The Statistician (1998)
47, *Part* 4, *pp.* 573–591

Can takeover targets be identified by statistical techniques?: some UK evidence

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[Received March 1996. Final revision July 1998]

Summary. This paper examines the proposition that takeover targets may be forecasted by using similar methods as bankruptcy prediction which has been very successful in both the USA and the UK. The study shows that they cannot be predicted simply by using published accounting data as inputs into these models. It also examines the possibility of combining such data with anticipatory share price changes, which are also publicly available information, but this did not improve the predictive accuracy. These results support the efficient capital market hypothesis in the semi-strong form—that the market may not be beaten by using publicly available information alone. The fact that there are anticipatory price changes suggests that the market may not be efficient in the strong form.

Keywords: Acquisitions; Efficient capital markets; Insider dealing; Mergers; Predictions; Takeovers

1. Introduction

The finance literature is adamant that it is not possible to 'beat the market' by consistently earning above market returns without the help of inside information. For instance, Brearley and Myers (1991), p. 289, wrote

> '*If capital markets are efficient, then purchase or sale of any security at the prevailing market price is never a positive-NPV* [*net present value*] *transaction*'

(their italics). At first glance, this implies that future economic events cannot be predicted. But some events may at least be anticipated or inferred, if not predicted. (Here the words inference and anticipation are used to suggest conclusions simply based on common sense and insight, whereas prediction suggests a much greater, almost magical, ability.) Corporate bankruptcy is an example. It is easy to anticipate eventual failure if the firm has been consistently making losses, losing funds, losing its market share, and so on. It is easy to understand the apparent success of bankruptcy forecasting models which claim to predict up to 4 years ahead. But can these forecasts be used to outperform the market or has it already digested the information, anticipating or inferring the event on the receipt of the basic published accounting data anyway and adjusting the share price in a once and for all movement at the time well before the publication of a forecast? Studies by Altman and Brenner (1981), Katz *et al.* (1985) and Zavgren *et al.* (1988) have shown that this may be the case, where the share price reaction precedes the forecast, suggesting that the market is efficient and traders would not be able to beat the market by using bankruptcy forecasts based on publicly available information. (The study by Katz *et al*. (1985) extends to recovering firms.)

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Does the prediction of mergers provide a better opportunity to outperform the market where it is more difficult to identify a takeover target from published raw accounting data alone? There have been claims that this may be done successfully. See Table 1. Until 1986 the published studies had boasted high predictive accuracies ranging between 60% and 90%. However, Palepu (1986) showed that these claims were largely unfounded because of statistical error. If they had been performed correctly, their conclusions would have been similar to his own and shown that the successful identification of targets and the earning of excess returns were not possible. The exception is Rege (1984) who found that the discriminating model did not distinguish between the two groups. What is surprising about these early studies is that the methodological pitfalls were well known elsewhere in similar applications at the time, i.e. in corporate failure prediction. For a review of these see Zmijewski (1984). More recently, studies by Bartley and Boardman (1986, 1990) and Walter (1994) have suggested that, although most of Palepu's methodological points are clearly correct, his empirical conclusions may not necessarily be the final word on the subject. An exception is his use of the minimization-of-errors criterion and his assumption that the costs of type I and type II errors are equal. See his subsection entitled 'General problems with these types of prediction models'. Whether accounting data, in particular inflation-adjusted accounting data in the USA, can be used successfully to identify takeover targets may still be an open empirical question. Walter (1994), using Palepu's methodological revisions, has shown that current cost accounting (CCA) information in the USA has quite a high predictive accuracy. Unfortunately, because of the losses sustained on a few of the incorrect forecasts, the model only earned quite modest excess returns overall. His ultimate conclusions, therefore, concurred with Palepu. However, as the number of firms providing CCA data is small, his sample was, and, if it had been larger, the large losses on a few of the incorrect forecasts would have been unlikely to have been repeated.

1.1. The use of anticipatory share price data

The objective of those studies was to develop a predictive model based on published accounting data. This, in a way, is an artificially created problem as other, potentially more predictive, data exist, notably early anticipatory share price movements or large changes in the volume of dealings

Table 1. Previous studies†

Researcher	*Country*	*Method*	*Classification (%)*	*Prediction (%)*
Simkovitz and Monroe (1971)	USA	MDA	77	63.2
Tzoannos and Samuels (1972)	UK	GLS	70	—
Stevens (1973)	USA	MDA	70	67
Belkaoui (1978)	Canada	DA	72	70
Wansley and Lane (1983)	USA	MDA	77.3	69.2
Dietrich and Sorensen (1984)	USA	Logit	92.5	—
Rege (1984)	Canada	MDA	—	—
Bartley and Boardman (1986)	USA	MDA	65	—
Palepu (1986)	USA	Logit	—	46
Bartley and Boardman (1990)	USA	MDA	82.5	—
Ambrose (1990)	USA	Logit	65.1	75.6
Barnes (1990)	UK	MDA	68.5	—
Ambrose and Megginson (1992)	USA	Logit	74.3	—
Walter (1994)	USA	Logit	65	66

†DA, discriminant analysis; GLS, generalized least squares; MDA, multiple discriminant analysis; —, not reported.

in the shares (and similarly in bankruptcy prediction where credit rating firms collect, use and quantify private and semiprivate information, e.g. the firms' current paying record and the success or failure of the directors' past companies). Given the difficulty of using accounting data alone, it seems obvious to use these also if a model's predictive accuracy and the earning of excess returns are to be maximized.

The difference between the prediction of bankruptcy victims and takeover targets is that, in the case of the former, whereas anticipatory share price movements are likely to be primarily based on an interpretation of the firm's past financial performance and an extrapolation of this into the future, in the case of the latter, they are more likely to be the result of insider dealing and based on rumour. Thus, on the one hand share price changes may be quick and once and for all, consistent with the efficient capital market hypothesis (ECMH). On the other hand, the total share price movement may be spread over a longer period beginning with the effects of insider anticipation. These price changes may only be small as the result of early buying by insiders expecting an eventual merger bid and perhaps coinciding with mere contemplation on the bidder or preliminary talks between the two firms. These changes may be followed by larger price changes brought about by arbitrage activity by speculators and, perhaps, coinciding with the crystallization of the merger proposal. A price adjustment which is spread over a relatively long period of time would therefore not be incompatible with the ECMH and could be rationalized as reflecting the changing probability of takeover (Asquith, 1983). If this were the case, it would be possible to use anticipatory price changes (or changes in volume or volatility data) to outperform the market. However, whether the market behaves in this way is more an open question.

It is Palepu's (1986) view that share price changes occur too late for any forecasting model to use. He quotes Jensen and Ruback's (1983), p. 29, authoritative review of share price behaviour to the effect that prices adjust to the news of a merger bid during a relatively short period around the time of the announcement. For instance, in the USA, Keown and Pinkerton (1981) and Halpern (1976) found that abnormal share price performance was largely confined to the month immediately before the announcement of the bid. However, there is other, more recent, evidence to suggest that, in the UK at least, the entire anticipatory movement occurred over a relatively long period and beginning sufficiently early to be used. Limmack (1991) found that targets' abnormal returns were significant for the month before the month in which the bid occurred (3.64% for completed bids and 5.4% for abandoned bids). In the preceding month the abnormal returns were again significant: 1.71% for completed bids and 0.58% for abandoned bids. Also, Barnes (1996) has shown that in the UK during the period 1987–1992 the share prices of target firms increased 31% over the period 2 months before the announcement of a merger to 1 month afterwards and 23% (almost three-quarters of the total movement) occurred before the announcement. Of that, a relatively small, but significant amount, 2%, occurred during the period up to 1 month before the bid. (It was statistically significantly different from zero at the 5% level suggesting that there was a systematic element and it represented 6.5% of the total movement). Thus, if these early adjustments could have been identified at the time, there would have been sufficient time to act and a sufficiently large portion of the total price adjustment still to occur in to earn large and significant excess returns. This impression is not recent and dates back to at least Firth (1976) who attributed the early price changes to insider dealing.

The likely success of such an approach is supported by another study in the UK. Holland and Hodgkinson (1994) showed that the share prices of 'identified' targets (those for which the press had reported the likelihood of a bid or the purchase of a large stake in the target firm, or that a takeover classification model identified the firm as a target) experienced significant overperformance during the month before the announcement of the bid. For their own purposes, Holland and Hodgkinson (1994) distinguish between these and those firms that were not so 'identified' which did not experience abnormal performance, other than during the day immediately prior. Unfortunately, Holland and Hodgkinson did not separate out of the 'identified' group those included solely by reason of the classification model and whether those firms also overperformed. This information is relevant to the present study as the inclusion of these firms is debatable given that Holland and Hodgkinson used the classification model and minimization of error cut-off point *ex ante* whereas it is computed and would, of course, only be known *ex post*. Certainly, the classifications and predictions of this model would not have been known at the time of the share price changes and, in this sense, the firms could not be termed as 'identified'. This matter is discussed in the methodological section of this paper and was one of the issues raised by Palepu (1986). This approach is also supported by an examination of the factors determining the probability of takeover in the USA by Ambrose and Megginson (1992). They found that the percentage stake of shares in target firms held by financial institutions increased during the quarter period before the announcement of the bid. Finally, although they did not provide directly relevant empirical evidence, the efficacy of this approach is implicit in Malatesta and Thompson (1985).

Nevertheless, although most merger announcements may be preceded by large share price adjustments, not all are. In some cases, news of the pending bid may be kept as a secret and the market taken by surprise. Similarly, although many large share price changes may be followed by a merger announcement, many others are not. Share price changes may be brought about by many factors, e.g. some anticipating other forms of 'good news' for shareholders, whereas others are based on rumours that do not materialize. Alone, share price changes may not be a sufficient indication. A modest share price rise may indicate

(a) a future merger for which there are further price rises,
(b) other 'good news' for which there may or may not be further price increases or
(c) nothing for which there are no further price increases.

From the price change alone, the investor does not know into which of these classifications the price change falls and whether the share price is likely to continue to rise. A forecasting model which *combines* both share price changes and accounting numbers, as proxies for economic variables affecting the probability of a merger bid, should have a higher predictive ability than a model which uses only one of these factors. For instance, if a share price change is not accompanied by the necessary values for the accounting variables, the model will not indicate a likelihood of takeover.

It is the purpose of this paper, recognizing the methodological issues raised by Palepu (1986), to investigate whether accounting data existing at the time, with or without the use of early anticipatory share price movements, may be used to earn excess returns. If either of these can be supported, it indicates that, although the market may be efficient, it may still be possible to earn excess returns from publicly available information. The remainder of the paper is arranged as follows. First, the remaining methodological issues are discussed, including the problem of how anticipatory price changes may be measured. The empirical study is then described and the results discussed.

2. Methodological issues

2.1. The determination of the cut-off

As the hold-out sample is likely to contain an unequal number of targets and non-targets, a weighted cut-off is used instead of 0.5. As the model is to be used predictively, this needs to be used *ex ante*. It may be estimated from the hold-out sample *ex post* as $(N_A P_B + N_B P_A)/(N_A + N_B)$ where N_A and N_B are the sample populations of groups A and B, the target group and non-target group respectively, and P_A and P_B are the group centroids of A and B (Hair *et al.* (1995), pages 200–201). However, as the centroids of the two groups are only available *ex post*, the *ex ante* values of 1 (for group A) and 0 (for group B) may be used as the best estimates available. The prior probability of a takeover bid during the relevant period may be estimated from historical experience of merger activity. Of the 4000 or so quoted public limited companies in the UK, of which around a half are quoted on the International Stock Exchange in London, the number of merger bids in a year ranges from about 50 to 100 according to the mood of the market. (In 1993 and 1992 these were 53 and 55 respectively, compared with 119 and 159 in 1990 and 1989.)

An alternative method of determining the cut-off point is the minimization-of-errors criterion. This is where the conditional marginal probability densities for targets and non-targets are equal: where the plotted distributions of the estimated probabilities of targets and non-targets intersect. A critical assumption of this is that the costs of type I and type II errors are equal (Hsieh, 1993). Consider the notation in Table 2. Also let c_{21} be the cost (lost excess return, $g - h > 0$) of n_{21} where g represents the average return from investing in takeover targets and h represents the risk-adjusted average return from investing in non-takeover targets, i.e. $c_{21} > 0$ as

$$g - \frac{(gn_{11} + hn_{21})}{(n_{11} + n_{21})} = c_{21}.$$

Similarly, let c_{12} be the cost of n_{21}. Here $c_{12} = 0$. This model is based on certain assumptions: an investor has a stock of money to invest in takeover targets to achieve a return of pr, the average return from investing in takeover targets, a return well in excess of the market return m. The investor will divide this money in some way between the forecasted targets. As long as these firms are bid for, pr should be achieved. However, if they are not, a total return of nearer m will be achieved, depending on the number of incorrect predictions. Thus, it is not necessary to invest in all targets but all the investments must be targets; hence $c_{12} = 0$. As $c_{21} > 0$ and $c_{12} = 0$, the optimal cut-off point r will occur where n_{11}/n_{21} is maximized. This is where $n_{21} = 0$ and will be referred to as the maximization-of-returns cut-off.

The minimization-of-errors and the maximization-of-returns cut-offs also need to be used *ex ante*. As their calculation requires knowledge of the outcomes, they may only be estimated approximately from the estimation sample on the assumption that the parameters of the two distributions are stable over time. This assumption was made by Palepu (1986) and Walters (1994) who used the minimization of errors to decide their predictions.

2.2. The use of early anticipatory share price changes

The critical question is: if anticipatory share price changes are to be used, are they sufficiently large to alert the investor of an impending bid, yet sufficiently early to enable him to invest in the target firm and sufficiently small to enable him to profit? Obviously, there is likely to be a trade-

Table 2. Predicted and actual targets and non-targets

Actual	*Predicted*	
	Target (1)	*Non-target (2)*
Target (1)	n_{11}	n_{12}
Non-target (2)	n_{21}	n_{22}

off between the probability of a bid and the expected remaining share price change which changes as the announcement of the bid becomes nearer. Following Holland and Hodgkinson (1994) and Barnes (1996), the point of 1 month before the announcement was taken in the empirical study as that point by which sufficient anticipatory price movement should have occurred as to signal a merger when combined with accounting numbers in a predictive model, yet still be capable of earning excess returns. As was mentioned earlier, the total share price increase in the UK over the period 2 months before the announcement to 1 month afterwards is about 31% and as the total premium offered in a merger bid is about 30% (Greenfield, 1992; Crawford and Lechner, 1996), it is very reasonable to conclude that a negligible amount of further anticipatory share price changes usually occurs earlier than then.

The most popular way of measuring significant share price changes is by estimating share price abnormal returns AR by using the market model,

$$\mathrm{AR}_{j,t} = r_{j,t} - (\alpha_j + \beta_j R_{m,t}) \tag{1}$$

where $r_{j,t}$ is the return for security j in month t, and $R_{m,t}$ is the return for the market in month t. The coefficients are usually estimated from data before the test period so that they are not affected by the event being studied. AR is then averaged for all the firms in the sample and a cumulative abnormal return calculated across time.

3. The empirical study

3.1. The data

The estimation sample consisted of accounting and other data for all UK publicly quoted companies that were the subject of a takeover bid (both successful and unsuccessful) from the beginning of 1991 to the end of 1993. Non-accounting data included stock price data and standardized industrial codes (SICs) for the principal activity of the firm. The accounting data consisted of all the main accounting numbers in the most recent accounts immediately before the bid and summary financial data reflecting trends for the previous 3 years. The database also contained similar data for matched companies, i.e. equivalent data for UK-quoted companies that were as similar as possible to the takeover targets in respect of, firstly, their principal business activity and, secondly, their size, as measured by their market capitalization at the time of the bid. The sample size is described later. A second database, which was used as a hold-out sample, comprised the latest reported accounting information for 1185 UK-quoted companies at January 1st, 1994, of which 16 companies experienced a takeover bid between then and December 31st, 1994. Because of the problems of ascribing principal industries for certain firms, the industry-specific hold-out sample was reduced to 886 of which 13 were targets.

3.2. The variables

The selection of variables and the choice of accounting ratios to form part of an explanatory or predictive model raise several problems. Firstly, it is unclear which variables are related to the probability of acquisition where the market for corporate control (and, therefore, individual mergers) is motivated at different times by different factors. Secondly, not only are several alternative accounting ratios available as proxies for a particular variable, but it is often unclear which is the best where the alternatives are not so much substitutes as having overlapping information content (Benishay, 1971). However, if all the available ratios were used, this would lead to multicollinearity in the estimation data and misspecification of, and bias in, the statistical model estimated. Palepu (1986) criticized the earlier studies for this. They typically started with a large number of popular financial ratios and then, simply on a stepwise basis, let statistical significance determine which ratios were retained. For example, Simkowitz and Monroe (1971) started with a set of 24 ratios which were finally reduced to seven. In contrast, in his own study, Palepu formulated six hypotheses of acquisition likelihood and chose, usually on an unequivocal basis, a single representative accounting ratio. Nine variables are actually used in which two are dummies, one is a measure of size and the remainder are accounting ratios, although in some models the accounting return on equity is replaced by a stock price measure of excess return. A similar approach was adopted by Walter (1994) where 11 variables were hypothesized which were represented by nine financial ratios and two dummy variables.

Although this appears to be neat and to avoid the problem of multicollinearity, it omits the multidimensional aspects of a particular hypothesis which may only be covered by the inclusion of more than one variable per hypothesis. This study attempted to resolve the conflicts of multicollinearity at the one extreme and oversimplification at the other extreme by constructing a comprehensive list of hypotheses of takeover likelihood, together with a list of variables, mostly accounting ratios, which proxied these but to varying degrees overlapped. This resulted in 42 variables. (These are not shown. A list is available from the author on request.) This list was reduced to 17 variables which were selected on the basis of the elimination of multicollinearity while retaining full representation of the hypotheses. This was done by examining the correlation matrix and removing the offending variables involved in correlations in excess of 0.65. This reduced the overall number of variables but still enabled the principal aspects of each hypothesis to be represented. In a sense, this approach is similar to that of the pre-Palepu studies which selected the variables to be used and removed the rest stepwise by using an asymptotic covariance estimate as a criterion for deselection. However, the approach used here ensures that each hypothesis is represented and that there are no adverse effects of overlap across hypotheses. The variables are listed in Table 3 and discussed here.

Table 3. Hypotheses and variables

Hypothesis	*Variable*
Inefficient management	R1, profit before tax/sales
	R2, profit before tax/shareholders' equity
	R3, growth of profit before tax over last 3 years
	R4, price (2 months before)/earnings
	R5, average dividend for last 3 years/shareholders' equity
	R6, dividend growth over last 3 years
	R7, market capitalization/shareholders' equity (market capitalization = share price 2 months before bid × number of shares)
Growth–resource mismatch	R8, sales/total assets
	R9, total remuneration/sales
	R10, sales growth over last 2 years
	R11, sales growth over last 3 years
	R12, current assets/current liabilities
	R13, current assets less current liabilities/total assets
	R14, long-term debt/total assets
	R15, (profits before tax + interest paid)/interest paid
	R16, long-term debt/shareholders' equity
Size	R17, market capitalization 2 months before the bid (£ million)
Anticipatory share price change	R18, cumulative average residual over the 2-month period before announcement of the bid

3.2.1. Inefficient management

It is often suggested that mergers are a market mechanism by which resources are transferred from inefficient managers to efficient managers (Marris, 1964). This implies that a firm with less than average profits for the industry in which it operates, and as a consequence pays relatively low dividends, is vulnerable to a takeover whereas a firm with higher than average profits is not (R1, R2, R3, R% and R6). Further, a firm's price-to-earnings ratio (R4) reflects the market's opinion of its future profitability. Also because of inefficient management, the firm may become undervalued on the stock-market and an acquirer may be able to 'break up' the company or to revive it at a quick profit. Thus, the lower the valuation ratio of a firm (i.e. the market value of the firm divided by its book value), the more is its attractiveness to raiders (R7).

3.2.2. Growth–resource mismatch

Another aspect of the inefficient management hypothesis is the notion of both low growth–resource rich and high growth–resource poor firms being natural acquisition targets (Cosh *et al.*, 1980; Levine and Aaronovitch, 1981). Although this may depend on each individual case, certain types of mismatch may be common and may be a factor in most acquisitions. Firms with low activity ratios (R8 and R9) may be attractive to ambitious management teams. Similarly, firms with low growth histories are likely to have a high probability of takeover.

The growth–resource mismatch may extend to the adequacy of finance for the firm. High growth may be held back if there is inadequate financial support. A firm that is constrained in this way would be an attractive acquisition for a firm with surplus resources available to help (R10 and R11). A cash rich acquirer may be attracted to a cash-starved target because it is a channel for the acquirer's funds (R12 and R13). In a similar way the opposite may occur; a cash rich firm may be a vulnerable target because it is attractive to a cash-starved acquirer.

Another aspect of the resources mismatch relates to the extent to which the firm departs from the 'optimal' financial structure and whether, as a result of a merger, advantage may be taken of reorganizing it, e.g. increasing leverage (R14, R15 and R16). Although low leverage may traditionally signal unused debt capacity, suggesting potential benefits (Lewellen, 1971), the reverse of this became the motivation for many mergers in the late 1980s and early 1990s in the UK. The recession made over-levered companies with severe financial difficulties vulnerable to takeover bids which reduced their leverage (Fallon and Srodes, 1988).

3.2.3. Size

In a predictive model where the predator is not known (and therefore its size), it is difficult to include a variable reflecting relative size, obviously an important aspect of a merger. Nevertheless, some general aspects of size need to be considered and allowed for (R17). The merger boom of the mid- and late 1980s, in contrast with those of earlier periods, was characterized by the very large size of the average targets (Hughes, 1989). However, Palepu (1986), using data from an earlier period, suggested that the likelihood of acquisition decreases with size mainly because of the size-related 'transaction costs'. There is another reason: the probability of acquisition decreases with an increase in size where the number of firms that are larger than the target decreases as its size increases.

These variables and hypotheses are similar to those of Palepu (1986) who also included the economic disturbance hypothesis (Gort, 1969) and an industrial sector dummy variable. Here the damaging effects of dummy variables (Hair *et al*. (1995), pages 129–132) are avoided as industry differences are handled by other methods. The variables used here also cover those used by Walter (1994) except for his inflationary tax loss variable, which is not relevant to the UK as current cost data are not reported, and his tax savings variable, which is also not appropriate here as this form of tax savings may not be obtained in the UK.

3.2.4. Anticipatory share price changes

The reasons for the inclusion of an anticipatory share price change variable (R18) have already been discussed. The period over which the cumulative average residuals (CARs) are measured differs between the estimation sample and the hold-out sample. For the estimation sample target firms, this is over the 2-month period before the bid using the published London Business School Risk Measurement Service (RMS) β at the beginning of that period, i.e. the CARs are calculated by using equation (1) above where $r_{j,t}$ is the firm's stock-market return over the 2 months estimated by the RMS, α_j is a constant, here assumed to be 0, β_j is the firm's RMS β at the beginning of the period (these are estimated and published monthly by RMS on the basis of monthly returns over 5 years) and $R_{m,t}$ is the market return over the 2-month period, again as estimated by the RMS. This is also computed over the same period for the non-target matched firms. However, in the case of the hold-out sample, for those firms which were subsequently subject to a bid, the RMS β 2 months before the bid and the returns over the period 2 months before the announcement of the bid to 1 month before were used to estimate the firm's CAR. As mentioned earlier, it was decided that the investor should be able to invest 1 month before the bid in an attempt at maximizing the bid probability–excess returns trade-off. For those firms which were not subject to a subsequent bid, the value of the price change was entered as 0 as this was its expected value and no other reference date existed as no bid was made.

3.3. The model estimates

Two submodels were estimated for both the non-share price model and the share price model, making four in all. These were a model across all industrial classifications based on industry relative ratios (subsequently referred to as the general models) and a set of models estimated separately for each industrial sector (subsequently referred to as the industry-specific models). The independent variables included in the models are similar and are those listed in Table 3. With the exception of variable R17, which is a measure of size, all the variables in the general model are expressed as industry relative ratios, i.e. a firm's ratios are divided by the relevant industrial average. In the case of the industry-specific models, separate models were estimated for each industrial sector according to the first digit of the SIC industrial classification. The sample size was 323. The general model was estimated from data for targets and matched non-targets that were the subject of a bid during the calendar year 1993, 82 of each. As the populations of some sectors were so small it was necessary to estimate each of the industry-specific models over the 3-year period 1991–1993.

The models were estimated by means of logit regression using the BMDP package where

$$\ln\{p_j/(1-p_j)\} = z_j = b_0 + b_1X_2 + b_2X_2 + \ldots + b_nX_n.$$

Here p_j is the probability of a bid for firm j and there are n independent variables, of which there are 17 in the non-share price model and 18 in the share price model. For each firm in the hold-out sample a bid probability was estimated as

$$p_j = 1/\{1+\exp(-zj)\}.$$

The logit model was preferred to discriminant analysis (DA) because of its relative popularity due to its theoretical superiority. This is partly because of the multivariate normality assumption concerning the independent variables made in DA. As here these are mainly accounting ratios, on both theoretical and empirical grounds, they are likely to be non-normally distributed (Barnes, 1987). Also, in a useful survey of some of the empirical studies, both within bankruptcy prediction and the natural sciences, Jones (1987) concluded that logit models tend to be slightly more accurate, and certainly no less accurate, than DA models.

4. The results

4.1. The estimated model

Estimates of the independent variable coefficients and accompanying statistics for the general submodel for both the share price model and the non-share price model are presented in Table 4. It is not possible in a paper of this size to present similar data for all the nine industry-specific submodels. In any case the principal interest of this paper is not the cause of takeovers but the predictive accuracies of the models. Further, the size of the estimation sample in some cases limits the significance of the coefficients considerably.

It is not possible to compute conventional R^2-type measures with the logit model as the explained variable is dichotomous. As is usual with the logit, the likelihood value and χ^2-statistics as measures of the goodness of fit are used. These are shown in Table 4. These show that, although the fit is not good, a relationship between the dependent and independent variables does exist. The most remarkable feature of the two models is their similarity. The difference between the likelihood values is negligible. As this represents the change in predictive fit between the equations, the addition of the share price anticipation variable does not improve the goodness of fit. The explanatory significance of the other variables is also not changed. In both cases there are four variables with coefficients that are statistically significantly different from 0. These indicate that profitability, sales growth and shareholders' equity were particularly important variables, i.e. firms with high profitability relative to sales were more likely than others to be bid for (R1), and firms with low profitability relative to shareholders' equity were less likely (R2), as were firms with a poor sales growth record (R10). Taken together, these suggest that firms which are underperforming in terms of sales growth and profitability (as a return to shareholders), yet are essentially profitable, as revealed by the profit-to-sales ratio and which may be improved on by further capital as a result of a merger are the most likely to be bid for. The positive R9-variable suggests the importance of not only sales growth but also the target firm's wage structure relative to other firms within the industrial sector. These variables suggest the importance of profit to the probability of takeover. Although it may have been thought that financial factors such as leverage would help to make a firm vulnerable to takeover, these results show that, for the analysis period at least, the fundamentals of growth and profit are important. The most surprising result is the high coefficient for the share price anticipation variable (R18), although it is not statistically significant. This suggests that, whereas in some cases there is an anticipatory share price change, in many other cases there is not.

4.2. The model estimates

For the non-share price model, the model estimates consist of a probability estimate p of the likelihood of takeover for each firm in the hold-out sample at January 1st, 1994, based on its most recent accounts. As company accounts are published yearly, this estimate applies until the publication of the next accounts. However, as this date varies between firms, so that the forecast may be checked with the actual outcome, it is assumed that the estimate relates to the calendar year 1994 only.

Table 4. General model estimated logit coefficient values and related statistics†

Variable	*Expected sign*	*Non-share-price model*	*Share price model*	*Variable*	*Expected sign*	*Non-share-price model*	*Share price model*
R1	–	4.0266	4.0672	R12	–	−0.4539	−0.4623
		(2.650)‡	(2.589)‡			(−1.197)	(−1.191)
R2	–	−1.2779	−1.2544	R13	–	0.6538	−0.4983
		(−2.697)‡	(−2.677)‡			(−0.753)	(−0.2259)
R3	–	3.1925	3.1840	R14	−, +	0.2307	−0.1908
		(1.398)	(1.388)			(−1.141)	(−0.9181)
R4	–	0.8885	0.8671	R15	−, +	0.04221	−0.07316
		(0.610)	(0.601)			(−1.071)	(−1.118)
R5	–	−0.9317	−0.9462	R16	−, +	1.7175	1.7227
		(−1.441)	(−1.096)			(0.878)	(0.9914)
R6	–	−0.04857	−0.01516	R17	−, +	-0.2999×10^{-6}	-0.03414×10^{-7}
		(−0.177)	(−0.0489)			(−0.325)	(−0.3323)
R7	–	0.5771	0.7683	R18	+		−8118
		(1.620)	(1.511)				(−0.8224)
R8	–	2.8631	2.760	Constant		1.009	1.159
		(0.996)	(0.9585)			(1.242)	(0.9007)
R9	–	0.01542	0.01536				
		(2.460)‡	(2.657)‡	Likelihood value		147.42	134.27
R10	–	−0.09404	−0.01231	χ^2- (Hosmer–Lemeshow)		5.393	6.274
		(−2.349)‡	(−2.404)‡	related p-values		0.452	0.483
R11	–	0.001755	0.001595				
		(0.325)	(0.3373)				

† *t*-statistics are given in parentheses.
‡Indicates statistically significant at the 5% level using a two-tailed test.

For the share price model, the p-estimate strictly relates to the 1-month period immediately following the anticipatory share price change during which the investor would be alerted by the p-estimate to buy shares in the target firm. In the case of the targets, the p-estimate would include the effects of R18. In the case of the non-targets, R18 is zero because there is no reference date for anticipatory share price behaviour to occur and, in any case, its expected value is 0. It should be noted that, whereas the non-share price model p-estimates relate to the year 1994, those for the share price model relate to a shorter period during that year—at least those for the targets do. These are aggregated for 1994 and compared with the p-estimates for the non-targets which do not change during that year.

4.3. Predictive accuracy

The values of the *ex ante* cut-off points, determined *ex post*, suggested earlier are as follows:

(a) where the sample sizes (and group membership probabilities) are unequal, a weighted cut-off point based on historical experience, 0.985 (as calculated earlier on the basis of 50 out of 2000 per year—the actual hold-out sample comprises for the general model 1185 firms and for the industry-specific model 886 firms of which 16 and 13 were subsequently bid for respectively; a weighted cut-off point determined *ex post* would be for the general model $(16 \times 0 + 1169 \times 1)/1185$ and for the industry-specific model $(13 \times 0 + 873 \times 1)/886$ which both equal 0.985);

(b) a cut-off based on the minimization of errors using the estimation sample—Figs 1 and 2 show the distributions of the estimated p-values for the targets and matched non-targets used in the estimation model; these are computed by using the estimated model coeffi-

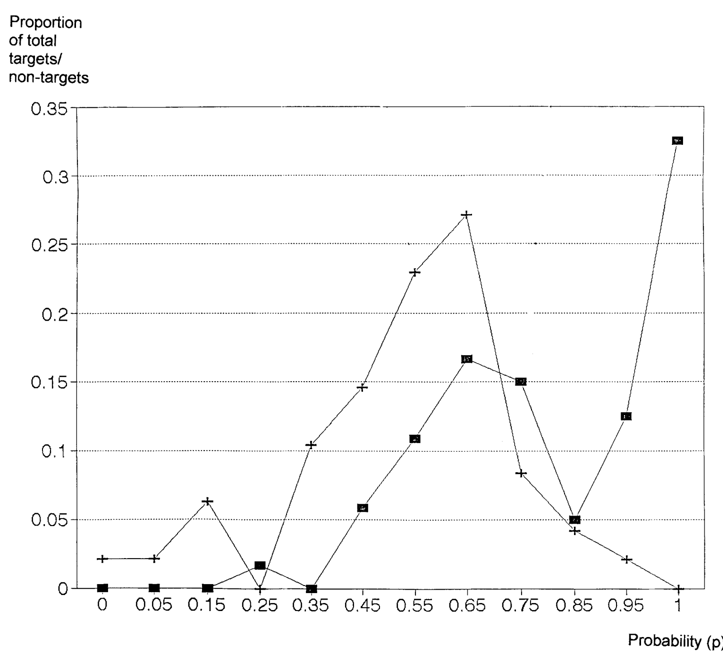

Fig. 1. Distributions of p-values for the estimation sample of targets (■) and non-targets (+): non-share-price model

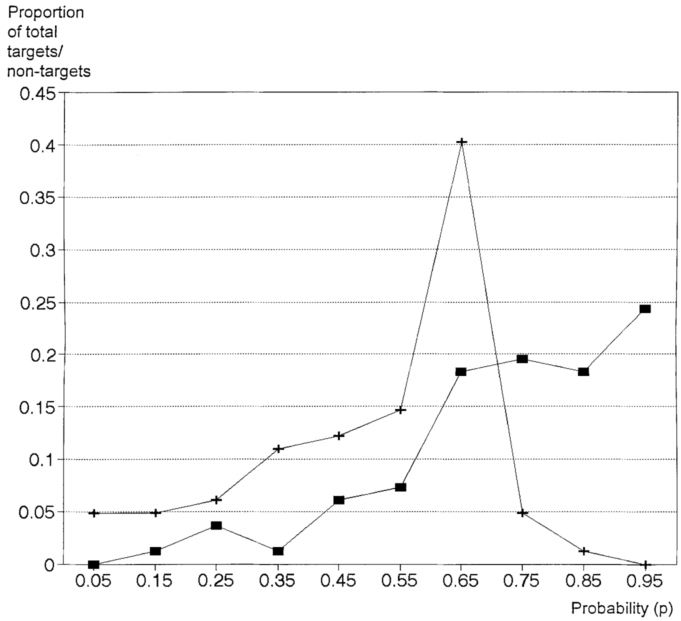

Fig. 2. Distributions of *p*-values for the estimation sample of targets (■) and non-targets (+): share price model

cients and the variables used for the estimation sample (to facilitate presentation, the distributions are based not on the absolute number of targets and non-targets but on the proportion of total targets to non-targets); Figs 1 and 2 indicate that the point at which the two distributions overlap is 0.705 and 0.715 for the non-share price model and the share price model respectively; the distributions do overlap more than once but clearly these points do not minimize the errors;

(c) a cut-off based on the maximization of returns using the estimation sample—in Figs 1 and 2, if $n_{21} = 0$, $r = 1$; so that there may be dichotomization the conditions $n_{21} > 0$ and $n_{11} > 0$ are added to $r = \max(n_{11}/n_{21})$; this occurs at $n_{11} = 1$ where r becomes 0.925.

Tables 5 and 6 show the distributions of the general and industry-specific model forecasts for the non-share-price model and the share price model respectively. They show that no model or submodel has any significant ability to predict takeover targets and that this is largely irrespective of the cut-off used. For instance, if a cut-off point of 0.5 were used, the non-share-price general model would have predicted 13 actual targets, out of a total of 16, together with 914 which were not! The share price general model would have done only slightly better, predicting correctly 14 targets and 883 others which were not. Neither of the two industry-specific submodels performed as well.

Tables 5 and 6 show the predictive accuracies of the models for selected cut-off points. They show that, whereas the general and industry-specific models performed slightly differently, they performed remarkably similarly for both the share price model and the non-share price model. Table 7 shows χ^2-values of the frequency of targets' and non-targets' p-values. Part (a) indicates that, with the exception of the specific model and non-targets, the distributions of the p-values using the share price and non-share price models were not significantly different. In contrast, part (b) indicates that in all cases there were significant differences between the p-value distributions for the general and specific models.

Table 5. Distributions of predicted *p*-values—non-share price model

p-value	*General model*		*Specific model*	
	Targets	*Non-targets*	*Targets*	*Non-targets*
Below 0.4	0	107	1	33
0.40–0.45	0	4	0	7
0.45–0.49	0	6	1	26
0.49–0.50	3	138	5	282
0.50–0.501	12	767	2	44
0.501–0.503	1	125	2	114
0.503–0.505	0	2	0	81
0.505–0.507	0	1	0	54
0.507–0.51	0	1	1	33
0.51–0.55	0	3	1	108
0.55–0.60	0	0	0	9
0.60–0.70	0	3	0	15
0.70–0.80	0	5	0	6
Above 0.8	0	7	0	61

Table 6. Distributions of predicted *p*-values—share price model

p-value	*General model*		*Specific model*	
	Targets	*Non-targets*	*Targets*	*Non-targets*
Below 0.4	0	105	1	34
0.40–0.45	0	5	0	7
0.45–0.49	0	7	2	93
0.49–0.50	2	169	5	221
0.50–0.501	13	737	1	43
0.501–0.503	1	123	2	110
0.503–0.505	0	2	0	85
0.505–0.507	0	1	0	48
0.507–0.51	0	2	1	33
0.51–0.55	0	3	1	105
0.55–0.60	0	0	0	13
0.60–0.70	0	3	0	13
0.70–0.80	0	5	0	8
Above 0.8	0	7	0	60

The magnitudes of these differences are reflected in the results when different cut-offs are used. See Table 8. For instance, using a weighted average cut-off (0.985), the non-share-price model had a predictive accuracy of 98.48% for the general model and 96.55% for the industry-specific model. The proportional chance probabilities of 97.34% and 97.15% and the significant t-statistics indicate that they both outperformed chance. These are calculated as

$$t = \frac{z - p}{\sqrt{\{z(1 - z)/n\}}}$$

where p is the proportional chance criterion which is a measure of the average expected predictive accuracy based on chance. It is calculated as

$$p = c^2 + (1 - c)^2$$

Table 7. χ^2-statistics for the comparison of the target and non-target distributions†

Model	*Targets*	*Non-Targets*
(a) Share price model versus non-share-price model		
General	0.58	7.82
Specific	1.5	189.7‡
(b) General model versus specific models		
Non-share price	55.3‡	12466.2‡
Share price	151.3‡	11570.6‡

†These were calculated as $\Sigma(n_{m1} - n_{m2})/n_{m2}$ where n_{m1} was the number of general model p-values in class m and n_{m2} was the number of specific model p-values in class m.
‡Significant at the 0.1 level.

where c is the actual proportion of individuals in group A where there are two groups, A and B, and z is the proportion of total individuals correctly classified (Hair *et al.* (1995), pages 202–205). The predictive accuracy was only minutely improved with the addition of the share price variable, i.e. their predictive accuracies were 98.57% and 98.08% respectively (again the proportional chance probabilities and t-statistics indicate that these were better than chance). The maximization-of-returns cut-off performed very similarly where, again, the addition of the share price variable did not improve the predictive accuracy. However, the minimization-of-error cut-off (0.705, 0.714) did have a slightly lower predictive accuracy of 97.64% and 91.08% respectively for the non-share-price model and 97.72% and 90.86% for the share price model. The proportional chance probabilities and t-statistics show that the industry-specific models significantly under-performed compared with chance whereas the general models significantly overperformed. Overall therefore the interesting finding, when comparing these models, is that the addition of the share price variable did not significantly improve their predictive performance. The principal difference in the performance of the various models was between the industry-specific and general models where the former had a lower predictive accuracy to such a degree that, in the case of the minimization-of-error cut-off, it significantly underperformed relative to chance. However, the important finding is that, although there may be variations between the general and industry-specific models and although they may perform well at identifying non-targets given the appropriate cut-off point, *neither the share price model nor the non-share price model* identified a single target by using either of the cut-off points. Although the t-statistics showed that the models predicted better than chance (depending on the cut-off chosen), they overstated the ability of the models to predict usefully because they were particularly poor at identifying targets, which is necessary to generate the excess returns. However, the predictions could not be significantly improved by the choice of cut-off and were not sensitive to it, especially the number of successful target predictions.

It is obvious that the use of none of these models is likely to earn excess returns here. Although this conclusion is consistent with that of Palepu (1986) and Walter (1994), the actual results are much clearer. Here the principal criterion is whether the models perform significantly better than chance. The main criterion adopted by Palepu (1986) and Walter (1994) was whether the investment return earned on the selected part of the hold-out sample was significantly better than a portfolio of securities with similar risk. As Palepu's cut-off classified 625 firms as targets but only 24 were, it is not surprising that his model did not earn excess returns. In Walter's model, which used current cost data, four of the 29 predicted firms were bid for, compared with 10 out of his

Table 8. Predicted and actual targets and non-targets according to cut-off point†

	Predicted			Predicted	
	Target	*Non-target*		*Target*	*Non-target*
(a) Non-share-price model			*(b) Share price model*		
(i) Cut-off 0.985			(i) Cut-off 0.985		
General model			General model		
Target	0	16	Target	0	16
Actual			*Actual*		
Non-target	2	1167	Non-target	1	1168
$p = 0.973,\ w = 0.985,\ t$-statistic $= -13.75$‡			$p = 0.973,\ w = 0.986,\ t$-statistic $= -14.77$‡		
Specific model			Specific model		
Target	0	13	Target	0	13
Actual			*Actual*		
Non-target	5	868	Non-target	4	869
$p = 0.971,\ w = 0.966,\ t$-statistic $= -7.73$‡			$p = 0.971,\ w = 0.981,\ t$-statistic $= -8.75$‡		
(ii) Cut-off 0.705			(ii) Cut-off 0.715		
General model			General model		
Target	0	16	Target	0	16
Actual			*Actual*		
Non-target	12	1157	Non-target	11	1158
$p = 0.973,\ w = 0.976,\ t$-statistic $= -3.62$‡			$p = 0.973,\ w = 0.977,\ t$-statistic $= -4.63$‡		
Specific model			Specific model		
Target	0	13	Target	0	13
Actual			*Actual*		
Non-target	66	807	Non-target	68	805
$p = 0.971,\ w = 0.911,\ t$-statistic $= 54.17$‡			$p = 0.971,\ w = 0.9086,\ t$-statistic $= -56.2$‡		
(iii) Cut-off 0.925			(iii) Cut-off 0.925		
General model			General model		
Target	0	16	Target	0	16
Actual			*Actual*		
Non-target	2	1167	Non-target	2	1167
$p = 0.973,\ w = 0.985,\ t$-statistic $= -13.75$‡			$p = 0.973,\ w = 0.977,\ t$-statistic $= -5.7$		
Specific model			Specific model		
Target	0	13	Target	0	13
Actual			*Actual*		
Non-target	10	863	Non-target	7	866
$p = 0.971,\ w = 0.974,\ t$-statistic $= 2.66$‡			$p = 0.971,\ w = 0.977,\ t$-statistic $= -5.7$‡		

†w, proportion of total correct classifications; p, proportional chance criterion.
‡Significant at the 0.005 level using a one-tail test.

total sample of 91. Although this represents a predictive accuracy greater than chance, the excess returns were marginal because of the below average performance of some of the firms that were incorrectly forecasted and the relatively small population of firms in the hold-out sample because it is only the very largest firms in the USA that report current cost data. None do in the UK.

5. Summarizing remarks and conclusions

This paper has examined whether it is possible to forecast takeover targets by using published accounting data as variables in a multivariate model to beat the market. The study attempted to build on the methodological issues raised by Palepu (1986) concerning the use of multivariate predictive models. The use of industry-relative ratios to avoid some statistical problems with raw accounting ratios was discussed and applied. It was found that a single general model, based on industry-relative ratios, performed rather better than industry-specific models. Nevertheless, takeover targets could not be identified. This contrasts with corporate bankruptcy which is commonly forecasted by means of this type of methodology. The likely explanation is that although bankruptcy prediction is relatively straightforward, as the mergers literature suggests, there are diverse reasons why a merger bid may occur making it very difficult (arguably impossible) for these all to be encapsulated in a single linear equation simply by using accounting data. Thus, it was no surprise when Palepu (1986) argued against the prevailing view held until that time that such an approach was likely to be unsuccessful.

To improve the predictive accuracy, an attempt was made to use anticipatory price changes which were also publicly available. It is well known that these often occur well before the bid announcement and it may be inferred from previous studies of the UK market that they may not be once and for all price changes but gradual, reflecting the changing probability of the merger, thereby facilitating the earning of excess returns. However, prediction was not improved. The likely explanation for this is that most of the total share price change arising from a merger bid occurs in the period immediately before the bid, i.e. during the previous month. Although there may be some share price movement before that, it is not sufficiently large or systematic to trigger a different prediction in a statistical model of the kind used here. Of course, by extending the share price anticipation period to nearer the announcement date may improve the forecast. However, the indication from this research is that the gains would not then be made. In this sense the market cannot be outperformed. Large changes in the volume of dealings in the shares may also be used for the same reason. However, there is no reason to suppose that such an alternative would perform differently or any better in a statistical study of this kind as significant volume changes are likely to result in price changes. Such a conclusion is consistent with the semi-strong form of the ECMH (although the anticipatory price changes may suggest that the market is not efficient in the strong form). This picture is quite different from that of bankruptcy prediction, which is also consistent with the ECMH in the semi-strong form for precisely the same reasons. As corporate bankruptcy may be forecasted—and is—using published accounting data, it is not surprising that it is anticipated by the market at an early stage. In fact, the evidence suggests that the market in the USA comes to that conclusion even before the publication of those forecasts! By contrast, corporate takeovers probably cannot be forecasted by using existing accounting data. They are not recognized by the finance industry as capable of being forecasted by statistical models and none are published. Anticipatory share price movements, if they occur, do so for different reasons. Although it may be thought that these may be capable of exploitation to earn excess returns, this was not possible (or at least not in the way suggested here). Thus, the semi-strong form of the ECMH is upheld in the sense that it was not possible to outperform the market by using publicly available information.

Acknowledgements

The author wishes to thank Mr Gordon Orjaller and Mr Graham Watson for their computational assistance. The research was funded by grants from the National Westminster Bank and Arthur Andersen. He would also like to thank the referee who helped enormously in bringing out both the significant points and certain methodological aspects of the paper. This paper was largely written when the author was Visiting Professor of Finance, Rutgers University, Camden, NJ, USA.

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