Are Corporate Restructuring Events Driven by Common Factors? Implications for Takeover Prediction

RONAN POWELL,* ALFRED YAWSON

School of Banking and Finance, the University of New South Wales, Sydney 2052, Australia

ABSTRACT

The paper shows that variables commonly used in takeover prediction models also help to explain the likelihood of several other restructuring events, including divestitures, bankruptcies and significant employee layoffs. This finding helps to explain the larger misclassification errors in binomial logit takeover prediction models, commonly used in prior research. The results show that modelling takeover prediction models in a binomial setting is likely to lead to misspecification in the parameter estimates and, further, result in erroneous conclusions about the determinants of takeover likelihood. The paper shows that controlling for other restructuring events by using a multinomial framework results in consistently lower misclassification errors in out-of-sample prediction tests, when compared to the benchmark of a typical binomial model.

JEL classification: G14; G33; G34

Keywords: Corporate restructuring; Takeovers; Divestitures; Layoffs; Bankruptcies; Type II error

1. INTRODUCTION

The motivation behind many takeover studies is to test whether commonly cited theories explain takeover likelihood and whether a model can be developed to predict takeovers to provide the basis for a successful investment strategy (e.g., Palepu, 1986; Powell, 2001). A common problem with the models used in a prediction setting is the high misclassification rates with many non-takeover target firms being incorrectly classified as targets (type II error). Palepu (1986), for example, finds that the abnormal returns to the correctly predicted takeover targets in his portfolio are reduced to zero by the large number of non-targets misclassified as targets.

We are not aware of any study that has examined the potential cause of large type II errors in takeover prediction. Instead, the focus of more recent research has centred on developing alternative econometric methods or optimal cut-off probabilities. For example, Espahbodi and Espahbodi (2003) recommend the use of recursive partitioning over traditional discriminant, probit and logit models, even though the technique also suffers from the problem of large type II errors.[1] Powell (2001) attempts to address the problem of large type II errors by deriving an optimal cut-off probability based on maximising the percentage of targets correctly classified in estimation sample portfolios, as opposed to minimising total error (the sum of type I and II errors) as is typically done in prediction studies. Whilst the resultant portfolios have significantly fewer type II errors, they also contain few correctly predicted targets.

This paper examines why predicting takeovers, and possibly other events, is likely to lead to large type II errors. We propose that one explanation for the large type II errors reported in prior takeover prediction studies is that they consider takeovers in isolation of other events. In developing takeover prediction models, researchers usually estimate a binomial model constructed using an estimation sample comprising only of takeover targets and a control sample of firms not taken over. Furthermore, variables selected for inclusion in the estimated models typically represent theories relating to inefficient management, undervaluation, capital structure and growth-resource imbalances; factors that are also likely to be significant in explaining not only takeovers, but other restructuring

[1] Espahbodi and Espahbodi (2003) do not actually test the predictive ability of their models on the population of firms, so it is difficult to interpret their results.

choices. For example, variable proxies for inefficient management (e.g., operating performance or abnormal returns) are also significant in explaining divestitures, bankruptcies and employee layoffs (Kang and Shivdasani, 1997; Lennox, 1999; Denis and Kruse, 2000). The inclusion of other restructuring events in the control sample is likely to lead to misspecification in parameter estimates. Further, from a prediction perspective, this will result in other restructuring events being misclassified as potential takeover targets, resulting in an increase in type II error. The problem is further exacerbated from an investment perspective, since the returns to other restructuring events (e.g., layoffs and bankruptcies) are significantly lower than the average non-restructuring firm, resulting in further dilution of the portfolio returns.[2]

The paper also investigates the contribution of several industry variables which recent research has demonstrated to be significant in explaining corporate restructuring. For example, Mitchell and Mulherin (1996) and Mulherin and Boone (2000) find that an industry shock variable, measured as industry-specific sales, helps to explain the variation in takeover rates across industries. Industry shocks necessitate change to an industry's structure which takeovers are likely to facilitate. In terms of other forms of corporate restructuring activity, Denis and Shome (2005) and Powell and Yawson (2005) also find industry sales shock significant in explaining divestitures (Powell and Yawson, 2005; Denis and Shome, 2005). Powell and Yawson (2005) also find high industry concentration, measured using the Herfindahl index, significant in explaining the variation in divestitures both across industry and over time. They also find that takeovers are more likely to occur in industries characterised with lower sales growth. Lastly, Schlingemann, Stulz and Walkling (2002) construct an industry corporate restructuring liquidity index and find it significant in explaining the incidence of divestitures. The index captures the liquidity of the market for corporate assets, predicting higher restructuring activity when liquidity is high.

Using a sample of 9,537 UK firms from the period 1992 to 2002, we estimate multinomial logit models to investigate whether key financial variables typically used in takeover prediction studies also help to explain the likelihood of divestitures, layoffs and bankruptcies. The results confirm that these

[2] For example, Fayez, Swales, Maris and Scott (1998) and Chen, Mehrotra, Sivakumar and Yu (2001) find a significant negative stock market reaction to the announcement of corporate layoffs. Clark and Weinstein (1983) and Lang and Stulz (1992) provide similar evidence for bankruptcy announcements.

events are motivated by poor performance, lower growth and higher leverage. The inclusion of industry variables to capture growth, broad sales shocks, concentration and the liquidity of industry assets also help explain the corporate restructuring decision. Comparing the multinomial results with a binomial model indicates differences in the determinants of takeover likelihood. The differences can be explained by the inclusion of other restructuring events in the control sample of the binomial model, which has the effect of introducing noise in the model making it difficult to separate takeover targets from the control sample. Examination of the predicted targets for the multinomial logit models indicates that the number of layoffs and bankrupts misclassified as takeover targets is lower than those reported for the binomial model.

The paper makes two important contributions to the takeover literature. First, the results demonstrate that takeover prediction using a typical binomial framework is misspecified in that it fails to control for other restructuring events that share similar characteristics to takeover targets. This gives rise to erroneous conclusions about the determinants of takeover likelihood. Further, the binomial framework leads to inefficient parameter estimates, and, as a consequence, higher misclassification errors in out-of-sample prediction tests. Second, the paper shows that using a multinomial framework results in lower misclassification errors, and, as such, demonstrates one source of the larger type II errors reported in previous studies.

The rest of the paper is organized as follows. Section 2 describes the process in developing a takeover prediction model. Section 3 describes the construction of the sample. Section 4 reports the results of the empirical study and Section 5 concludes the paper with a summary of the main results.

2. TAKEOVER MODEL DEVELOPMENT

(i) Variable selection

We start with a takeover model specification typically used in prior studies. Palepu (1986) developed a takeover prediction model by selecting variables to test six hypotheses: (1) inefficient management; (2) growth-resource imbalance; (3) firm size; (4) price-earnings; (5) asset undervaluation; and (6) industry disturbance. Later papers by Ambrose and Megginson (1992), Powell (2001) and Espahbodi and Espahbodi (2003) follow a similar approach in selecting variables, but add to the Palepu (1986) list by including variable proxies for tangible fixed assets, free cash flow and whether the target had takeover defensive measures in place prior to takeover. Using a step-wise procedure to select variables, Espahbodi and Espahbodi (2003) find only 4 variables significant in explaining takeovers: (1) free cash flow; (2) asset undervaluation; (3) defensive measures (golden parachutes); and (4) state of incorporation. Of the four, however, only free cash flow and defensive measures are significant across different models. Asset undervaluation and state of incorporation are only significant in a discriminant model.

In developing a takeover prediction model we employ firm-level variables to represent inefficient management, growth-resource-imbalance, firm size, asset undervaluation, tangible fixed assets and free cash flow. We supplement the firm-level variables with four industry level variables found to be significant in more recent studies (e.g., Mitchell and Mulherin, 1996; Mitchell and Boone, 2001; Schlingemann, Stulz and Walkling, 2002; Denis and Shome, 2005; and Powell and Yawson, 2005). They include industry-adjusted sales growth (industry shock), industry sales growth, industry sales concentration (Herfindahl index) and industry asset liquidity. We do not use defensive takeover measures as an explanatory variable since they are rarely used in the UK. The takeover hypotheses, variable definitions and empirical support are discussed briefly below and summarised in Table 1.

Inefficient management

Several takeover prediction studies have tested the inefficient management hypothesis, whereby firm performance is used as a proxy for poorly performing management (Palepu, 1986, Morck, Shleifer and Vishny, 1989; Powell, 2001). Firms who underperform some benchmark, e.g., industry average performance, are more likely to be targeted for takeover with the objective of removing target managers. The hypothesis derives from Manne’s (1965) paper, which argues in favour of less stringent anti-trust laws since takeovers help provide a useful check on managerial performance. Later papers by Jensen (1986; 1993) and Morck et al. (1988; 1989) further emphasise the importance of takeovers as a disciplinary check on managerial performance. We use average abnormal returns, measured over the previous 24 months. Abnormal returns are defined as the return on a firm less the return on the market index (Financial Times All-Share Index).

Growth-resource-imbalance

The hypothesis predicts that firms with an imbalance between growth and available resources are likely to be targeted for takeover (Palepu, 1986). More specifically, firms with high growth, but low resources are more likely to be acquired by firms with the opposite imbalance - low growth and high financial resources. Similarly, firms with low growth, but high financial resources are likely to be acquired by firms with the opposite imbalance - high growth and low financial resources. Merging with a firm that has the opposite imbalance should give rise to performance improvements. Growth is measured as average sales growth over the previous 2 years. Financial resources are measured using a liquidity ratio (cash and equivalent to total assets) and leverage (debt to total assets), both measured at the accounting year-end prior.

Insert Table 1 about here

Firm size

Larger firms are more difficult to acquire due to costs associated with absorbing a large target into the acquirer’s organisation structure. Larger targets are also likely to involve higher costs associated with prolonged takeover battles and, furthermore, the pool of potential bidders is likely to be smaller for large targets. Similar to Palepu (1986), size is measured as the natural log of total assets, measured at the accounting year-end prior.

Asset undervaluation

A strong motivation for some takeovers is the acquisition of ‘cheap’ or undervalued assets. Firms whose market value of assets is less than the book value (low market-to-book) represent bargains to acquiring firms who want to acquire specific assets in place, as opposed to new assets, which are likely to be more expensive (Hasbrouck, 1985). While the market-to-book (MTB) ratio is also likely to reflect other factors, including managerial quality, growth options and intangible assets, findings in the takeover literature show that targets tend to have significantly lower MTB ratios compared to acquiring firms. For example, Jovanovic and Rousseau (2002) show that a firm's investment rate increases with a variant of the MTB ratio (Tobin's q) and that high q firms acquire low q firms. The MTB ratio is measured as the market value of equity scaled by net tangible assets, measured at the accounting year-end prior.

Tangible fixed assets

Firms with a high proportion of tangible fixed assets in their asset structure are likely to be targets for takeover due to their higher debt-capacity (Stulz and Johnson, 1985). Physical assets serve as collateral and may be attractive to a potential bidder who requires debt financing to help fund the takeover. Non-core physical assets can also be sold post-takeover to help pay for the takeover, whilst facilitating restructuring to core business activities (Ambrose and Megginson, 1992). Tangible fixed assets are measured as net total fixed assets to total assets, measured at the accounting year-end prior.

Free cash flow

Firms who accumulate large free cash flows are likely to be targets of acquiring firms who can better utilise the excess cash (Jensen, 1986). Firms who accumulate free cash flows are also likely to suffer from agency problems since managers have incentives to waste cash on excessive perquisites and value reducing investments (Lehn and Poulsen, 1989). Agency problems arsing from free cash flow are likely to be exacerbated in firms with poor governance structures and poorly performing managers. Free cash flow is measured as operating cash flow less capital expenditures scaled by total assets.

Industry variables

Mitchell and Mulherin (1996) argue that industries affected by broad shocks (e.g., sudden changes in interest or exchange rates, consumer preferences or product markets) are likely to see an increase in takeovers and possibly other forms of restructuring activity. This is because takeovers facilitate the restructuring of industries more quickly and probably at a lower cost compared to internal restructuring. Since broad shocks could have either a positive or negative affect on restructuring activity, Mitchell and Mulherin (1996) define the shock as the absolute industry-adjusted growth rate in sales. More specifically, sales shock is calculated as the absolute difference between an industry's 5-year growth rate and the average 5-year growth rate across all industries.

The second industry variable included in the model is industry sales performance. While Mitchell and Mulherin (1996) fail to find industry sales growth significant in explaining takeovers at the industry level, using a UK dataset Powell and Yawson (2005) find that takeovers are more likely to occur in low growth industries. This is consistent with many of the consolidation-type takeovers observed in the mid to late 1990s where the reduction in excess capacity in low growth industries was the underlying motive (Powell and Yawson, 2005). The targeting of low growth industries is also consistent with the bankruptcy avoidance hypothesis in that managers of low-growth financially distressed firms would rather be acquired than face certain bankruptcy (Shrieves and Stevens, 1979). A competing argument is the 'empire building' theory which predicts that low growth acquirers are more likely to target high growth firms (industries) to achieve an immediate increase in size and enhance overall value (Myers and Majluf, 1984). Industry sales performance is also likely to be important in explaining divestitures, bankruptcies and layoffs since these events tend to follow poor industry performance (Schlingemann et al., 2002; Denis and Shome, 2005). Industry performance is measured using industry sales growth, calculated using a 5-year growth rate which is consistent with the industry sales shock variable.

The third industry variable added to the model is sales concentration, measured using the Herfindahl index. Industry concentration is likely to have an impact on takeovers and divestitures with low concentration industries more likely to experience takeovers and high concentration industries more likely to experience divestitures. Low concentration facilitates takeovers from a market power perspective since the larger the number of firms within an industry the greater the opportunity to increase market share. High concentration industries are also likely to have more segments or divisions so increasing the likelihood of asset sales. Powell and Yawson (2005) find that divestitures are more likely to occur in highly concentrated industries, but fail to find concentration significant in explaining takeover activity.

The fourth industry variable included in the model is a liquidity index. The index captures the level of liquidity in the market for corporate assets and was found to be a significant factor in explaining divestiture activity in the US (Schlingemann et al., 2002). Clearly, higher asset liquidity indicates a greater number of potential buyers for the divested asset and, potentially, a higher price. While Schlingemann et al. (2002) use a liquidity index to explain divestitures the index may also be useful in explaining takeovers since higher liquidity implies more sellers (targets) and buyers (bidders) resulting in higher takeover activity. Following Schlingemann et al. (2002) we calculate a liquidity index for each industry as the ratio of the market value of all takeover and divestiture activity scaled by the total book value of assets of the industry.[3] Industrial classification is defined by Datastream's level 6 classification system, which is similar to the US four-digit SIC scheme. This construction is a little different from Schlingemann et al. (2002) since they calculate the index for each industry in year *t* excluding divestiture activity in year *t* since including divestitures would only increase the liquidity index. Since we are examining both takeovers and divestitures, excluding both would result in an index with few transactions. To overcome this we measure industry liquidity with a lag (*t-1*) and include both takeovers and divestitures. The index therefore captures the level of liquidity (i.e., the value of total activity) in the year prior and suggests that higher takeover and divestiture activity should follow high liquidity. The intuition is similar to studies of merger waves in that takeover activity clusters over certain time periods (see, e.g., Mitchell and Mulherin, 1996; Mitchell and Boone, 2000; Powell and Yawson, 2005).

(ii) Takeover model specification

The variable proxies for the different takeover hypotheses are modelled using a pooled multinomial logit specification, estimated as follows:

$$P_{ij} = \frac{\exp(\beta'_j X_i)}{\sum \exp(\beta'_j X_i)} \tag{1}$$

[3] We test the sensitivity of this metric by using two alternative specifications: (1) using the market value of assets of the industry in the denominator instead of the book value and; (2) the number of takeovers and divestitures in the industry during the year prior scaled by the total number of firms in the industry.

The model specifies the probability P_{ij} that firm i will belong to outcome j (i.e., be a non-restructuring firm if $j=0$, a takeover target if $j=1$, engages in divestitures if $j=2$, layoffs if $j=3$ and bankruptcies if $j=4$). X_{ij}, is a vector of measured attributes of the firm and β is a vector of unknown parameters to be estimated. In order to identify the parameters of the models, we impose the normalisation $\beta_0=0$. The parameters of the model are estimated using maximum likelihood estimation within STATA (version 9). To benchmark our results with prior takeover prediction studies, we also estimate a binomial model in which $j=1$ for takeover targets and $j=0$ for non-targets. By comparing the significance and sign of the coefficient estimates for takeover targets across multinomial and binomial models, we are able to draw conclusions as to the robustness of takeover hypotheses in a binomial setting. Further, if differences in variable sign and significance occurs across models, this suggests that the binomial model may be misspecified resulting in biased takeover probabilities and higher misclassification errors.

One potential concern with using a pooled regression approach to estimating the models is that in a panel data setting the residuals may be correlated across firms, industries and time leading to biased standard errors. This study uses the population of firms each year from 1992 to 2001 (see Section 3 below) to estimate the models. Firms, in particular non-restructuring firms can be observed repeatedly over time resulting in clustering and potential correlation in the residuals. In a pooled estimation the standard errors are calculated under the assumption that the errors of each firm are uncorrelated, resulting in standard errors that will be biased downwards in a panel data setting. This could result in incorrect inferences being made about the determinants of restructuring activity. Further, research by Mitchell and Mulherin (1996) and Mulherin and Boone (2000) confirm that takeovers and divestitures cluster across industries and over time suggesting both an industry and a time effect. Using simulated and real panel datasets, Petersen (2005) finds that the Rogers (1993) method for correcting standard errors for correlation within a cluster results in unbiased standard errors. In this paper, we report three versions of the estimated models: (1) standard errors corrected for heteroscedasticity; (2) Rogers standard errors corrected for heteroscedasticity and firm clustering; and (3) Rogers standard errors corrected for heteroscedasticity and both industry and time clustering. To estimate 3 we create a unique industry-year variable for each firm using Datastream's level 6 industry classification system.

3. SAMPLE CONSTRUCTION

This paper is based on UK firms listed on the London Stock Exchange for the period 1992-2002 that have financial data stored on Datastream.[4] Table 2 below reports the annual distribution of sample firms. The total number of firm-year observations is 15,684 over 11 years. From this number, 6,147 observations do not meet the data requirements and are excluded from the sample, leaving 9,537 firm-year observations with complete data for further analysis.

We use the Security Data Company's (SDC) Platinum Database to identify the list of successful takeover targets and divestitures. Successful takeovers are defined as deals where the acquiring firm holds less than 50% of the target's stock pre-takeover and achieves more than 50% at the takeover completion date. Divestitures are defined as the sale of a subsidiary with a value of at least $50 million. This value restriction ensures that only significant divestitures are included in the sample and is similar to that used by previous studies (e.g., Mulherin and Boone, 2000; Powell and Yawson, 2005).[5] Consistent with Kang and Shivdasani (1997) and Chen et al. (2001), we define a layoff as a significant reduction in the number of employees. To be recorded as a layoff firm, the firm should have a two-year average reduction in labour force of at least 20%.[6] The incidence of layoffs in our sample is correlated with divestitures since we find 16 firms that divested and laid off workers in the same year. We assume that the layoffs were precipitated by the sale of subsidiaries, so we record them for divestitures only. Finally, the list of bankrupt firms is identified from the annual Stock Exchange Yearbooks.

Insert Table 2 about here

[4]A firm is included in the initial sample for each year if it reported total assets (DS#392).

[5] In identifying divestitures, multiple events for a given firm are consolidated. Thus, if a firm divested two or more times in the same year, only one observation is recorded. This approach reduces the number of divestitures but since the point of interest is whether a sample firm divested or not, it should not have any adverse effect on the results.

[6] Kang and Shivdasani (1997) show that on average, layoffs constitute a 20.9% reduction of the workforce in Japanese firms, but it could be over 30% for some firms. By using at least a 20% 2-year average reduction in the labour force, we are able to capture all significant layoffs.

The lists of takeovers, divestitures, layoffs and bankrupts are then cross-checked with the population of firms from 1 January 1992 through 31 December 2002 in order to identify the restructuring choices affecting them. For example, if a firm existed in 1992 and meets all the data requirements, it is followed through to 2002. If the firm did not go through any restructuring event we observe it for each of the 11 years. If, for example, this firm divested in 1995, we record this restructuring activity for 1995 and follow the firm for the remaining years. If the firm disappears in 1998, for example, through a takeover or bankruptcy, it drops from the sample for the rest of the period. This procedure is followed for each of the firms in the sample. New firms coming onto the Stock Exchange are included in the sample for as long as they continued to exist and meet the data requirements.

From the population of firms each year, we identify a total of 482 successful takeovers and 360 divestitures. We also identify 631 firms that laid off workers over the 11-year period and 82 firms which filed for bankruptcy. The total number of firm-year observations for firms that did not engage in any form of restructuring over the period 1992 to 2002 is 8,048.

4. RESULTS

Table 3 (Panel A) reports median values for the variables used in the estimated models. Differences in medians are also reported for restructuring and non-restructuring firms in Panel A and Panel B reports correlation coefficients. The results of the estimated logit models are reported in Section 4(ii) and misclassification errors reported in Section 4(iii).

(i) Descriptive statistics

Table 3 (Panel A) reports median values for each explanatory variable for restructuring and non-restructuring samples.[7] The statistics show that restructuring firms share several common financial characteristics. For example, restructuring firms have lower stock market performance (AAR), lower MTB ratios (excluding divestitures), lower growth (GRO) and higher leverage (LEV). Industry

[7] Several outliers are identified in the sample. We deal with these observations by winsorizing them to ±3 standard deviations from the mean.

variables are also significant, in particular, industry growth (IGRO) and broad industry shocks (ISHK). The results are particularly strong for takeovers, layoffs and bankruptcies, each reporting significant differences.

Correlation coefficients are also reported in Panel B of Table 3. Consistent with the descriptive statistics, they indicate a negative relationship between all forms of corporate restructuring and stock market performance (AAR) and growth (GRO) and a positive relationship with leverage (LEV). MTB is only negatively correlated with takeovers and layoffs. Consistent with Powell and Yawson (2005) broad industry shocks (ISHK) are positively (negatively) correlated with takeovers (divestitures). Further, takeovers, bankruptcies and layoffs appear to be more prevalent in low growth industries (IGRO). Contrary to expectations, industry concentration is positively correlated with takeovers and bankruptcies. Consistent with Schlingemann et al. (2002) industry liquidity is positively correlated with divestitures.

Insert Table 3 about here

(ii) Logit results

Table 4 reports the results of the estimated binomial and multinomial logit models. Powell (1997) shows that takeover target characteristics are time variant. To test the robustness of our results over time, we estimate models using the whole time period, 1992-2001 (Pool 1) and two sub-periods, 1992-1996 (Pool 2) and 1997-2001 (Pool 3). Further, as discussed in Section 2(ii), we also test whether the standard errors are biased by reporting Rogers standard errors corrected for heteroscedasticity and firm, industry-time clustering (see the Appendix).

Insert Table 4 about here

Panel A in Table 4 reports the results for the whole time period. Consistent with the descriptive statistics reported in Table 3, restructuring firms have lower stock market performance (AAR), growth (GRO) and higher leverage (LEV), although the results are not always statistically significant. For takeovers, lower stock market performance (AAR) and lower growth (GRO) is consistent with Palepu (1986). There are also some notable differences between restructuring types. For example, takeover and divestiture likelihood increases with firm size (SIZE), whereas layoffs are more likely to affect smaller firms. While larger firms divesting is consistent with expectations, both Palepu (1986) and Powell (1997) find that smaller firms are more likely to be targeted for takeover.[8] Broad industry shocks (ISHK) have a significant impact on the decision to divest and layoff employees, whereas lower industry growth (IGRO) significantly increases the likelihood of takeovers and bankruptcies. Interestingly, divestitures are more likely to occur in high growth industries. Higher industry concentration (ICON) increases the likelihood of takeovers and bankruptcies whereas layoffs are more prevalent in industries with lower concentration. While we expected divestitures to increase with industry concentration, the results do not bear this out. Consistent with Schlingemann et al. (2002), industry liquidity (ILIQ) significantly increases the likelihood of divestitures, but again, surprisingly, has no impact on takeover likelihood.

The results from the sub-periods reported in Panel B and C (Pools 2 and 3) of Table 4 confirm some variation in takeover and other restructuring characteristics over time. For example, the results for the binomial model suggest that in addition to industry characteristics (IGRO and ICON) as significant determinants for the 1992-1996 period (Panel B) asset tangibility (ITNG) is also important for the 1997-2001 period (Panel C). The results for the multinomial logit models suggest that some of the insignificance in characteristics for the binomial model can be explained by model misspecification. Since the binomial model does not control for other restructuring events, noise is introduced making it difficult to separate the characteristics of takeover targets from other restructuring events. The results from the multinomial logit model suggest that firm size (SIZE) also explains takeover likelihood during the 1992 to 1996 time period. Larger differences occur across models for the 1997 to 2001 time period (Panel C), with firm growth (GRO), average stock market performance (AAR) and firm size (SIZE) showing significance for the multinomial model, but insignificance for the binomial model. Note also that industry concentration is insignificant for the multinomial model. The results indicate differences in takeover characteristics between the binomial and multinomial logit models. These differences not only lead to incorrect inferences about the

[8] One possible explanation for the difference is that both Palepu (1986) and Powell (1997) use a choice-based sampling scheme in which target firms are matched with a random sample of non-targets. The non-target (non-restructuring) sample used in this study consists of the total population of non-target (non-restructuring) firms so includes significantly more (smaller) firms.

characteristics of takeover likelihood, but are likely to result in larger misclassification errors in prediction tests. This issue is examined in Section 4(iii). One final observation from Table 4 is that the results strongly suggest that the determinants of other restructuring choices, in particular, divestitures and layoffs vary over time.

The Appendix reports the results for the models with standard errors corrected for clustering across firms and industry-time, respectively. The panel dataset has 1,412 clusters at the firm level and 747 industry-time clusters so controlling for correlation across firms, industries and time is important to ensure unbiased standard errors. The standard errors reported in Panel A and B for the pooled sample are, on average, higher than those reported in Panel A of Table 4 suggesting firm and industry-time effects.[9] However, with a few exceptions, and specific only to the multinomial model, the results are remarkably robust and consistent with those reported in Table 4. The exceptions include industry concentration (ICON) for takeovers, which is no longer statistically significant and stock market performance (AAR) and firm size (SIZE) for layoffs which are significant when we control for industry-time effects (Panel B), but insignificant when we control for firm effects (Panel A).[10]

The primary concern from a takeover prediction perspective is the overlap in the characteristics of takeover targets with other forms of restructuring, which may result in higher misclassification errors. The finding that poor stock market performance (AAR) and lower growth (GRO) is common across restructuring types is not unexpected. For example, Denis and Kruse (2000) and Kang and Shivdasani (1997) show that restructuring in the form of asset restructuring, divestitures and employee layoffs is more common amongst poorly performing firms. Furthermore, high leverage (LEV) is an important factor in determining the likelihood of takeovers, bankruptcies, divestitures and layoffs. Many takeovers are the result of firms being rescued from certain bankruptcy, as a result of high debt and poor performance (Pastena and Ruland, 1986; Clark and Ofek, 1994). There is overwhelming evidence that firms that go bankrupt have high debt in their capital structure (e.g., Lennox, 1999; Platt, Platt and Pedersen, 1994). Divesting firms are also likely to have high debt,

---

[9] For example, the mean standard error for the binomial model reported in Table 4 (Panel A) is 0.22. This increases to 0.25 when corrected for firm effects (Appendix, Panel A). Similar increases are evident in the multinomial models.

[10] Unreported results for the sub-periods are also consistent with those reported in Table 4 (Panel B and C).

which is a strong factor in motivating the divestiture of a subsidiary (Lang, Poulsen and Stulz, 1995). Moreover, to the extent that layoff decisions are taken to cut costs, it is reasonable to expect layoff firms to have higher debt.

(iii) Misclassification errors

The results so far indicate that corporate restructuring events are in part attributed to common underlying factors, in particular, prior stock market performance (AAR), growth (GRO) and leverage (LEV). To test whether this results in higher misclassification errors, we examine portfolios of predicted takeover targets, paying particular attention to the other restructuring events misclassified as takeover targets (type II errors). Since the results in Table 5 indicate some sensitivity to time effects, we calculate out-of-sample classifications using 4-year rolling models. More specifically, starting with the 1992 to 1995 period, we re-estimate models for each subsequent year, i.e., 1993 to 1996, 1994 to 1997 and so forth to 1998 to 2001. This procedure provides us with 12 models (6 binomial and 6 multinomial) and 14 out-of-sample prediction tests. Out-of-sample prediction tests are performed on the population of firms in the year following the pooled estimation samples, i.e., 1996 for the 1992 to 1995 estimation sample, and so forth to 2002 for the 1998 to 2001 estimation sample. Following Palepu (1986), we first estimate appropriate cut-off probabilities for both the multinomial and binomial models using the estimated coefficients from the 12 models. The selected cut-off probability for each model is selected as that which minimises the total error rate of the model. The total error rate is the sum of type I (targets misclassified as non-targets) and type II (non-targets misclassified as targets) errors.

Insert Table 5 about here

Table 5 reports the prediction results for each out-of-sample test (Panel A) and a summary of the prediction results across all periods (Panel B). The results show that the percentage of other restructuring events misclassified as takeover targets (type II error) is consistently higher for the binomial models compared to the multinomial models. Furthermore, the multinomial models are on average better at identifying targets in the population, predicting on average 68.19% correctly, compared to 62.34% for the binomial models. In terms of other restructuring events, the binomial models misclassify a larger percentage of bankruptcies (62.71%) and layoffs (63.39%) as targets compared to the multinomial model (38.98% and 34.82%, respectively).

5. SUMMARY AND CONCLUSIONS

The paper provides evidence that takeovers, divestitures, layoffs and bankruptcies are driven by poorer firm performance, lower firm growth and higher leverage. The inclusion of industry variables to capture growth, broad sales shocks, concentration and the liquidity of industry assets also help explain the corporate restructuring decision. Comparing the multinomial results with a binomial model indicates differences in the determinants of takeover likelihood. The differences can be explained by the inclusion of other restructuring events in the control sample of the binomial model, which has the effect of introducing noise in the model making it difficult to separate takeover targets from the control sample. This gives rise to erroneous conclusions about the determinants of takeover likelihood.

The overlap in some key financial variables across restructuring events also results in higher misclassification errors in a takeover prediction setting. Controlling for other restructuring events by using a multinomial framework gives rise to fewer misclassification errors in out-of-sample prediction tests. The results from the paper suggest that predicting takeovers (and possibly other events) in isolation of other restructuring events is likely to result in higher misclassification errors. The use of a multinomial model goes some way to reducing misclassification errors, although does not eliminate the problem.

Appendix

Variables	Takeover	Std. error	Takeover	Std. error	Bankrupt	Std. error	Divest	Std .error	Layoff	Std.error
Panel A: Pooled models (1992-2001) corrected for firm clustering (clusters=1,412)										
	Binomial model		*Multinomial model*							
GRO	0.0335	0.0715	-0.0691	0.2073	-0.2653	0.5821	-1.2227**	0.5700	-8.7228***	1.1022
LIQ	-0.4080	0.5541	-0.4507	0.6086	0.4810	1.1028	-1.9952*	1.1732	0.5540	0.6426
LEV	0.0258	0.1245	0.2405	0.1868	0.7312**	0.3658	0.6007**	0.2915	0.1932	0.2108
MTB	-0.0180	0.0197	-0.0169	0.0212	0.0065	0.0272	0.0272	0.0193	0.0135	0.0138
AAR	-0.4422**	0.2117	-0.8679***	0.2378	-2.0759***	0.6666	-0.8629**	0.4244	-0.3817	0.2624
SIZE	0.0597**	0.0302	0.2166***	0.0454	0.1023	0.0828	1.2443***	0.0856	-0.0780	0.0620
TNG	0.5483	0.4821	0.4523	0.5469	-0.0676	0.8277	-0.0837	0.8062	-0.7794	0.5897
FCF	0.3952	0.3328	0.0961	0.4772	-0.0199	0.6856	-0.4961	1.1463	0.2158	0.5119
ISHK	0.0528	0.1341	0.0147	0.1395	0.1741	0.2873	-0.5224*	0.2800	-0.3123**	0.1588
IGRO	-0.4166***	0.1037	-0.4083***	0.1073	-0.3689*	0.2300	0.3434*	0.2113	-0.1056	0.1254
ICON	0.8024***	0.3097	0.4433	0.3526	1.1442*	0.6353	-0.5803	0.7036	-0.6597*	0.4120
ILIQ	-0.1073	0.2224	-0.0091	0.2370	0.3322	0.4311	0.8261**	0.3517	0.0320	0.2631
Constant	-4.0267***	0.6032	-4.9702***	0.7736	-5.5181***	1.3853	-17.5777***	1.2887	-0.2943	0.9543
Pseudo-R^2	0.02					0.27				
LR	49.31***					465.02***				
Panel B: Pooled models (1992-2001) corrected for industry and time clustering (clusters=747)										
GRO	0.0335	0.0705	-0.0691	0.2064	-0.2653	0.5843	-1.2227***	0.4717	-8.7228***	0.9672
LIQ	-0.4080	0.4919	-0.4507	0.5080	0.4810	1.2105	-1.9952**	0.8877	0.5540	0.4728
LEV	0.0258	0.1107	0.2405	0.1504	0.7312**	0.3478	0.6007***	0.2142	0.1932	0.1704
MTB	-0.0180	0.0187	-0.0169	0.0196	0.0065	0.0265	0.0272	0.0171	0.0135	0.0119
AAR	-0.4422**	0.2154	-0.8679***	0.2394	-2.0759***	0.6917	-0.8629*	0.4559	-0.3817*	0.2377
SIZE	0.0597**	0.0262	0.2166***	0.0368	0.1023	0.0769	1.2443***	0.0549	-0.0780*	0.0421
TNG	0.5483	0.4265	0.4523	0.4660	-0.0676	0.7440	-0.0837	0.4805	-0.7794**	0.3769
FCF	0.3952	0.3318	0.0961	0.4767	-0.0199	0.6904	-0.4961	0.9758	0.2158	0.4805
ISHK	0.0528	0.1308	0.0147	0.1274	0.1741	0.2877	-0.5224**	0.2482	-0.3123**	0.1318
IGRO	-0.4166***	0.0988	-0.4083***	0.0983	-0.3689*	0.2303	0.3434*	0.1927	-0.1056	0.1006
ICON	0.8024***	0.2893	0.4433	0.2976	1.1442*	0.6407	-0.5803	0.4647	-0.6597**	0.2977
ILIQ	-0.1073	0.2381	-0.0091	0.2315	0.3322	0.4192	0.8261***	0.2948	0.0320	0.2270
Constant	-4.0267***	0.5471	-4.9702***	0.6662	-5.5181***	1.2933	-17.5777***	0.8348	-0.2943	0.6163
Pseudo-R^2	0.02					0.27				
LR	51.93***					956.48***				

The table reports the coefficient estimates of binomial and multinomial logit models and corrected standard errors for clustering. The variable definitions are described in Table 1. The standard errors are corrected using the Rogers (1993) method for clustering by firm (Panel A) and industry-time (Panel B) for the whole sample period (1992-2001). The likelihood ratio (LR) is chi-square distributed and tests the null hypothesis that the vector of coefficients is equal to zero. The Pseudo-R^2, calculated as 1-(log likelihood at convergence/log likelihood at zero) is an indication of explanatory power. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively using a two tailed test.

REFERENCES

Ambrose, B. and W. Megginson (1992), ‘The Role of Asset Structure, Ownership Structure, and Takeover Defences in Determining Acquisition Likelihood’, *Journal of Financial and Quantitative Analysis*, Vol. 27, pp. 575-89.

Chen, P., Mehrotra, V., Sivakumar, R., and W. Yu (2001), ‘Layoffs, Shareholders’ Wealth and Corporate Performance’, *Journal of Empirical Finance,* Vol. 8, pp. 171-199.

Clark, A. and M. Weinstein (1983), ‘The behavior of the common stock of bankrupt firms’, *Journal of Finance*, Vol. 38, pp. 489-504.

Clark, K. and E. Ofek (1994), ‘Mergers as a Means of Restructuring Distressed Firms: An Empirical Investigation’, *Journal of Financial and Quantitative Analysis*, Vol. 29, pp. 541-565.

Denis, D. and T. Kruse (2000), ‘Managerial Discipline and Corporate Restructuring following Performance Declines’, *Journal of Financial Economics*, Vol. 55, pp. 391-424.

Denis, D. and D. Shome (2005), ‘An empirical investigation of corporate downsizing’, *Journal of Corporate Finance,* Vol. 11, pp.427-448.

Espahbodi, H and P. Espahbodi (2003), ‘Binary Choice Models and Corporate Takeover’ *Journal of Banking and Finance,* Vol. 27, pp. 549-74.

Fayez A., Swales, G., Maris, B., and J. Scott (1998), ‘Market Reactions, Characteristics, and the Effectiveness of Corporate Layoffs’, *Journal of Business Finance and Accounting*, Vol. 25, pp. 329-351.

Hasbrouk, J. (1985), ‘The Characteristics of Takeover Targets: Q and Other Measures’, *Journal of Banking and Finance,* Vol. 9, pp. 351-62.

Jensen, M. (1986), ‘Agency Costs of Free Cash Flow, Corporate Finance and Takeovers’ *American Economic Review*, Vol. 76, pp. 323-29.

Jensen, M. (1993), ‘The Modern Industrial Revolution and the Challenge to the Internal Control Systems’ *Journal of Finance*, Vol. 48, pp. 831-80.

Kang, J. and A. Shivdasani (1997), ‘Corporate Restructuring during Performance Declines in Japan’, *Journal of Financial Economics,* Vol. 46, pp. 29-65.

Lang, L. and R. Stulz (1992), ‘Contagion and Competitive Intra-industry Effects of Bankruptcy Announcements: An Empirical Analysis’ *Journal of Financial Economics,* Vol. 32, pp. 45-60.

Lang, L., A. Poulsen and R. Stulz (1995), ‘Asset Sales, Firm Performance, and the Agency Costs of Managerial Discretion’, *Journal of Financial Economics*, Vol. 37, pp. 3-37.

Lehn, K. and A. Poulsen (1989), ‘Free Cash Flow and Stockholder Gains in Going Private Transactions’, *Journal of Finance*, Vol. 44, pp. 771-87.

Lennox, C. (1999), ‘Identifying Failing Companies: A Re-Evaluation of the Logit, Probit and DA Approaches’, *Journal of Economics and Business*, Vol. 51, 347-64.

Manne, H. (1965), ‘Mergers and Market for Corporate Control’, *Journal of Political Economy*, Vol. 3, pp. 110-20.

Mitchell, M. and Mulherin J. (1996), ‘The Impact of Industry Shocks on Takeover and Restructuring Activity’, *Journal of Financial Economics,* Vol. 41, pp.193-229.

Morck, R., A. Shleifer and R. Vishny (1988), ‘Characteristics of Targets of Hostile and Friendly takeovers, in: Alan J. Auerbach, ed., Corporate Takeovers: Causes and Consequences (National Bureau of Economic Research, Chicago, IL), pp. 101-29.

Morck, R., A. Shleifer and R. Vishny (1989), ‘Alternative Mechanisms for Corporate Control’, *American Economic Review*, Vol. 79, pp. 842-52.

Mulherin J. and A. Boone (2000), ‘Comparing Acquisitions and Divestitures’, *Journal of Corporate Finance*, Vol. 6, pp. 117-139.

Myers, S. and N. S. Majluf (1984), ‘Corporate Financing and Investment Decisions when Firms have Information that Investors do not have’, *Journal of Financial Economics*, Vol. 13, pp. 187-221.

Palepu, K. (1986), ‘Predicting Takeover Targets: A Methodological and Empirical Analysis’, *Journal of Accounting and Economics*, Vol 8 pp. 3-35.

Pastena, V. and Ruland, W. (1986), ‘The Merger/Bankruptcy Alternative’, *Accounting Review*, Vol. 61, pp. 288-301.

Petersen, M. (2005), 'Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches', *Kellogg School of Management Working Paper*.

Platt, H., M. Platt and J. Pedersen (1994), 'Bankruptcy Discrimination with Real Variables' *Journal of Business Finance and Accounting*, Vol. 21, pp. 491-510.

Powell, R. (1997), 'Modelling Takeover Likelihood', *Journal of Business Finance and Accounting,* Vol. 24, pp. 1009-30.

Powell, R. (2001), 'Takeover Predictions and Portfolio Performance: A Note', *Journal of Business Finance and Accounting*, Vol. 28, pp. 993-1011.

Powell, R. and A. Yawson (2005), 'Industry Aspects of Takeovers and Divestitures: Evidence from the UK', *Journal of Banking and Finance*, Vol. 29, pp.3015-3040.

Rogers, W. (1993), 'Regression Standard Errors in Clustered Samples', *Stata Technical Bulletin*, Vol. 13, pp. 19-23.

Schlingemann, F., R. Stulz and R. Walkling (2002), 'Divestitures and the Liquidity of the Market for Corporate Assets', *Journal of Financial Economics,* Vol. 64, pp.117-144.

Shrieves, M. and D Stevens (1979), 'Bankruptcy Avoidance as a Motive for Merger', *Journal of Financial and Quantitative Analysis*, Vol. 14, pp.504-515.

Stulz, R. and H. Johnson (1985), 'An Analysis of Secured Debt' *Journal of Financial Economics*, Vol. 14, pp. 501-521.

.

Table 1
Variable definitions and expected signs

Variables	*Empirical support*	*Definition*	*Datastream codes*	*Expected sign*
Growth (GRO)	Palepu (1986)	Sales growth	102	+/-
Liquidity (LIQ)	Powell (1997)	Total cash and equivalent/total assets	375/(389+391)	+/-
Leverage (LEV)	Palepu (1986); Powell (1997)	Total debt/total share capital	321+306/322	+/-
Market to book (MTB)	Hasbrouck (1985); Espahbodi & Espahbodi (2003)	Market value equity/net tangible assets	MV/(305-344)	-
Average abnormal return (AAR)	Palepu (1986)	$\frac{1}{2}\sum_{i=1}^{24}(R_{it})-(R_{mt})$	(RI)	-
Size (SIZE)	Palepu (1986)	Log of total assets	(389+391)	-
Tangible fixed assets (TNG)	Ambrose and Megginson (1992)	Net total fixed assets/total assets	339/(389+391))	+
Free cash flow (FCF)	Jensen (1986); Lehn & Poulson (1989); Powell (1997); Espahbodi & Espahbodi (2003)	Free cash flow/total assets	1118/(389+391)	+
Industry shock (ISHK)	Mitchell & Mulherin (1996); Mulherin & Boone (2000); Denis and Shome (2005); Powell & Yawson (2005)	Industry 5-year sales growth - mean industry 5-year sales growth	102	+
Industry growth (IGRO)	Denis & Shome (2005); Powell & Yawson (2005)	Industry 5-year sales growth	102	+/-
Industry concentration (ICON)	Powell & Yawson (2005)	Herfindahl index	102	-
Industry liquidity (ILIQ)	Schlingemann et al., (2002)	Market value of takeover & divestitures transactions/book value of assets for the industry	MV/(389+391)	+

The table reports the variable proxies used for the main hypotheses and their expected signs. A positive sign indicates that the variable increases the likelihood of takeover and a negative sign implies the opposite.

Table 2
Annual distribution of sample

Year	*Takeovers*	*Bankruptcies*	*Divestitures*	*Layoffs*	*Non-restructuring*	*Multiple events*	*Total sample*
1992	16	9	20	128	743	8	908
1993	21	4	26	70	789	5	905
1994	13	6	21	54	800	2	892
1995	39	4	29	43	772	5	882
1996	26	3	25	28	792	1	873
1997	41	6	41	26	796	3	907
1998	57	8	41	39	763	2	906
1999	89	11	39	53	719	12	899
2000	63	18	41	56	661	8	831
2001	28	8	34	67	648	1	784
2002	89	5	43	67	565	19	750
Total	482	82	360	631	8,048	66	9,537

The table reports the annual distribution of sample firms. A takeover occurs when the acquiring firm accumulates a controlling interest in the target firm. A divestiture is defined as the sale of a subsidiary by the parent company to a third party (otherwise known as a sell-off) or to management (otherwise known as a management buyout) with a value of at least $50 million. Layoff refers to firms with at least a 20% average reduction in the labour force over two years. A firm is deemed to have gone bankrupt when it enters into receivership, administration or liquidation as defined by the Insolvency Act, 1986. Multiple events records firms that engaged in two or more different restructuring activities in the same year.

Table 3

Summary statistics and correlation coefficients for restructuring firms

Panel A: Summary statistics

Variables	*Takeovers*	*Bankruptcies*	*Divestitures*	*Layoffs*	*Non-restructuring*	*Z Test for Difference*			
	(1)	(2)	(3)	(4)	(5)	(1)-(5)	(2)-(5)	(3)-(5)	(4)-(5)
GRO	0.0626	0.0013	0.0581	-0.2070	0.1009	-0.0383	-0.0996***	-0.0428	-0.3079***
LIQ	0.0600	0.0550	0.0700	0.0700	0.0700	-0.0100*	-0.0150	0.0000	0.0000
LEV	0.1550	0.1675	0.2825	0.1175	0.1100	0.0450***	0.0575*	0.1725***	0.0075
MTB	1.3200	1.4150	1.8050	1.0750	1.7100	-0.3900***	-0.2950**	0.0950***	-0.6350***
AAR	-0.0573	-0.1327	-0.0226	-0.1204	-0.0055	-0.0518***	-0.1271***	-0.0171	-0.1149***
SIZE	11.0777	10.7618	14.2320	9.9364	10.6438	0.4340***	0.1181	3.5882***	-0.7074***
TNG	1.0000	1.0000	0.9993	1.0000	1.0000	0.0000	0.0000	-0.0007***	0.0000
FCF	0.0153	0.0057	0.0141	0.0149	0.0093	0.0060	-0.0035	0.0049	0.0056
ISHK	0.2610	0.3177	0.1776	0.2387	0.2278	0.0332**	0.0899***	-0.0502***	0.0109
IGRO	0.1339	0.0663	0.2007	0.1446	0.2206	-0.0867***	-0.1543***	-0.0199	-0.0760***
ICON	0.1882	0.2042	0.1884	0.1568	0.1664	0.0218***	0.0379*	0.0220	-0.0095
ILIQ	0.0955	0.0866	0.2133	0.0646	0.0630	0.0325	0.0236	0.1503***	0.0016

Table 3 (continued)

Panel B: Correlation coefficients

	TAK	*BANK*	*DIV*	*LAY*	*GRO*	*LIQ*	*LEV*	*MTB*	*AAR*	*SIZE*	*TNG*	*FCF*	*ISHK*	*IGRO*	*ICON*
TAK	1														
BANK	-0.045	1													
DIV	-0.012	-0.015	1												
LAY	-0.037	0.066	-0.106	1											
GRO	-0.007	-0.017	-0.026	-0.191	1										
LIQ	-0.034	-0.012	-0.051	0.038	0.114	1									
LEV	0.029	0.063	0.112	0.035	-0.014	-0.154	1								
MTB	-0.037	0.000	0.007	-0.033	0.157	0.194	0.031	1							
AAR	-0.045	-0.075	-0.012	-0.171	0.137	0.147	-0.077	0.139	1						
SIZE	0.067	-0.006	0.479	-0.164	-0.018	-0.121	0.137	-0.078	0.059	1					
TNG	0.021	0.008	-0.061	0.012	-0.100	0.031	-0.029	-0.094	-0.074	-0.102	1				
FCF	0.017	0.004	0.030	-0.018	-0.212	-0.118	0.033	-0.075	-0.005	0.117	0.014	1			
ISHK	0.024	0.032	-0.064	0.001	0.017	0.051	0.019	0.050	-0.025	-0.077	-0.011	-0.049	1		
IGRO	-0.078	-0.049	0.002	-0.046	0.084	0.117	-0.047	0.121	0.082	-0.035	-0.094	-0.113	-0.013	1	
ICON	0.034	0.037	0.013	-0.031	0.018	-0.030	0.037	0.001	-0.034	0.045	0.003	-0.045	0.217	0.052	1
ILIQ	0.000	0.013	0.095	-0.016	0.028	-0.017	0.040	-0.001	0.018	0.093	-0.031	-0.066	-0.052	-0.062	0.096

The table reports medians, differences in medians (Panel A) and correlation coefficients (Panel B) for restructuring firms and non-restructuring firms. See Table 1 for the definitions of variables. ***, **, * indicates significance at the 1%, 5% and 10% level (two-tailed), respectively using a Mann-Whitney U-Test.

Table 4

Pooled binomial and multinomial logit models

Panel A: Pooled models (1992-2001)										
	Binomial model		*Multinomial model*							
Variables	*Takeover*	*Std. error*	*Takeover*	*Std. error*	*Bankrupt*	*Std. error*	*Divest*	*Std. error*	*Layoff*	*Std. error*
GRO	0.0335	0.0697	-0.0691	0.2055	-0.2653	0.5807	-1.2227***	0.4707	-8.7228***	0.9727
LIQ	-0.4080	0.4989	-0.4507	0.5071	0.4810	1.0609	-1.9952**	0.8301	0.5540	0.4531
LEV	0.0258	0.1084	0.2405	0.1520	0.7312**	0.3541	0.6007***	0.2385	0.1932	0.1749
MTB	-0.0180	0.0190	-0.0169	0.0202	0.0065	0.0268	0.0272	0.0189	0.0135	0.0127
AAR	-0.4422**	0.2120	-0.8679***	0.2402	-2.0759***	0.6674	-0.8629**	0.4509	-0.3817	0.2617
SIZE	0.0597***	0.0234	0.2166***	0.0336	0.1023	0.0776	1.2443***	0.0548	-0.0780*	0.0438
TNG	0.5483	0.4311	0.4523	0.4675	-0.0676	0.7838	-0.0837	0.4917	-0.7794**	0.3878
FCF	0.3952	0.3188	0.0961	0.4632	-0.0199	0.6832	-0.4961	1.0210	0.2158	0.4784
ISHK	0.0528	0.1279	0.0147	0.1275	0.1741	0.2829	-0.5224**	0.2400	-0.3123**	0.1420
IGRO	-0.4166***	0.0982	-0.4083***	0.0991	-0.3689*	0.2273	0.3434*	0.1840	-0.1056	0.1060
ICON	0.8024***	0.2550	0.4433*	0.2656	1.1442**	0.5964	-0.5803	0.4789	-0.6597**	0.2990
ILIQ	-0.1073	0.2126	-0.0091	0.2156	0.3322	0.4237	0.8261***	0.2950	0.0320	0.2272
Constant	-4.0267***	0.5191	-4.9702***	0.6259	-5.5181	1.3188	-17.5777***	0.8548	-0.2943	0.6620
Pseudo-R^2	0.02					0.27				
LR	60.69***					866.46***				
Panel B: Pooled sub-sample (1992-1996) models										
GRO	0.0675	0.0644	0.1130	0.0889	-1.8199	1.7014	-0.4800	0.6283	-7.4005***	1.4745
LIQ	0.4185	0.9806	-0.3974	0.9736	-1.5305	2.4576	-4.0494***	1.3151	0.7473	0.6345
LEV	0.0453	0.2018	0.4203	0.3004	0.0327	1.7477	0.7826*	0.4880	0.6420***	0.2358
MTB	-0.0768	0.0781	-0.0614	0.0748	0.0561*	0.0330	0.1205***	0.0228	0.0169	0.0204
AAR	-0.0723	0.4089	-0.6312	0.4396	-2.4306**	1.1508	-0.9208	0.6860	-0.6153*	0.3550
SIZE	0.0523	0.0458	0.2400***	0.0646	0.0946	0.1416	1.3187***	0.0997	-0.0713	0.0638
TNG	-0.4045	0.7670	-0.7942	0.7619	0.1319	1.2921	-0.4578	0.8553	-0.6963	0.5380
FCF	-0.1717	0.5113	-0.2568	0.7230	-0.8897	0.7659	-0.2231	1.5844	0.6263	0.4800
ISHK	0.2465	0.2370	0.0386	0.2166	0.1628	0.4277	-1.1494***	0.4518	-0.7442***	0.2889
IGRO	-0.4359**	0.1780	-0.4731***	0.1726	-0.4607	0.4001	0.2519	0.3961	-0.3936*	0.2250
ICON	1.1186**	0.4566	0.8242*	0.4710	0.3113	1.0439	0.3320	0.7525	-0.6347	0.4496
ILIQ	-0.1528	0.4479	0.0888	0.4521	0.0760	0.9571	1.3737***	0.4745	-0.0862	0.3263
Constant	-3.5800***	0.9236	-4.4632***	1.0710	-5.2709**	2.2779	-18.5111***	1.5512	-0.1495	0.9801
Pseudo-R^2	0.02					28.38				
LR	16.36					372.15				

Table 4 (continued)

Panel B: Pooled sub-sample models (1997-2001)

	Binomial model		*Multinomial model*							
Variables	*Takeover*	*Std. error*	*Takeover*	*Std. error*	*Bankrupt*	*Std. error*	*Divest*	*Std. error*	*Layoff*	*Std. error*
GRO	-0.2003	0.1302	-0.6170**	0.2838	-0.0796	0.3298	-1.5781***	0.4810	-10.3605***	1.2252
LIQ	-0.8565	0.5817	-0.5705	0.6193	1.4653	1.1489	-1.1099	1.0985	0.2701	0.6569
LEV	0.0455	0.1290	0.1510	0.1805	0.9126***	0.3012	0.6100**	0.2735	-0.3170	0.2169
MTB	-0.0168	0.0181	-0.0149	0.0193	-0.0285	0.0316	0.0074	0.0213	0.0242	0.0168
AAR	-0.4118	0.2741	-0.6718**	0.3121	-1.5553*	0.8962	-0.7524	0.6060	-0.3896	0.4284
SIZE	0.0395	0.0284	0.1805***	0.0413	0.1161	0.1000	1.2335***	0.0678	-0.0586	0.0583
TNG	1.2472**	0.5552	1.0014*	0.5990	0.2246	1.0032	-0.0447	0.5812	-1.2214**	0.6096
FCF	0.2931	0.3801	-0.1392	0.5239	0.2124	0.8713	-0.1879	1.5252	0.1452	0.9447
ISHK	-0.2275	0.1760	-0.1289	0.1742	0.1638	0.3406	-0.2498	0.2723	-0.0733	0.2011
IGRO	-0.3425***	0.1276	-0.3189***	0.1267	-0.3063	0.2517	0.3948**	0.1926	-0.0907	0.1480
ICON	0.6531**	0.3083	0.3143	0.3230	1.5519**	0.7294	-1.1156*	0.6182	-0.7104*	0.4291
ILIQ	-0.2682	0.2593	-0.1777	0.2593	0.2422	0.5181	0.5653	0.3946	0.3227	0.3408
Constant	-3.9123***	0.6488	-4.6369***	0.7794	-6.0225***	1.6719	-17.3351***	1.0576	-0.4429	0.9434
Pseudo-R^2	0.02					26.85				
LR	43.43					590.68				

The table reports the coefficient estimates of binomial and multinomial logit models and standard errors corrected for heteroskadacity. The variable definitions are described in Table 1. Panel A reports the results for the whole time periods (1992-2001) and Panel B and C reports the results for sample sub-sets, 1992 to 1996 and 1997 to 2001, respectively. The likelihood ratio (LR) is chi-square distributed and tests the null hypothesis that the vector of coefficients is equal to zero. The Pseudo-R^2, calculated as 1-(log likelihood at convergence/log likelihood at zero) is an indication of explanatory power. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively using a two tailed test.

Table 5
Out-of-sample prediction tests

Panel A: Yearly results	*Takeovers*	*Bankruptcies*	*Divestitures*	*Layoffs*	*Type II error*
Population 1996	26	3	25	28	
Binomial portfolio	6	1	18	12	31
% predicted as targets	23.08%	33.33%	72.00%	42.86%	18.45%
Multinomial portfolio	10	1	23	3	27
% predicted as targets	38.46%	33.33%	92.00%	10.71%	9.61%
Population 1997	41	6	41	26	
Binomial portfolio	14	3	27	9	39
% predicted as targets	34.15%	50.00%	65.85%	34.62%	12.58%
Multinomial portfolio	20	2	35	5	42
% predicted as targets	48.78%	33.33%	85.37%	19.23%	10.80%
Population 1998	57	8	41	39	
Binomial portfolio	30	6	25	16	47
% predicted as targets	52.63%	75.00%	60.98%	41.03%	11.75%
Multinomial portfolio	34	3	35	7	45
% predicted as targets	59.65%	37.50%	85.37%	17.95%	9.16%
Population 1999	89	11	39	53	
Binomial portfolio	57	7	28	37	72
% predicted as targets	64.04%	63.64%	71.79%	69.81%	12.46%
Multinomial portfolio	67	6	34	21	61
% predicted as targets	75.28%	54.55%	87.18%	39.62%	8.88%
Population 2000	63	18	41	56	
Binomial portfolio	47	10	28	38	76
% predicted as targets	74.60%	55.56%	68.29%	67.86%	14.56%
Multinomial portfolio	49	5	37	17	59
% predicted as targets	77.78%	27.78%	90.24%	30.36%	12.63%
Population 2001	28	8	34	67	
Binomial portfolio	22	7	32	58	97
% predicted as targets	78.57%	87.50%	94.12%	86.57%	15.50%
Multinomial portfolio	23	4	31	22	57
% predicted as targets	82.14%	50.00%	91.18%	32.84%	11.85%
Population 2002	89	5	43	67	
Binomial portfolio	69	3	32	43	78
% predicted as targets	77.53%	60.00%	74.42%	64.18%	14.61%
Multinomial portfolio	65	2	24	42	68
% predicted as targets	73.03%	40.00%	55.81%	62.69%	13.91%
Panel B: Average prediction results					
Population size	56	8	38	48	
Binomial portfolio	35	5	27	30	63
% predicted as targets	62.34%	62.71%	71.97%	63.39%	14.02%
Multinomial portfolio	38	3	31	17	51
% predicted as targets	68.19%	38.98%	82.95%	34.82%	10.93%

The table (Panel A) reports out-of-sample prediction results for binomial and multinomial logit models using the population of firms for each year 1996 to 2002. The models are estimated using pooled samples from the previous 4 years. The cut-off probability for each model is estimated by selecting the probability which minimises the total error rate. Panel B shows the mean prediction results across all years. Type II error is calculated as the number of other restructuring firms misclassified as takeover targets.