear models used to approximate complex multivariate situations. The use of heuristic models has already been referred to with respect to both the resource-based view of the firm (Chapter 2) and the job scheduling problems of Chapter 6.

However, there is the danger that biased decision outcomes may result because inefficient information strategies have been adopted and/or the heuristics employed to overcome information overload are statistically inaccurate. Five particular areas of concern may be identified where heuristics can potentially cause bias:

- Availability – undue emphasis is given to recent or imaginable cases, for example recent instances of equipment failure may be accorded inappropriate seriousness because equipment histories and the probability distribution of breakdowns have not been examined.
- Representativeness – decisions are made on flimsy evidence which ignores prior probabilities. In practice hard numerical data giving the likely distribution of outcomes may be ignored, especially if ‘softer’ qualitative or narrative information is supplied simultaneously. Kahnemann and Tversky (1972) suggest that such narratives may be accorded a greatly inflated level of importance compared to their information content, a suggestion borne out by empirical evidence.
- Integration – inconsistent simplification methods might be adopted to combine information from different sources. For accounting information, this may coincide with the choice of inappropriate cues, inappropriate cue weightings, inappropriate mathematical relationships in the formation of multivariate models, or the erroneous amalgamation of time series and cross-section estimates.
- Concreteness – decisions are made using only explicitly stated information, ignoring that which may be assumed or derived indirectly. Inadequate investigations may, therefore, yield biased outcomes.
- Anchoring and adjustment – overconfidence in these initial estimates exists, which provides an ‘anchor’ to further adjustments made when additional information becomes available. Irrelevant information may form the basis of the initial ‘anchor’ so that subsequent adjustments result in hopelessly biased estimates.

The implication is that a heuristic approach, especially where conflicting messages are being conveyed by the available information sources, may result in biased outcomes.

PROBABILISTIC SIMULATION

Rather than limiting simplifying procedures to instances of ‘information overload’, some form of decision model may have to be introduced because of a lack of available data. Simulation or ‘Monte Carlo’ methods make it possible to ‘create’ hypothetical observations where no actual observations exist. In project planning and in predicting outcomes there may be no real observations, only estimates of values and relationships. This information is far from perfect, but is certainly better than nothing. It may be very representative of future outcomes and can be used to generate realistic future scenarios based on many fictitious observations where each of the outcomes satisfies known or assumed relationships between the variables, and each of the outcomes is representative for the variables.

The simulation approach necessitates the use of a computer model and multiple iterations (at least 100) to cope with the quantity of data, but the approach is essentially a simple one. Alternative approaches are possible

depending on the assumptions made. This technique is best illustrated through reference to a numerical example, but since this will simultaneously address both 'risk' and 'return' issues, this illustration is delayed until our discussion of risk measurement later in this chapter.

The remaining sections of this chapter focus on analytic approaches to problem-solving using mathematical models for forecasting.

TIME SERIES ANALYSIS

Classical time series decomposition analysis assumes a relationship $Y = f(T, C, S, R)$ such that the variable to be forecast (Y) is subject to the influence of:

- a time trend (T), the directional trend of the series for Y over time, which may be upwards, downwards or static. The trend line may be linear or curved, either of which may be modelled with regression-type methods.
- the trade cycle (C), imposing short-term periods of boom and slump on the long-term trend. A curved pattern is likely, possibly extending over a period of many years. In practical terms it may be very difficult to isolate the 'cycle' and we may have to be satisfied with estimating a composite of 'trend and cycle' together, despite the errors so introduced.
- seasonal factors (S). Seasonal fluctuations do not necessarily correspond with seasons of the year; they are concerned with any systematic variation occurring within the time period under consideration. They would include quarterly variations within the year, monthly variations within the quarter, weekly variations within the month, daily variations within the week and hourly variations within the day. All are seasons as long as they are associated with a systematic variation within the time period, *whatever the time period*. The italicized phrase provides the clue to the elimination, and then isolation, of seasonal factors. If identical variation is attributable to Monday in any week, then Monday in week 1 is equated with Monday in week 2 for averaging purposes. Seasonal variation will cancel out completely when the week is totalled, and a moving average over successive time periods can be calculated.
- random fluctuations (R). Random fluctuations are by definition unpredictable. Over time we must expect positive and negative variations to cancel out. Summation of a series (provided that it is long enough) will eliminate random variation totally.

The irregular nature of the observed data usually means that a forecast of future values of Y cannot be made simply by eye. Instead we attempt to break up the series into its components so that each can be projected separately and the separate forecasts combined to give an integrated prediction. We therefore need to specify carefully the different components.

The simplest of assumptions allow basic arithmetic processes to be used to model the time series:

- Summation of the series eliminates R .
- Moving averages eliminate S . Subtraction of the remainder from the original series allows S to be isolated for each time period.
- Fitting a straight-line trend allows T to be identified, so that the C pattern can also be isolated.

However, before we proceed to fit the model and make predictions, we must expand the simple functional relationship $Y = f(T, C, S, R)$ into something more specific. Most commonly this would be either the simple additive model,

$$Y = T + C + S + R,$$

or the simple multiplicative model,

$$Y = T \times C \times S \times R.$$

The former is the easiest to fit and works well as long as the trend, T , is not too pronounced. When T is moving steeply (up or down) it will tend to blanket out all other fluctuations, so that a multiplicative model measuring the other factors relative to trend is to be preferred.

In practice there are infinite numbers of possible models, with various weightings and combinations. More sophisticated models can be introduced which weight the data items (e.g., giving greater emphasis to more recent time periods) as well as the components.

The additive and multiplicative models so far considered treat all items of data as of equal value, however outdated they might be, and weight all the forecasting variables equally. A number of alternative time series forecasting methods exist which attempt to relax one or both of these constraints. Their added complexity makes computer-based analysis essential.

Exponential smoothing uses a 'smoothing constant' at the moving average stage to place more emphasis on the most recent data items. Each smoothed data point is equal to the previous smoothed data point, plus a fraction of the difference between that and the actual data point. The calculations of successive values are linked so that they form an exponential series. Thus,

$$D_t = D_{t-1} + a(Y_t - D_{t-1}),$$

where Y_t is the actual data point, for time period t and D_t, D_{t-1} are smoothed data points. So, for $a = 0.2$,

$$\begin{aligned} D_t &= D_{t-1} + 0.2(Y_t - D_{t-1}) \\ &= 0.2Y_t + 0.8D_{t-1}, \end{aligned}$$

a relationship which will smooth out 80% of the random errors in the data points Y_t . The value of a is chosen arbitrarily in the first place and modified in the light of the outcomes.

Similar smoothing methods can be used for trend and seasonal factors, each employing separate arbitrary smoothing constants, in order to build up a composite forecasting model. Thus a trend (T_t) is calculated from

$$T_t = (1 - \beta)T_{t-1} + \beta(D_t - D_{t-1}),$$

where β is the trend smoothing constant. A seasonal factor (S_t) is calculated from

$$S_t = (1 - g)S_{t-p} + g,$$

where g is the seasonal smoothing constant and p the length of the season in time periods. Forecasts are again based on trend (T) and seasonal (S)

components, but have the advantage of not requiring large quantities of historical data. But they are sensitive to the choice of arbitrary smoothing constant and may require fine tuning.

Fortunately a detailed knowledge of these algorithms is not usually necessary since most statistical software (e.g., SPSS-X) accommodates them within sophisticated time series forecasting models. For example, the Box–Jenkins procedure (Box and Jenkins, 1976) provides the opportunity for data transformation in the fitting and forecasting of time series using an iterative procedure requiring multiple computer runs in which the sensitivity of smoothing constants can easily be monitored.

REGRESSION ANALYSIS

Whereas time series analysis can provide us with trend projections for a key variable, in practice this may not be enough. If we wish to influence future values through appropriate management action, we need to know which variables impact on the values assumed by the key variable. In essence, we wish to establish

- degrees of association between variables (correlation) and
- causal relationships between variables (regression), in order to develop
- an explanatory relationship which allows us to show why a key variable is changing, not just how.

If we consider the simple two-variable situation (for a dependent variable Y and an explanatory variable X), then a scatter diagram with Y on the vertical axis and X on the horizontal would reveal the strength of any relationship between the two variables. Depending on the outcome, we might be able to speculate on the existence of a linear relationship of the form $Y = a + bX$.

The ordinary least-squares (OLS) method measures the deviation of points away from a fitted line, either vertically or horizontally, and ensures that the optimum fit is such that the sum of the squares of these distances, over all the points, is as small as possible.

The strength of the fit of the relationship may allow us to be confident about predicting values of Y for new values of X , but we must still be wary of making predictions outside the original range of X values. OLS regression methods attempt to estimate the actual relationship $Y_i = a + bX_i + m_i$ with an estimated relationship based on a finite sample size of n observations. The error term, m_i , in the relationship is estimated by the residual of the equation e_i .

OLS fits make a number of assumptions, the violation of which can result in unreliable equations. The most serious of these are autocorrelation in time series data (interrelated time periods) and multicollinearity for cross-section data, indicating that two or more explanatory variables are too closely related (i.e., essentially different measures of the same thing!).

For time series data we would therefore ensure that the Durbin–Watson statistic (d) is within acceptable bounds; and for cross-section data that correlation coefficients between potential explanatory variables are acceptable. Thus for an equation like $Y = a + bX_1 + cX_2 + dX_3$, we would need to check all combinations of correlations between the three X values to ensure that each was less than 0.8. Where the inter-correlations between

the explanatory variables are all high and statistically significant we have a potential problem. The simplest solution is to avoid bringing one of the 'offending' variables into the equation.

In practice it is easy to miss evidence of multicollinearity, because changes of a large magnitude may not occur. The strength of the interrelationship may be destructive but may not, for example, cause sign changes in the regression equation. It is therefore vitally important that we monitor the inclusion of new variables into an equation on a step-by-step basis. We want to improve on the explanatory power of the equation, through the addition of new variables, while at the same time ensuring:

- coefficients remain statistically significant;
- coefficients and standard errors remain relatively stable;
- signs of coefficients remain intuitively correct.

In the regression process the construction of the correlation coefficient matrix is, arguably, the single most useful piece of preliminary information, because it serves three vital functions:

- It establishes the direction of any relationship, which should be intuitively correct and which would normally correspond with the sign of this variable in any regression equation.
- It suggests those variables likely to be useful explanatory variables, because they are highly correlated with the dependent variable.
- It highlights potential multicollinearity problems by specifying the inter-correlation between competing explanatory variables.

As with most of our analyses, it is just not enough to 'provide the numbers'. There must also be some indication of how these numbers might aid decision-making, and facilitate the implementation of new strategies. Sometimes regression analysis fails to satisfy these conditions because the key variables identified are beyond our control. Thus although the final regression equation may be a statistical optimum, it may be impossible to implement its recommendations (e.g., increase the value of those variables having a positive impact on the dependent variable), or a cost-benefit analysis may reveal that it is not financially viable to contemplate the changes envisaged. The treatment of regression analysis presented here is necessarily simplified, for mathematical expediency, but it attempts to demonstrate the potential strengths and pitfalls associated with the use of the technique.

DISCRIMINANT ANALYSIS: FAILURE PREDICTION AND CORPORATE TURNAROUND

The use of OLS regression methods, as in the previous section, requires a dependent variable which can be measured continuously. However, there will be occasions where the variable which we want to explain and predict is not of a continuous nature. It may be categorical – of the form high/medium/low, good/bad, or success/failure. These can be quantified by assigning dummy variables of the (1, 2, 3) or (0, 1) variety to reflect the alternative states, but in each case these are the only values that the dependent variable can take. Changes in the value of the explanatory

variable cannot change the continuous value, only its classification into one or other of the categories. In such circumstances we cannot use simple regression methods, but seek an alternative. Linear discriminant analysis (LDA) can be used when:

- the groups being identified are clearly separate;
- the explanatory variables are close to being normally distributed, or can be transformed to be so – this ensures ‘univariate normality’ where the stricter requirement of ‘multivariate normality’ is more difficult to test for in practice;
- there is no multicollinearity between the explanatory variables.

We seek to construct an equation of the form:

$$Z = a + bX_1 + cX_2 + dX_3 + \dots,$$

such that the resulting value of Z allows the categorization of cases. Effectively we are generating the equation of a line (or lines) which can be positioned to divide the cases into the required groups. If we return to our failure prediction model of Chapter 3, then the construction of a three-variable discriminant model based on financial ratios might be visualized relative to the space in a rectangular room where axes are constructed in the corner of the room: the profit ratio (P) stretches vertically towards the ceiling, and liquidity (Q) and debt (R) axes at right angles along the skirting boards. The company cases under consideration appear as points in space, representing three-ratio combinations, and discriminant analysis would try to position a plane in this space such that all the failed companies were on one side of this plane and all the healthy ones on the other. The equation of the optimum plane, even if it were impossible to classify all company cases correctly on either side, would be a discriminant equation of the form:

$$Z = a + bP + cQ - dR$$

where b , c and d are the weightings attached to each of the three ratios, P , Q , and R ; a is a constant term whose value determines the cut-off between failed and non-failed groups; and Z is the value of the composite function, such that $Z > 0$ corresponds with a state of financial health and $Z < 0$ corresponds with a state of financial distress, in that the company has a financial profile similar to that of a previously failed company.

Discriminant analysis minimizes the number of misclassifications and determines the corresponding optimum variable weightings. Whereas various alternative multivariate techniques have been used to develop failure prediction models, including quadratic discriminant analysis (Altman et al., 1977), logit and probit (Ohlson, 1980; Zavgren, 1985), non-parametric methods (Frydman et al., 1985) and neural nets (Altman et al., 1994), there is no evidence of significantly superior performance associated with such approaches compared with traditional linear discriminant analysis (e.g., Hamer, 1983; Lo, 1986). Hair et al. (1998: 276) and McLeay and Omar (2000) argue that logistic regression is more robust than linear discriminant analysis when the univariate normality and homogeneity of variance–covariance assumptions are not met, and Collins and Green (1982) and Lennox (1999) suggest that a logistic regression model could identify failing companies more accurately than discriminant analysis, provided that specification problems are overcome. The univariate normality and homogeneity of variance–covariance

assumptions are rarely satisfied in practice, but this does not appear to impact on the classificatory ability of discriminatory models, attributable by Bayne et al. (1983) to its robust nature and non-ambiguous group cut-off scores. For these reasons linear discriminant analysis continues to be the preferred method of analysis in many studies.

Failure prediction

Scope of models

There are considerable differences between the discriminant models constructed in different countries, both in terms of the financial ratio variables included and the weighting accorded them. Similarly, there are considerable differences between the models constructed for separate industry groupings. Pacey and Pham (1990) provide an excellent example of the dangers of over-aggregation and ignoring industry differentiation. Their model, embracing Australian companies across the whole of the industrial sector over a 20-year period (in order to generate a reasonable sample size) is, not surprisingly, an extremely poor predictor of impending failure.

An excellent instance of the need for different models in different industries lies in the application of the working capital ratio, given by

$$\frac{\text{Current assets} - \text{current liabilities}}{\text{Net capital employed}}$$

Successful manufacturing companies will usually give a positive value for this ratio, indicating a positive net current assets balance. Successful large food retailers, however, will often exhibit negative values for this ratio because of the fast-moving, cash-based nature of their business and the power they can exert over their suppliers. Clearly, a single model for manufacturers and retailers could not normally accommodate such a ratio – necessitating the construction of separate models.

Nevertheless, a succession of authors have attempted to apply the US model developed by Altman (1968) to UK companies for which it was not intended, and, even more erroneously, to apply manufacturing models to non-manufacturing companies or to unlisted companies. The strict industry requirements of a particular model limit its application to a narrow sector of companies for which it was derived. Often a separate model will be necessary for each industry in each country, and we must recognize that there may be significant differences even between regions.

Ratio variables

Differences between countries and industries mean that no single optimum combination of financial ratios will exist, although we might expect that particular ratios are widely applicable.

Several studies have found a dividend-based ratio to be a useful discriminator, but it is absent from most UK models. Similarly, liquidity ratios have been found to be of only limited usefulness in models constructed outside the UK. Interestingly, Taffler's (1982, 1983) UK profitability ratio (profit before tax over average current liabilities) has been found to be a very useful discriminator for a number of industrial sectors of overseas models.

Whatever ratio combinations are employed in the construction of the model, it is essential that identical variables, variable weightings and cut-off points are used in their application. If such details are not publicly available

then no attempt should be made to apply models 'approximately'. The errors which flow from this are unnecessary and have potentially dire consequences.

Models constructed on old data are not necessarily useless. The Altman (1968) and Taffler (1982) models, in the USA and UK respectively, are seen by some as remaining relatively robust and still of considerable use almost 40 years on, with reliable, long-term evidence of their discriminatory ability.

The definition of failure

There are numerous definitions of business or corporate failure, from the strict legal sense of liquidation to a more liberal definition of inability to repay monies as due. At least five common definitions of failure or distress, varying with their degree of stringency, might be employed: receivership; voluntary liquidation; compulsory liquidation; provisional liquidation; and stock exchange suspension or investigation. Models might be developed based on different definitions to suit user requirements; for example, Houghton and Smith (1991) included 'stock exchange investigation' as a failure measure, while Smith et al. (2004) included a PN4 designation by the Kuala Lumpur Stock Exchange in Malaysia within their failure definition. Almost all existing models suffer from the problem that they are based on artificially derived samples of companies and businesses, and therefore have an unreal probability of failure and non-failure. This problem is difficult to overcome without employing the whole population of listed companies so that the probability of failure is the same as the real-world incidence of failure.

The timing of failure

Most discriminant models will identify those companies exhibiting financial distress. Within this set they can highlight those most at risk – the worst companies, those most likely to fail within the following year. However, the precise timing of failure is determined by the bankers through their decision to appoint receivers or withdraw financial support. Financial profiles alone are therefore unable to specify the precise timing of failure, which is largely determined by the whim of the principal bankers. Clearly, the shorter the time between the prediction and the likely event the easier the prediction task is, but the less useful it would be in formulating an optimum investment strategy.

Predictive ability

Existing models are only predictive in the sense that they identify those companies which are currently trading but have financial profiles similar to previous failures. All models will highlight a 'distressed' set which overpredicts failure, in that it will also contain some companies who recover and some who will be taken over before they are allowed to fail. Recent studies argue that the cost of a type 1 error (missing a failed company) is much greater than a type 2 error (overpredicting failure). They suggest the relative importance of the type 1 error to the decision-making context is of the order of 40 : 1. Such factors should be incorporated into models and reflected in the cut-off point for predictions. Any reference to the overall classificatory ability of such models is fatuous if the type of error being made is not identified. Most researchers claim to demonstrate predictive ability while only demonstrating classificatory ability. All new models demonstrate only the

latter, and their usefulness as predictive tools can only be demonstrated with time and with the application of the models to new data.

Model development: From univariate to multivariate models

Whereas traditional univariate balance sheet ratios like those for liquidity may give an adequate indication of vulnerability to current and short-term fluctuations, longer-term predictions require a better indication of cash flows. In the absence of publicly available information relating to internal cash budgets, this must come via projections of cash-generating abilities from the published accounts.

The Altman (1968) study for listed US manufacturing companies provides a benchmark against which all other multivariate studies can be measured. The Altman model is a linear combination of five variables, and records a 95% classification accuracy of failed/non-failed companies:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5,$$

where

$$X_1 = \frac{\text{Current assets - current liabilities}}{\text{Total assets}},$$

$$X_2 = \frac{\text{Retained earnings}}{\text{Total assets}},$$

$$X_3 = \frac{\text{Earnings before interest and tax}}{\text{Total assets}},$$

$$X_4 = \frac{\text{Market value of preferred and common equity}}{\text{Book value of total liabilities}},$$

$$X_5 = \frac{\text{Sales}}{\text{Total assets}},$$

and a Z-score below 1.8 corresponds with a company considered to be a 'prime candidate for bankruptcy'. The lower the Z-score, the higher the perceived probability of failure.

In the UK the Taffler (1983) model, detailed in Chapter 2, is the most widely exposed failure prediction model and the one which has been subject to the most extensive testing. In many other countries, the shortage of failed cases and their distribution across many industries has caused problems of much greater severity than those experienced in the UK and USA. Nevertheless, a number of other studies have used publicly available accounting information, with varying degrees of success, to predict failure.

To date, economic theory has played a negligible part in the development of failure prediction models. Given the absence of a substantial theoretical underpinning, most research studies have been exploratory, trying to establish the model, method, variables and firms which give the best predictions. Research to date has demonstrated that the classification performance of predictive models is not highly sensitive to the mathematical relationship chosen or the statistical method employed. Linear additive models based on linear discriminant analysis are the simplest to construct and interpret, and their outcomes are not dissimilar to any comparable model.

Corporate turnaround

Existing failure prediction models are only *predictive* in the sense that they identify those companies currently trading which have financial profiles similar to previous failures. Without verification over an extensive time period they are *classification* rather than *predictive* models. As with all similar models the 'distressed' set will overpredict failure, in that it will also contain some companies who effect recoveries and some who will be taken over before they are allowed to fail. Some of the 'distressed' set of companies might eventually effect a financial recovery if they were to implement appropriate turnaround strategies. This provides a positive angle for early warning models in that it identifies some cases in need of remedial action. From a strategic perspective it might also help to associate the achievement of 'recovered' status with the implementation of key management actions. Slatter (1984: 105) identifies a number of generic recovery strategies that might be adopted, depending on the cause of the 'distressed' state. He specifies seven major causes of decline and potential failure:

- poor management;
- inadequate financial control;
- high cost structure;
- lack of marketing effort;
- competitive weaknesses;
- financial policy;
- ill-advised acquisitions and projects.

Each of these is associated with a particular set of generic recovery strategies:

- Poor management is associated with autocratic leadership, an ineffective board, the neglect of core businesses and lack of management depth. Appropriate remedial action would require new blood in the management team, organizational change and decentralization.
- Inadequate financial control is associated with a poorly designed accounting system, misuse of information, the distortion of costs through misallocation of overheads and an organizational structure which hinders rather than facilitates control. This would be improved by new management and decentralization if accompanied by tighter financial controls.
- High cost structure is associated with operational inefficiencies, competitor control of raw materials and proprietary knowledge, low scale economies and high labour costs. Cost reduction strategies and a revised product-market focus are appropriate for recovery. Cost reduction strategies would include those directed towards: raw material costs, aimed at improved buying practices, better utilization and the possible substitution of materials; unit labour costs, aimed at increasing productivity and reducing headcount; and overhead costs, targeting manufacturing, marketing and distribution.
- Lack of marketing effort is associated with inadequate or inflexible response to changing patterns of demand and product obsolescence. Improved marketing pursues a revenue-generating strategy embracing changed prices, more selling effort, rationalizing of the product line, focused promotion, and a closer focus on customer needs.

- Competitive weakness is reflected by lack of strength in both price and product competition and an absent product-market focus. A reliance on old products will be apparent, with inadequate differentiation and no new product ideas on the horizon. Cost, marketing and product weaknesses must be addressed, with growth via acquisition considered as a means of overcoming deficiencies in the product-market area.
- Financial policy weakness is characterized by high debt–equity ratios, expensive sources of funding and conservative financial policies. A new financial strategy will likely include debt restructuring and revenue-generating policies.
- Failed acquisitions are characterized by the purchase of losers at a price which is set too high. Poor post-acquisition management often results in a quick resale. Ill-advised big projects, which threaten the company's survival, are associated with start-up difficulties, the loss of major contracts and the underestimation of capital requirements and market entry costs.

Asset reduction is the most appropriate recovery strategy in the circumstances, embracing:

- reducing fixed assets, through divesting operating units and specific assets, management buyouts and sale and leaseback arrangements;
- reducing working capital, through extending creditors and reducing both inventories and debtors – this would include cancelling orders, returning goods, the sale of surplus raw materials, tighter credit and possibly factoring arrangements for debtors.

The extent to which these strategies are appropriate will also be determined by the severity of the crisis and peculiar industry characteristics. Where short-term survival is threatened we might anticipate a recovery strategy comprising four strands:

- cash generation
- asset reduction;
- debt restructuring; and
- very tight financial control, embracing cash management, cost reduction, product refocus and improved marketing.

RISK MEASUREMENT

Traditional approaches to cash-flow evaluation, such as the measurement of capital expenditures, place far too much emphasis on expected returns and far too little on the potential risks incurred. Spreadsheet software has facilitated the use of sensitivity analysis to the extent that no project appraisal is complete without its consideration. However, an awareness of the impact of realistic variations on outcome is not enough; we should pay more attention to the risk element in any venture, appropriately quantified, in order to provide improved decision support.

Most accounting textbooks emphasize discounted cash flow, payback, internal rate of return and net present value as appraisal tools. Arguably, these are all concerned with quantifying the returns from the project and

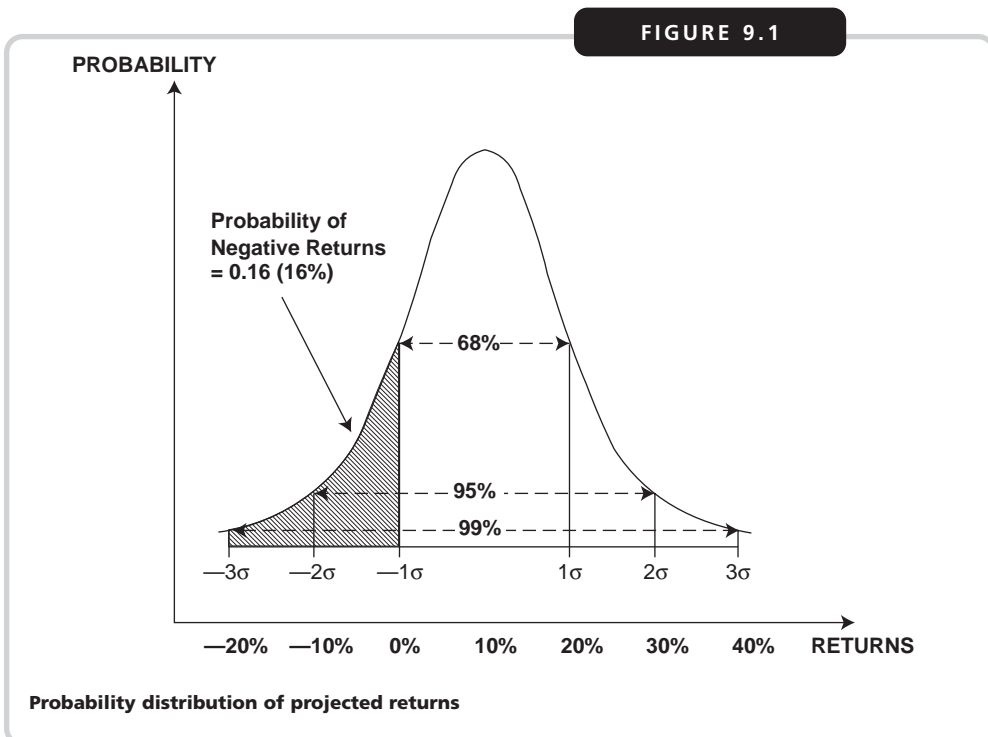
not the risk. (The payback period might additionally be viewed as a measure of risk since it indicates the time taken to recover sums invested.)

The survey evidence discussed in Chapter 2 suggests that strategic factors – rather than discounted cash-flow results – are of increasing importance in determining capital expenditure decisions; similarly, the survey evidence discussed in Chapter 7 suggests that managers would like a more detailed analysis of risk levels prior to decision-making.

Too often the income or cost savings employed are point estimates which are, at best, educated guesses, at worst crystal-ball gazing. Alternative scenarios are frequently ignored, and the probability of alternative outcomes rarely quantified. Incorporating a range of realistic cash-flow outcomes will at least generate a better idea of what might happen, replacing a single point estimate with a best–worst range. Spreadsheet software is well equipped to accomplish such a task, and to go further in generating a distribution of outcomes where we have an idea of the likelihood of alternative scenarios.

Where probabilities can be estimated, a full-blown distribution of outcomes can be produced, so that risk management becomes an essential part of the evaluation.

Figure 9.1 demonstrates the ideal circumstances, with each level of potential returns linked to a specified degree of likelihood so that it is possible to evaluate quantitatively the level of risk associated with a particular project. Such an ideal picture can only be generated when the likelihood of alternative cash flows can be estimated accurately. But even if such accuracy is not possible – and in practice it rarely will be – the ability to state that one outcome is more likely than another is important. Such weightings could then be included in an analysis of the risk of a project.



Project evaluation pitfalls

Any appraisal of the quality of investment decisions should address the way in which the decisions have been taken as well as their consequences. This would include the following stages:

- Project generation: which projects are put forward for examination?
- Cash flows: how and by whom are these estimated?
- Analysis: what methods and assumptions are employed?
- Selection: importance of financials/non-financials in project choice?
- Authorization: documentation of monitoring process for project implementation?
- Evaluation: do the project outcomes match/exceed expectations?

A post-audit investigation can potentially have a significant impact on the manner in which future appraisals are conducted. If it is viewed as a learning experience, seeking improvement opportunities, rather than as a witch-hunt of those who have made errors, then real bottom-line benefits are achievable.

Problems with implementing post-audit schemes range across the whole gamut of which? where? how? and by whom? Big companies may be able to audit internally, others may need to employ consultants. Either way, the continued co-operation of those individuals involved in implementing the project is essential. Any breach of confidence or finger-pointing will reduce the levels of active co-operation and, potentially, destroy the learning opportunities. The post-audit could extend over:

- all projects currently underperforming;
- all projects implemented (underperforming or not);
- all projects considered (implemented or not); and
- a sample of any of the above.

The post-audit case study (Alumina PLC) discussed in Chapter 4 demonstrates the potential for devious managerial action which can both mask underperformance and aid the pursuit of a personal agenda.

RISK ANALYSIS

The focus on returns frequently causes the assessment of the risk attaching to a project to be neglected. Managerial decision-making requires information on both risks and projected returns to be available. Risk assessment should, at the very least, incorporate an examination of the likelihood and outcomes of the best and worst scenarios.

It might be argued that cash-flow projections are only estimates, so that the probabilities attaching to such estimates can only be figments of the imagination! But if we have evidence to suggest that one outcome is more likely than another then that is useful, and potentially significant, information that can be incorporated into the analysis with probability weightings of, say, 0.55 and 0.45 respectively. Probability estimates for alternative outcomes can be combined through decision trees to give an indication of the distribution of possibilities.

Consider a simple numerical example in the form of a company, Cable Technology, which is heavily dependent on export markets and with sales revenues highly susceptible to variations in economic factors, particularly exchange rates, interest rates and the rate of price inflation. It sources much of its raw material requirements overseas too, so that its import prices can vary wildly. It exercises a tight control over those costs under direct control, particularly labour costs. Forecasts of price and wage-cost inflation are an important part of Cable Technology's planning and budgeting process and it relies heavily on estimates from the Marketing Department.

Current estimates suggest that the rate of price inflation will lie between 6% and 9% over the next quarter, with 7% the most likely figure, with a 40 per cent chance. There is a 30 per cent chance of it being 8%, 20 per cent of it being 9% and only 10 per cent of it being as low as 6%. The rate of wage-cost inflation is reckoned to be 1% or 1.5% higher than the corresponding rate of price inflation. For the two lower rates of price inflation there is a 40 per cent chance of a 1% difference, a 60 per cent chance of a 1.5% difference. For the two higher rates of price inflation there is thought to be a 70 per cent chance of a 1% difference and only a 30 per cent chance of a 1.5% difference. If the expected rate of wage-cost inflation exceeds 8.5% or the chances of a blow-out to a figure greater than 9.5% exceed a 10 per cent chance, then Cable Technology institutes further short-term cost-cutting measures.

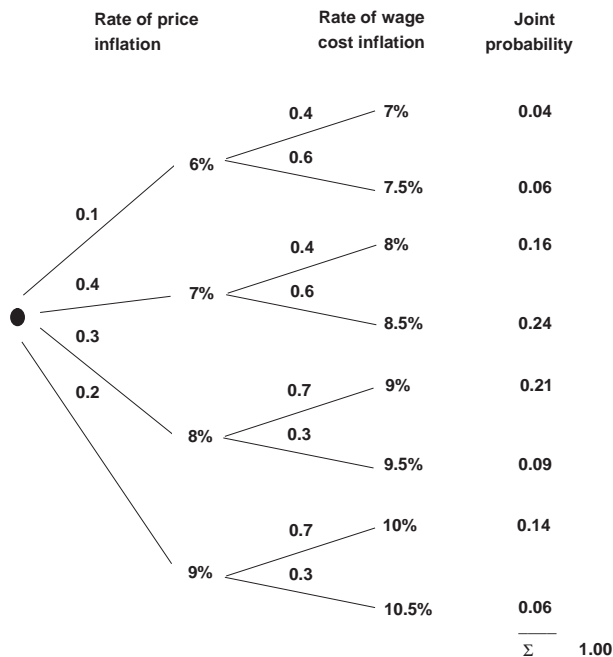
The rates of price and wage-cost inflation, together with their respective probabilities, can be represented in the form of a decision-tree structure. The rates of wage-cost inflation are conditional on a predetermined rate of price inflation and the associated conditional probabilities measure the coincidence of two separate events. The joint probability of a particular rate of wage inflation is, therefore, the product of two separate probabilities: that for a particular rate of price inflation, and the subsequent conditional probability. These are detailed in Figure 9.2.

Weighted arithmetic means reveal an expected rate of price inflation of 7.6%, and an expected rate of wage inflation of 8.825%. The latter figure marginally exceeds Cable Technology's target figure of 8.5%. Reference to the distribution of rates of wage-cost inflation in the final column of Figure 9.2 indicates a 20 per cent chance (i.e., $0.14 + 0.06$) of a rate greater than or equal to 10%. The likelihood of a rate in excess of 9.5 per cent is, therefore, well beyond Cable Technology's acceptable levels. Both of these outcomes will trigger increased cost-cutting activity.

In practice decision-tree structures can be much larger than those in Figure 9.2 – both longer (representing more separate outcomes identified) and wider (with additional dependent outcomes and more probabilities). In theory there is no limit to the number of conditional probabilities that might be considered jointly. When all outcomes, and their distribution, have been determined a thorough spreadsheet-based sensitivity analysis might be conducted to evaluate the significance of any probability assumptions. Brewer et al. (1993) discuss the use of 'fuzzy logic' which adds a new dimension to the spreadsheet-based appraisal of risk by incorporating uncertainty into each of the cells of the analysis. Although helpful in situations where we are short of data, some decision-tree models may quickly become very complicated, and simulation methods or Monte Carlo methods may be preferred.

The simulation method might be used in our Cable Technology case to predict the likely rate of wage-cost inflation in a particular period.

FIGURE 9.2



Decision tree for Cable Technology

Economic estimates reveal that the rate of price inflation will be 6% (with a probability of 0.1), 7% (with a probability of 0.4), 8% (with a probability of 0.3), or 9% (with a probability of 0.2).

The simplest method of simulating observations involves making no assumptions about the *actual* distribution of the price inflation variable. The probabilities provided are accepted as fact, and no possibilities outside the 6–9% range are considered. Random numbers from a two-digit range 00 to 99 are assigned to the variable values in accordance with the stated probability. For example, price inflation of 6% has a 0.1 (i.e., one in ten) probability. Ten of the one hundred random numbers are, therefore, allocated to this possibility (i.e., 00 to 09).

The complete allocation would be:

Price inflation (%)	Probability	Random (no. range)
6	0.1	00–09
7	0.4	10–49
8	0.3	50–79
9	0.2	80–99

The appropriate random number range is simple to derive and corresponds exactly with the probabilities provided. Thus, the generation of a random number equal to 23, say, from tables or from a random number generator would select 7% as the corresponding value for inflation. This value can

then be treated as a representative observation in any further analysis. Given a rate of price inflation of 7%, the corresponding rate of wage inflation will be either 8% or 8.5%. A second random number generation allows this selection to be made in accordance with the respective probabilities of 0.4 and 0.6:

Price inflation (%)	Wage-cost inflation (%)	Random no. range
7	8	00–39
	8.5	40–99

Successive random numbers of 23 and 31, say, would, therefore, select a price inflation of 7% and a wage-cost inflation of 8%. If price inflation is not a relevant variable for further analysis and forecasting we could go straight to wage-cost inflation by directing attention to the right-hand column of Figure 9.2. A random number range in accord with the stated conditional probabilities allows the selection of a single rate:

Rate of wage-cost inflation (%)	Probability	Random no. range
7	0.04	00–03
7.5	0.06	04–09
8	0.16	10–25
8.5	0.24	26–49
9	0.21	50–70
9.5	0.09	71–79
10	0.14	80–93
10.5	0.06	94–99

A single random number of, say, 67 would then select a 9% rate of wage cost inflation.

Alternatively, we might assume that the 'rate of price inflation' is actually distributed normally, with our estimates representing sample observations from a normal population. Then we can use the calculated sample mean and standard deviation to smooth out the discontinuities of the estimated pattern and provide a normal distribution with the following ranges of values and associated probabilities:

INF % (X)	PROB (P)	PX	$X - \bar{X}$	$P (X - \bar{X})^2$
6	0.1	0.6	-1.6	0.0256
7	0.4	2.8	-0.6	0.1440
8	0.3	2.4	0.4	0.0480
9	0.2	1.8	1.4	0.3920
		7.6		0.6096

The mean is thus

$$\bar{X} = \sum PX = 7.6\%$$

and the standard deviation

$$S = \sqrt{P(X - \bar{X})^2} = \sqrt{0.6096} = 0.78076\%.$$

Here the normal distribution ordinate $Z = (X - \bar{X})/S$ within the distribution of values, and associated normal probabilities can be established by calculating $Z = (X - 7.6)/0.78076$ for different class boundaries. These are detailed in Table 9.1.

The normal curve area is derived from tables of the normal distribution, and the difference in these values provides the probability of an observation occurring between the respective class boundaries. This probability establishes the range of random numbers to be selected from the two-digit random number range 00–99.

Thus the probability of an observation in the range 7.75 to 8.25 is 0.22, equivalent to 22 of the 100 random numbers, from 58 to 79 inclusive.

If any of these random numbers is chosen in the simulation it will generate a value of 8% for 'price inflation'. Other random numbers will generate different values, directly in accordance with their relative probability. Similar distributions, and corresponding sets of random numbers, for each variable in any analysis allow all combinations to be considered and a distribution of overall outcomes produced. This method might, therefore, be applied to the rate of wage-cost inflation too by using the data of Figure 9.2 as the basis for the construction of the normal distribution.

Now the foregoing may sound very theoretical and devoid of practical application, but let us return to our earlier point about matching method with data. Suppose we are in a start-up situation, with a new venture for which we have little guidance on outcomes. We need to make forecasts of

TABLE 9.1

Normal distribution simulation					
Mid point	Class boundaries	Z Ordinate	Normal Curve Area	Z probability	Random Number Range
	5.25	-3.01	0.49869		
5.5	5.75	-2.37	0.49111	0.01	00
6	6.25	-1.73	0.45818	0.03	01–03
6.5	6.75	-1.09	0.36214	0.10	04–13
7	7.25	-0.45	0.17364	0.19	14–32
7.5	7.75	0.19	0.07535	0.25	33–57
8	8.25	0.83	0.29673	0.22	58–79
8.5	8.75	1.47	0.42922	0.13	80–92
9	9.25	2.11	0.48257	0.05	93–97
9.5	9.75	2.75	0.49702	0.02	98–99
				<u>Sum 1.00</u>	

costs and revenues so that we can budget. The information available may be confined to the views of others, and to the outcomes of other similar ventures. All we have, then, are educated guesses for forecasts, but that is better than nothing at all, if it allows us to project a range of outcomes, so that an analysis of possible risks and returns can be conducted. The next section details just such a case, which is concerned with the potential risks and returns of an investment opportunity. It combines probabilistic risk estimates, via decision trees or simulation methods, through traditional spreadsheet methods, to allow the development of a risk profile.

CASE STUDY

Casual Fashions: A risk analysis case study

Casual Fashions is a hypothetical national retail chain considering an expansion in the number of its outlets by moving into the Meadowhall shopping centre in Sheffield. It is conducting a full project appraisal, covering estimates of sales, costs, profits and movements in the economy. The market research team has established the likelihood of alternative trading patterns in order to generate decision trees and facilitate a simulation study. They have estimated the number of visitors to the centre, the proportion likely to enter the new shop and the spending patterns within the shop; all have been allocated probabilities over a realistic range. Their aim is to produce a probability distribution for projected sales in the first year of operations. They believe that annual sales will initially be in the range £3 million to £48 million, with mean value of £15.6 million. Their analysis reveals that the distribution of outcomes is not symmetrical, but skewed significantly, as illustrated by Figure 9.3.

FIGURE 9.3



Probability distribution of sales turnover

CASE STUDY (cont.)

Cost projections allow the group's management accountant to construct a spreadsheet in the form shown in Figure 9.4 in order to calculate profit, tax liabilities, cash flows and discounted present values. Fundamental to the spreadsheet is the projected year 1 sales figure, the variation of which has already been established in Figure 9.3. By substituting sales figures into the spreadsheet, internal rates of return (IRR) can be generated for each level of activity. By directing the output to a graphics package, the management accountant can produce a scatter diagram of the type shown in Figure 9.5, mapping IRR against year 1 sales. From this we know that the mean sales level (£15.6 million) in the first year of trading will correspond with an IRR of around 22%, marginally in excess of the group's 18% cost of capital hurdle for new investment projects.

The common axes in Figures 9.3 and 9.5 (relating to sales turnover in the first year of operations) allows the data from the two to be combined in order to graph probability against IRR. The resulting diagram, detailed in Figure 9.6, gives the required

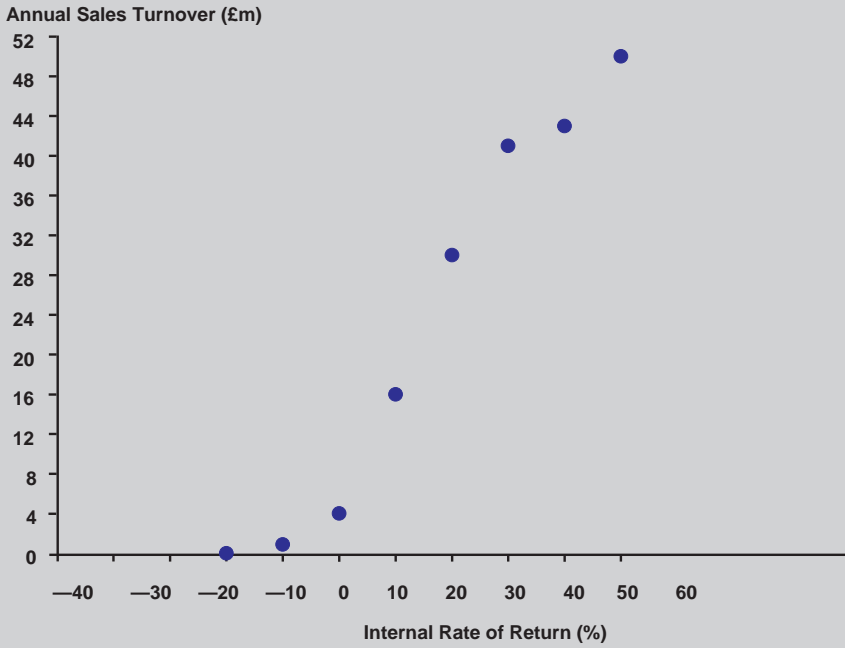
FIGURE 9.4

Profit statement (£ million)	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Sales	0	15.6	20.7	24.4	28.9	32.3
less cost of goods sold						
Opening stock						
plus purchases						
less closing stock						
Gross profit						
less other expenses						
Lease expense						
Staffing costs						
Stockholding costs						
Depreciation on maintenance costs						
Depreciation on start-up costs						
Net profit (loss) before tax						
Income tax payable						
Net profit after tax						
Carried forward tax loss						
Cashflow statement (£ million)						
Cash inflows						
Sales						
less cash outflows						
Sales						
less cash outflows						
Purchases						
Lease payments						
Staffing costs						
Stockholding costs						
Start-up costs						
Maintenance costs						
Income tax paid		2.31				
Net cash flows		22.1				
Net present value @ 15%						
Internal rate of return (%)						

Spreadsheet for cashflow analysis

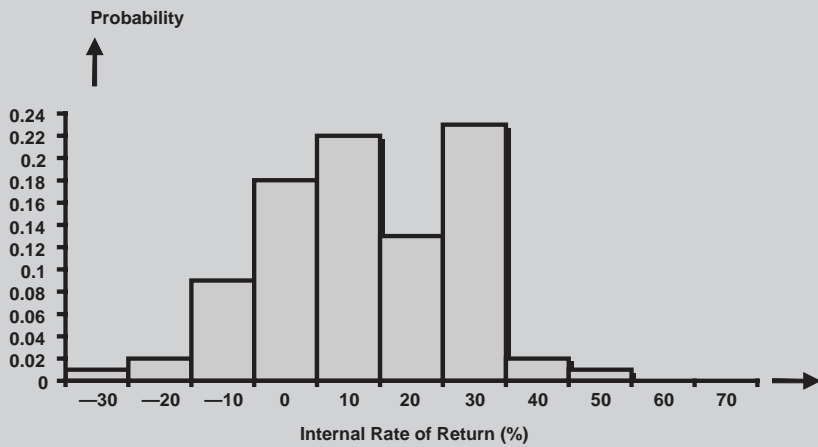
CASE STUDY (cont.)

FIGURE 9.5



Scatter diagram of rates of return

FIGURE 9.6



Probability distribution of rates of return

CASE STUDY (cont.)

indication of risk. It goes beyond the spreadsheet output of expected returns to a distribution of the projected returns.

The results are not uniformly encouraging. There is a 15% likelihood (a probability of 0.15) that the project will actually lose money. Worse still, the likelihood of returns less than the cost of capital is a staggering 49%. Despite the potential benefits in the form of returns, the likelihood of achieving the required level of returns is almost as likely as not – vitally important information for the decision-makers.

The combination of risk and returns is, therefore, not at all hopeful at this stage, and a detailed sensitivity analysis has still to be conducted! In particular, we must consider the impact of economic variables and realistic time delays. It is quite possible that the project will be sensitive to such changes, reducing the likely rates of return and further increasing the variability of potential outcomes. In this case the importance of year 1 sales makes this project particularly vulnerable if there is any possibility of delays in attracting revenue.

The general messages from the case are clear. It is essential that we appreciate:

- alternative scenarios;
- the impact of the risk element on the decision-making process;
- the sensitivity of outcomes to realistic variations;
- the power of spreadsheet software in conducting a relatively complex financial analysis; and
- the potential pitfalls of internal rate of return calculation where misleading outcomes might be generated by the existence of negative cash flows in the evaluation stream.

VALUE-BASED MANAGEMENT

Strategic management to optimize the value of a business in terms of returns to shareholders has received much attention in recent years, through shareholder value analysis and, in particular, through the use of economic value added (EVA).¹ EVA is a measure of shareholder value that has become popular, initially in the USA, and now worldwide (see Adler and McClelland, 1995). The fundamentals underpinning EVA are not new. As long ago as the 1920s, Alfred Sloan at General Motors used 'return on capital' systems to assess performance, and GEC used 'residual income' in the 1930s. EVA has the same basic structure as the residual income measure in that it compares earnings with the cost of capital. Residual income has always been popular with academic accountants, but has never been widely adopted in practice; the same cannot be said of EVA, which has replaced return on investment (ROI) as the prime performance measure in many organizations.

Stern (1993a, 1993b) details the value-based planning approach implicit in EVA, where the goal is to increase shareholder value by focusing on the share

price. If the goal of the firm is 'growth' then an emphasis on size and market share may cause the return on capital to be inadequate to compensate shareholders for the risks they are taking; share prices will fall as a result. EVA attempts to align the interests of managers and shareholders by managing physical and human assets to yield optimum returns. The implications are:

- performance measurement in terms of changes in shareholder value; and
- managerial incentive schemes which link salaries and bonuses to operational performance, via shareholder value.

A number of authors (e.g., Tully, 1993; Walbert, 1993; McConville, 1994) emphasize the use of EVA as a performance yardstick of widespread application within organizations, embracing acquisition and investment decisions as well as employee compensation schemes.

The supposed advantages of EVA are as follows:

- There are no artificial upper or lower bounds to bonus earning capacity, and so none of the earnings smoothing and associated manipulation of the kind reported by Healy (1985).
- It provides a clear and unambiguous earnings goal (i.e., share price improvement) rather than one which is artificially or politically derived through the negotiation of interested parties (e.g., beating budgeted or target performance levels).
- Some portion of 'earned' bonuses may not be awarded immediately, but deferred to ensure that increases in EVA achieved are not just 'one-offs' but can be sustained in the medium term.
- A 'golden handcuffs' clause may be introduced to prevent executive resignations without the loss of accumulated deferred bonus earnings.

Shareholders view incentive schemes expressed in such terms as pursuing interests congruent with their own, so it is not surprising that the introduction of an EVA-based compensation scheme induces an immediate increase in share prices. Shareholders clearly expect more of the same.

Whereas residual income is defined as profit (before tax) minus cost of assets (as a percentage of assets employed), EVA takes an economic income approach:

$$\text{EVA} = \text{Accounting income} - \text{Cost of capital.}$$

It moves towards a cash base by adjusting traditional accounting income for the impact of those accounting policies which do not have a cash effect, but which do influence accounting income. This means reversing the impact of many accounting standards in the calculation phase.

The notional percentage interest term of the residual income calculation is replaced by the weighted cost of capital (WACC) to reflect both the cost of equity, the cost of debt and the relativities between the two. The overall EVA calculation, therefore, provides a direct measure of shareholder value of potential benefit for measuring firm performance.

Tully (1993) details the calculation of EVA for two US companies (see Table 9.2): the goal is a positive EVA outcome, one which indicates that the operation is creating wealth through the efficient management of capital. In the case of Anheuser-Busch, for example, WACC is calculated as

$$0.67 \times 14.3\% + 0.33 \times 5.2\% = 11.3\%,$$

TABLE 9.2

Calculation of EVA for two companies

	Anheuser-Busch	Spiegel
Operating profit (£m)	1,756	188
Tax payable (£m)	617	69
Profit after tax (£m)	1,139	119
Cost of equity	14.3%	18.3%
Cost of debt	5.2%	6.8%
Equity weighting	67%	37%
Debt weighting	33%	63%
Weighted average cost of capital	11.3%	11.1%
Total capital (£m)	8,000	1,600
Cost of capital (£m)	904	178
Economic value added (£m)	+235	-59

the cost of capital is

$$11.3\% \times £8000\text{m} = £904\text{m},$$

and then the cost of capital is subtracted from profit after tax to give

$$\text{EVA} = 1139 - 904 = £235\text{m}.$$

Good performance, a positive EVA outcome, therefore equates with 'beating the cost of capital', rather than 'beating budget' or achieving positive operating earnings. EVA may be raised by:

- earning more profit from less capital – by cutting costs and withdrawing capital from activities in which costs exceed returns; and
- investing in high-return projects – by achieving growth through investment where returns exceed costs.

Neither of these recommendations is at all startling. Like residual income, EVA will tend to penalize:

- companies with good future prospects which are not necessarily reflected in one year's cash flows;
- asset-intensive companies;
- companies expanding aggressively through an acquisitions strategy;
- resource-rich companies, notably those in extractive industries, oil and gas and mineral exploration.

The complexity in the calculation of an apparently simple measure like EVA lies in the specification of its components – 'accounting income' and 'cost of capital'.

The EVA approach to performance measurement relies on cash flows, and requires adjustments to be made to historic cost accounting numbers derived from the profit and loss account and the balance sheet. These adjustments eliminate (or at least alleviate) the effect of alternative accounting opinions, as reflected by accounting standards so that the profit

and loss account approximates cash revenues and expenses and the balance sheet approximates the actual cash invested. The clearest impact is apparent in, for example, the depreciation of investments against expected future cash flows and the capitalization of research and development expenditures which are then expensed over the lives of successful projects.

Adjustments to accounting numbers have to be considered in a number of areas, including:

- provisions;
- advance revenues;
- research and development costs;
- reserves;
- depreciation;
- extraordinary losses and gains;
- leases;
- goodwill;
- deferred tax.

Provisions about payments or write-offs may be so conservative as to understate both the profits and assets of the business. A reversal of these provisions may give a more accurate indication of the cash costs of these expenses and better reflect their timing and certainty. In practice, provisions for employee entitlements, warranty claims, inventory diminution and doubtful debts would all be reversed because of the conservative guesswork they embrace.

Advance payments (e.g., premiums, fees, subscriptions and progress payments) may be received from customers well before accounting standards permit them to be recognized as revenues in the profit and loss account. The recognition of such as revenue as and when it is received more accurately reflects the timing of cash flows.

Research and development (R&D) costs may be accounted for in a number of alternative ways as permitted by accounting standards, normally either as 'full costs' (all R&D expensed in the year in which it occurs) or 'successful efforts' (unsuccessful R&D expensed and successful R&D amortized over the length of the project). Value-based adjustments demand consistency and require all R&D expenditures and exploration costs (both successful and unsuccessful) to be capitalized and written off over the life of successful research and development.

Reserves attributable to asset revaluations and foreign exchange fluctuations are reversed and deducted from capital. Asset revaluations have no impact on cash flows, and deductions from capital associated with their reversal give a more accurate indication of the cash cost of the assets. Some assumptions may be necessary to accommodate asset revaluations that have been made in previous time periods. Changes in the value of foreign-held assets and liabilities similarly have no impact on cash flows until those assets are realized.

Depreciation charges over the useful life of the asset are permitted. Although depreciation is not a cash item, it does reflect that assets (and the cash flows generated by these assets) have a finite life. Long-life assets or those where the length of life is uncertain remain undepreciated.

Extraordinary, non-recurring and abnormal losses are added to capital on an after-tax basis; such gains on the same basis are deducted from capital to reflect a 'full cost' (rather than 'successful efforts') approach.

Leases are all treated in a similar manner (i.e., existing operating leases are treated in the same way as finance leases). Operating leases are thus defined as non-cancellable leases to separate the performance of the company from its means of finance and to eliminate the erroneous distinction between 'rent' and 'buy' in the accounts. This may necessitate some discount rate assumptions to perform present value calculations.

Goodwill amortization is reversed from the profit and loss account and added back to capital to remove erroneous assumptions about the lives of assets and businesses.

Deferred tax provisions in the tax charge of the profit and loss account mean that the latter does not give an accurate indication of the actual tax paid in cash by a business. Again, timing differences cause the problem, this time a variation between the recognition for accounting purposes and assessment for income tax purposes. In practice many of these deferred tax provisions will be associated with differences between 'useful life' and 'taxation' depreciation on fixed assets. The adjustment requires future tax benefits to be netted off the provision for deferred tax and the net increase (or decrease) in deferred tax provision to be deducted from (or added to) the taxation charge in the profit and loss account.

Despite these adjustments EVA remains a historic cost measure since it does not incorporate market value assessments. The subjectivity of the revaluation of non-traded assets and the non-trivial costs of continual revaluation drive this decision. However, we must not confuse the motivation of improved performance with purely financial issues. For example, accounting manipulations (e.g., asset revaluations) might be employed in a strategic manner to ensure that debt covenants are satisfied and that the company is portrayed in a favourable light by statutory financial reporting obligations.

The need for consistency in the adjustments made to accounting income is paramount if comparability is to be reliable. Estimates of the cost of equity, the cost of debt and of the relativities between the two in the WACC must also be reliable, because the EVA outcome is potentially sensitive to errors in this area.

EVA undeniably ignores the non-financial factors which drive a business, using a measure which is essentially short-term and based on historic costs. Its strength is its unerring focus on increasing market value as a goal pursued by shareholders, and whose interests can be aligned with management.

Where the goal is to increase shareholder value by focusing on the share price, the targets for attention are corporate goals which may not be in the interests of shareholders; thus if 'growth' is the stated goal of the firm, but the emphasis on size and market share causes the return on capital to be inadequate to compensate shareholders for the risks they are taking, then the share price will fall. Shareholder value analysis attempts to reorient goals so that the interests of managers and shareholders are aligned; the implications of such an approach are that management performance is measured in terms of changes in shareholder value, and that managerial incentive schemes will link salaries and bonuses to operational performance via shareholder value. Shareholders apparently view such incentive schemes as consistent with their own interests, in that they are likely to reduce short-term management manipulation and encourage the pursuit of long-term share price growth. Dunlap (1996) details how such a philosophy can be fundamental to the achievement of strategic goals.

Dunlap is infamous for his work in turning around troubled enterprises worldwide. These firms, which include American Can, Cavenham Forest Industries, Australian Consolidated Press Holdings, Scott Paper and

Sunbeam, have been restructured at great speed, refocused on what they do best, and redirected to protect and enhance shareholder value. The strategy adopted by Dunlap in pursuing shareholder value is described by his 'Ten Commandments' for a smart approach to business:

- 1 Business is simple and needs to follow four simple rules:
 - Get the right management team – as small as is feasible.
 - Cut costs to improve the profit and loss account.
 - Focus on the core business and dispose of non-core assets to improve the balance sheet.
 - Get a real strategy – one which requires setting a few major attainable goals and tenaciously pursuing them.
- 2 Squeeze corporate headquarters to eliminate perks and retrench high-priced but unproductive management. Top of the list for elimination are company cars (for all but salespeople), subscriptions to trade journals and associations, and charitable donations. By eliminating the excess baggage, which might be brands, suppliers, inventory or working capital, and which is neither adding value nor producing profit, a slimmer more efficient operation results. He cites his rule of 55 (1996: 59) as a suitable starting point for such action:
 - 50% of a company's products typically generate only 5% of their revenues and profits;
 - 50% of a company's suppliers provide only 5% of their purchased goods and services.
- 3 Focus on shareholder value in order to align the interests of the board of directors with those of the shareholders. Dunlap decries recent moves to emphasize 'stakeholder interests' on the grounds that they are impossible to measure, and recommends a focus on share price because that can. He recommends director compensation in the form of share equity and cites studies by Elson in the USA (Dunlap, 1996: 226) which show that those companies whose directors hold few shares have poorer corporate performance, together with chief executives who are more likely to be overpaid. He is adamant in the view that 'shareholders own the company; they take all the risks' and that, therefore, the company's top priority is towards the shareholder, rather than towards customers or employees.
- 4 Develop a marketing strategy to achieve 20% earnings growth, 20% return on sales and 20% sales growth. The approach to marketing is entirely consistent with the 'First Commandment' in that it depends on building the right team, tenacity in pursuing difficult goals and the establishment of strong monitoring and control systems.
- 5 Link employee incentives directly to corporate performance in the pursuit of goal congruency. Dunlap cites a study showing that 73% of US companies that lost money still incentivized their chief executives; he asks why. He asks the same question again with respect to the abject failure of boards of directors to fire underperforming chief executives. Both questions are in some respects rhetorical in that he supplies the reason in terms of the personal interrelationships between board members and the existence of a 'club' mentality which often precludes such behaviour. He demands that executive compensation be tied to shareholder value.
- 6 Use consultants sparingly, because most of them will only tell you what you want to hear.

- 7 Reward leadership and outstanding performance at every level. Ideally these rewards will be in the form of shares (not share options) to encourage congruent behaviour from management at all levels.
- 8 Put your money where your reputation is. The adoption of the 'shareholder value' message at board level should establish a transparent process for the development of an objective compensation programme, with targets set for director share ownership.
- 9 Be outrageous, but be prepared to take responsibility and criticism for actions. Dunlap has always been outspoken, and makes no secret of the fact that he has become a multimillionaire by investing heavily in the companies that he has successfully turned around.
- 10 Remember you are not in business to be liked. He suggests that 'if you want a friend, get a dog' (1996: xii). He has two!

Approaches to business, such as that proposed by Al Dunlap, show that the longer-term interests of shareholders and management can be aligned and that 'shareholder value' can assume a fundamental role in the strategic management of a business.

SUMMARY

This final chapter is concerned with developing measures of performance in areas of extreme uncertainty – even embracing speculation on performance levels for activities that have not yet commenced. The forecasting of cash flows is an essential activity for budgeting, project appraisal, investment decisions and value-based management, among others, so the emphasis accorded to forecasting here is wholly appropriate. We recognize that forecasts will not always be accurate, indeed that recognition is more important than accuracy itself. A sensitivity analysis of alternative assumptions and an analysis of the risk associated with variations in outcome will yield a realistic picture of alternative scenarios – and dictate appropriate management action.

NOTE

- 1 EVA is a registered trademark of Stern Stewart & Co. Ltd.