Takeover Prediction Using Forecast Combinations

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Abstract:

The ability to identify likely takeover targets at an early stage should provide an investor with valuable information to profit from investing in potential target firms. In this paper we contribute to the takeover forecasting literature by suggesting the combination of probability forecasts as an alternative method to improve forecast accuracy in takeover prediction and to realize improved economic return from portfolios made up of predicted targets. Forecasts from several non-linear forecasting models, such as logistic and neural network models and a combination of them, are used to explore the methodology that better reduces the out-of-sample misclassification error. We draw two general conclusions from our results. First, the forecast combination method outperforms that of the single models and should be used to improve the prediction accuracy of takeover targets. Second, we demonstrate that an investment in a portfolio of the combined predicted targets results in significant abnormal returns being made by an investor in the order of up to two times the market benchmark return using a portfolio of manageable size.

Keywords: combining forecasts, forecast accuracy, economic value, abnormal returns, panel data, neural networks.

1. Introduction

Mergers and acquisitions have long been a major research area in finance. Several studies have demonstrated that the target's share price increases substantially during the period before the bid announcement date. It has also been observed that most gains in mergers and acquisition deals accrue to the shareholders of the target firm. Consequently, the ability to identify likely takeover targets at an early stage could provide an investor with valuable information to profit from investing in potential target firms. Assuming that abnormal returns can be achieved by trading in advance of acquisition announcements, the development of takeover prediction models based on publicly available information are important tools to guide investment strategies.

Even after considering the methodological improvements from several recent studies in the takeover prediction area, the answer to the question of whether takeover targets can be predicted remains unclear. If the conclusions from a study are based on one single forecast, then only little information is available on the robustness of these predictions. Powell (2004) advised that modelling takeovers exclusively using a binomial framework may be misleading since takeovers may occur for many reasons not present in the selected hypotheses and the corresponding predictor variables. From an investment perspective, it is crucial to be aware of the risk and the stability of a model. It hardly seems optimal for an investor to invest capital in a portfolio of potential target companies unless the selection process was based on other than robustly evaluated predictions.

Forecast combination has long been viewed as a simple and effective way to improve the robustness of forecasting performance over that offered by forecasts from just one model. The perception that model instability is an important determinant of forecasting performance and a potential reason for combining forecasts from different models, started with Bates and Granger (1969). It was further supported by Diebold and Pauly (1987), as well as Pesaran and Timmermann (2005). Nonetheless, the combination of probability forecasts of a binary variable defined on the [0, 1] interval appeared later when Kamstra and Kennedy (1998) introduced a method to combine log-odds ratios using logit regressions. Further development was carried out in this area with Riedel and Grabys (2004) generating multilevel forecasts, along with Clements and Harvey (2007) comparing several methods for combining probability forecasts.

The motivation underlying this paper is to explore the possible economic gains accruing to a portfolio of predicted target companies. The forecasts are estimated from a combination of probability forecasts generated by established takeover prediction models. It is anticipated that by combining forecasts from individual models, a portfolio of targets will be created that achieves abnormal returns and lower misclassification rates. This research contributes to the takeover prediction literature by exploring the gains that can be achieved by predicting potential targets using forecast combinations from a number of panel data logistic regression models and neural network models. This methodology significantly reduces misclassification error and forms a portfolio of targets that achieves abnormal returns. Further, this study extends previous research by observing model consistency over time, analysing a wider range of companies over a decade, and considering firms of different sizes from a variety of industries. In addition, new explanatory variables are recommended to those already discussed in the literature.

A background to takeover prediction is summarized in the next section. In section 3, takeover hypotheses and their corresponding explanatory variables are discussed. Section 4 outlines the data used in the study, while the design of the forecasting strategy that includes the combination of forecasts is detailed in section 5. Section 6 contains results with conclusions following in section 7.

2. Background

The takeover prediction literature relies on hypotheses arising from the Market for Corporate Control as a theoretical background. This theory assumes that takeovers can be predicted using published financial data. It includes factors hypothesised to increase the probability of a takeover announcement, such as inefficient management and poor growth resources mismatch. Barnes (2000) explains that, although there may be many reasons for mergers, targets are not selected arbitrarily. Instead they arise from a desire by a bidding company to gather benefits from a takeover or merger. Proposed and evidenced theories explaining the reasons behind takeovers include profitability (Hogarty, 1970), economies of scale (Silberson, 1972), market power (Sullivan, 1977; Thomadakis, 1976), information signaling (Bradley et al., 1983), and management efficiency (Jensen and Ruback, 1983). In particular, researchers have found financial synergy to be a strong motive for mergers (Gahlon and Stover, 1979). However, each individual takeover has a specific rationale and, due to its complexity, the finance literature has been unable to determine a catch-all model to anticipate these events. It follows that an important challenge for the researcher who attempts to forecast targets is the issue of identifying the most appropriate model or models.

From a theoretical perspective, knowing the reasons behind a takeover bid should prove useful and provide a key to understanding merger and acquisition dynamics and motivations. As a consequence, economic benefit derived from the management of a portfolio of forecasted targets depends critically on the accuracy of the predictions from the forecasting model utilized. An assortment of models has been applied in an attempt to identify common characteristics of takeover targets. They include univariate analysis in Harris et al. (1982), multiple discriminant analysis in Stevens (1973) and Barnes (1998), logit analysis in Meador et al. (1996), along with neural networks in Cheh et al. (1999) and Dencic-Mihajlov (2006). Stevens (1973) defended multiple discriminant analysis as a model that was well suited to many financial problems where the dependent variable is dichotomous. However, most of the studies conducted in the 1980's and 1990's switched to logistic regression models for predicting takeover targets. Dietrich and Sorensen (1984) were the first to apply logistic regression to bankruptcy prediction following the 1980 article by Ohlson. Palepu (1986) was able to formally improve the validity and the consistency of the prediction procedure by analysing the influence of the cut-off probability on the predictability rate. Subsequently, the direction taken in recent research has concentrated on the development of alternative methods in order to determine optimal cut-off probabilities to reduce misclassification error. The end of the 1990s saw the emergence of additional methodological improvements such as the profit maximization criterion proposed by Barnes (1999), and the use of a standard feed-forward backpropagation neural network model in Cheh et al. (1999).

The classification models reported in the literature have demonstrated varying degrees of success with predictive accuracy up to 90% better-than-chance in-sample, while out-of-sample, ranging from below 50% to around 120% better-than-chance. For example, the best results in Powell (1995) were achieved by the use of multinomial models that reported an overall classification accuracy of 4.76%. Stevenson and Peat (2009) used a combined logistic model to achieve results up to 118% better-than-chance. However, the ability to generate abnormal returns has been questioned by many authors who could not replicate the results of previous studies when applying their methodologies in different markets or periods. In contrast to the classification ability claimed by many studies, empirical applications of the models have generally failed to confirm the out-of-sample predictive expectations formed from in-sample results.

3. Takeover Hypotheses and Explanatory Variables

Literature on the Market for Corporate Control presumes that targets can be forecasted using mainly publicly available data. The crucial question raised however, is whether future economic events, including takeovers, can be predicted without the market presence of inside information. Barnes (1998) expressed the view that, while these events cannot be normally predicted, some of them may at least be anticipated. Earlier studies centred on motivations for corporate mergers and acquisitions. The variables explained below and used in takeover target prediction models point to these motivations. As a consequence, the use of operational and financial characteristics of target firms, along with accounting and market data, has become common place in recent studies of the identification and prediction of takeover events

From the several theories purported to explain firm acquisition, eight main hypotheses have been formulated. Explanatory variables identified with these hypotheses are suggested as covariates for inclusion in the predictive models. These variables are collected at the firm level, as well as from within industry and market categories. The resultant number of variables is thirty five and the full list of hypotheses with their respective proxy variables is described below.

H1: Inefficient Management

This hypothesis is based on the Market for Corporate Control theory that states that inefficiently managed firms will be acquired by more efficient firms to increase capital gains. Therefore, companies managed inefficiently are more susceptible to poor performance. Accordingly, the explanatory variables suggested as proxies for this hypothesis include:

V1 ROA (EBIT/Total Assets - Outside Equity Interests)
V2 ROE (Net Profit After Tax / Shareholders Equity - Outside Equity Interests)
V3 EBIT/Operating Revenue
V4 Dividend/Shareholders Equity

V5 Asset Turnover (Net Sales/Total Assets)
V6 Growth in EBIT over past year,
V7 Growth in EBIT over past three years
V8 Growth of 1 year Total Assets
V9 Growth of 3 year Total Assets
V10 Inventory/Working Capital
V11 Inventory/Total Assets
V12 Net profit / Market Value

H2: Undervaluation

There is consistent agreement across most studies that the greater the level of undervaluation, the greater the likelihood a firm will be acquired. Undervalued stocks are seen as a bargain in the market, especially from overvalued entities. The explanatory variables suggested by this hypothesis are:

V13 Market to Book ratio (Market Value of Securities/Net Assets)
V14 Market Capitalisation/ Total Assets

H3: Price to Earnings Ratio

The price-to-earnings (P/E) ratio is closely linked to the undervaluation and inefficient management of a company. The earnings of a firm with low P/E ratio will be valued at the multiple of the acquirer, allowing an immediate gain to be realised. Consequently, a high P/E ratio will decrease the likelihood of acquisition. Thus, the P/E ratio is a likely candidate for inclusion in models.

V15 Price/Earnings Ratio

H4: Growth Resource Mismatch

Acquisition will create opportunities for a better allocation of the target firm resources to generate profitable investments. Firms which possess low growth / high resource combinations or, alternatively, high growth / low resource combinations will have an increased likelihood of acquisition. However, the explanatory variables used to examine this hypothesis capture growth and resource availability separately. The following explanatory variables suggested by this hypothesis are:

V16 Growth in Sales (Operating Revenue) over the past year
V17 Growth in Total Sales over 3 years
V18 Capital Expenditure/Operating Revenue.
V19 Quick Assets (Current Assets – Inventory)/Current Liabilities
V20 Invested Capital Turnover
V21 Long Term Asset Turnover
V22 Working Capital Turnover

H5: Dividend Payout

The behaviour of some firms to pay out less of their earnings in order to maintain enough financial slack (retained earnings) leads to higher growth potential and, consequently market value. It is assumed that low payout ratios will lead to an increased likelihood of acquisition. The explanatory variables suggested by this hypothesis are:

V23 Dividend Payout Ratio
V24 Dividend Yield
V25 Dividend per share / Earnings per share

H6: Inefficient Financial Structure

Rectification of capital structure problems is a motivation for takeovers given that increases in debt demands more return on equity. High leverage will lead to decreased likelihood of acquisition. The explanatory variables for this hypothesis are:

V26 Net Interest Cover (EBIT/Interest Expense)
V27 Net Debt/Cash Flow
V28 Growth in Net Debt over past 1 year
V29 Growth in Net Debt over past 3 years
V30 Current Assets/Current Liabilities

H7: Merger and Acquisition Activity

The more important industry sectors in the economy and the most traded companies will attract more investments and, as a result, create more opportunities for mergers and acquisitions. The explanatory variables for this hypothesis are:

V31 Industry Dummy variable for companies from the mining industry
V32 Dummy variable indicating company listing on the ASX300[1] in that year

H8: Size

There are two rationales underlying this hypothesis. The first states that smaller firms will have a greater likelihood of acquisition because larger firms are generally exposed to fewer bidding companies with sufficient resources to acquire them. In that case it follows that there is a negative effect of size on the probability of acquisition. The second proposes a positive relationship between size and takeover likelihood. It is based on the assumption that managers would prefer larger, rather than smaller, acquisitions to increase the size of the company. Both lines of argument are tested using the variables below:

V33 Log (Total Assets)
V34 Market Capitalisation

V35 Sales and Revenues

4. Data

The collected sample includes financial data from all listed companies on the Australian Stock Exchange (ASX) for 13 years, spanning the financial years from 1999 to 2011. It includes their respective accounting, market and historical takeover data. The dataset is divided into 12 panels, each corresponding to one financial year[2]. The financial year 2009 is used as an out-of-sample data period for the first in-sample panel estimation period from 1999 to 2008. It follows that 2010 and 2011 are the out-of-sample data periods corresponding to the second in-sample estimation period (1999 to 2009) and the third (1999 to 2010), respectively. The out-of-sample data are used to evaluate takeover forecast accuracy based on the estimation and cut-off probabilities from their respective in-sample periods. The estimation and one year prediction for three distinct periods allows verification of the stability of the models under changing economic conditions.

The main sources used to collect the financial and corporate information are the AspectHuntley and Connect4 databases. The first of these databases contains published available financial information of all listed companies in Australia, including industry classification and a complete list of financial variables and ratios.[3] Connect4 has historical records of takeover bids with their respective dates and details of transactions.

5. Forecasting Strategy

It has not yet been demonstrated in the literature that such a complex problem as takeover prediction can be solved efficiently using only one forecasting model. It requires a more robust approach. The discrete choice modelling framework proposed in this paper is divided into two segments. Firstly, a logistic regression and two other specifications of panel data logistic models are estimated, each assuming a different time relationship between the variables. Secondly, three architectures of feed-forward neural networks are trained to forecast takeover likelihood using the same database. The aim behind the use of such variety of models is to capture different non-linear relationships among the variables in order to improve the robustness of the forecast.

5.1 Logistic Models

M1 - Logistic regression

The first modelling procedure used is the logistic regression model commonly utilised for dichotomous state variable problems. The model is given by the equations (1) and (2) below.

$$P_i = E(Y = 1|X_i) = \frac{1}{1+e^{-Z_i}} \quad (1)$$

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} \quad (2)$$

where P_i is the probability of company *i* being taken over, β_0 is the intercept and each of the β_k (k = 1, …, N) is the coefficient corresponding to the financial variable X_k. The logistic regression model was developed to overcome the rigidities of the linear probability model in the presence of a binary dependent variable. Equations (1) and (2) show the existence of a linear relationship between the log-odds ratio and the explanatory variables. However, the relationship between the probability of the event and acquisition likelihood is non-linear. This non-linear relationship has a major advantage in that it measures the change in the probability of the event as a result of a small increment in the explanatory variables. However, the incremental impact of a change in an explanatory variable on the likelihood of the event is compressed, requiring a large change in the explanatory variables to change the classification of the observation.

M2 - Panel data mixed effects logistic regression

Panel data models make the most of the data on hand with the ability to analyse the relationship between variables simultaneously within a time dependent structure. Although these models share similar structure to the logistic regression model, the panel structure allows the historical records for each variable to be considered in the estimation procedure. The mixed-effects logistic regression adds other components to the panel structure by estimating both fixed effects and random effects. The presence of fixed effects captures the effect of all the unobserved time-invariant factors that influence the dependent variable.[4] In contrast, the random effects capture the intra-panel correlation. That is, observations in the same panel (year) are correlated because they share common panel-level random effects. The fixed effects are estimated directly as an additional regressor and the random effects take the form of either random intercepts or random coefficients.

An important characteristic of such models is the grouping structure of the data. It consists of multiple levels of nested groups that allow for one or more levels. In this study, the two-level model assumes that industries are the first level and companies the second level. Companies are nested within industries and random effects are unique to companies within an industry. Assuming that company effects would be nested within industries is natural as companies are generally unique to industries.

$$L_{ij} = \ln\left(\frac{P_{ij}}{1-P_{ij}}\right) = Z_i = \beta_0 + \beta_1 X_{ijk} + Z_{ijk} u_i + \varepsilon_{ij} \tag{3}$$

In the model given by equation (3) above, i=1...M panels (years), with each panel i consisting of j=1,..., N observations. In a two-level panel, k=1,...,L corresponds to the industry sectors, while the X_{ijk} are the covariates for the fixed effects that quantify a general mean process for the company j in the panel i. The covariates corresponding to the random effects are given by Z_{ikj} and can be used to represent random intercepts and random coefficients, respectively (see Rabe-Hesketh et al., 2005 for further explanation). The random effects, u_i, are not directly estimated as model parameters but are instead summarized according to the unique elements of the covariance matrix. The errors ε_{ij} are distributed as logistic with mean zero and variance $\pi^2/3$ and are independent of the u_i.

M3 - Panel data crossed effects logistic regression

This model inherits the same structure from the previous panel data model, but with a different approach to the random structure. While it is safe to assume that all mixed-effects models contain nested random effects, in this analysis it makes sense to assume that the random effects are not nested, but instead crossed. This means that the random effects are the same regardless of the industries. The panel data crossed effects logistic model with the j^{th} company within the i^{th} panel in the k^{th} industry is given by equation (4) below.

$$L_{ij} = \ln\left(\frac{P_{ij}}{1-P_{ij}}\right) = Z_i = \beta_0 + \beta_1 X_{ijk} + Z_{ij} u_i + \varepsilon_{ij} \tag{4}$$

where X_{ijk} are the covariates for the fixed effects and the $Z_{ij,}$ for the random effects.

5.2 Neural Network Models

Logistic regression is the most commonly used technique in the takeover prediction literature. However, such parametric models require a pre-specified functional relationship between the dependent and independent variables. This is difficult to validate in many empirical studies due to the complexity of the problem and the relationship between variables. The advantages of neural networks over conventional methods of analysis dwell in their ability to analyse complex patterns quickly, with a high degree of accuracy and with no assumptions about the nature of the underlying distribution of the data. As explained in Dencic-Mihajlov and Radović (2006), the limitations of this model lie in its inability to explain the relative importance of the inputs separately, as well as the requirement to have a sufficiently large dataset to train, validate and generalize the network.

Neural networks consist of a large number of processing elements, known as neurons. At the input level they are represented by a weighted sum that is squashed by a non-linear function. The squashing function maps a set of input-output values by finding the best possible approximation to the function. This approximation is coded in the neurons of the network using weights that are associated with each neuron. The weights are calculated using a training procedure during which examples of input-output associations are successively exposed to the network. After each iteration, the weights are updated so that the network starts to mimic the desirable input-output behaviour. Due to its structure, the feed-forward neural network uses parallel processing to capture complicated non-linear relationships between the dependent and independent variables. The neural network output is specified in equation (5) below.

$$y = v_0 + \sum_{j-1}^{NH} v_j \, g\left(w_j^T X\right) \tag{5}$$

where X represents the inputs (explanatory variables), w_j is the weight vector for j^{th} hidden node, while $v_0, v_1, \ldots, v_{NH}$ are the weights for the output node and y is the output (dependent variable). The function g represents the hidden node output and, in this study, it is given in terms of the logistic and hyperbolic tangent squashing functions.

Specifying the architecture of the net determines the network complexity and is a critical task in the process of fitting a neural network. If the network size is not adequately controlled, the network can easily overfit the data in-sample resulting in poor out-of-sample forecasts. Unfortunately, no clear rule has yet been developed for determining the optimal number of hidden nodes. Usually, the number of nodes is determined empirically through trial-and-error by selecting the number that produces the best in-sample result. In theory, a single hidden layer feed forward neural network can approximate any nonlinear function to an arbitrary degree of accuracy with a suitable number of hidden neurons (White, 1992). The models are trained using from one to a maximum number of thirty five neurons, and with logistic-sigmoid and tangent-sigmoid activation functions. In general, the models with the higher number of neurons resulted in over-specification in-sample and lower ability to forecast out-of-sample.

The following architectures achieved the best results in-sample and, therefore, were the predictive models selected.

M4 - 1 hidden layer, 10 neurons, logistic-sigmoid squashing (activation) function

M5 - 1 hidden layer, 3 neurons, tangent-sigmoid squashing function

M6 - 1 hidden layer, 4 neurons, tangent-sigmoid squashing function

5.3 Forecast Combinations

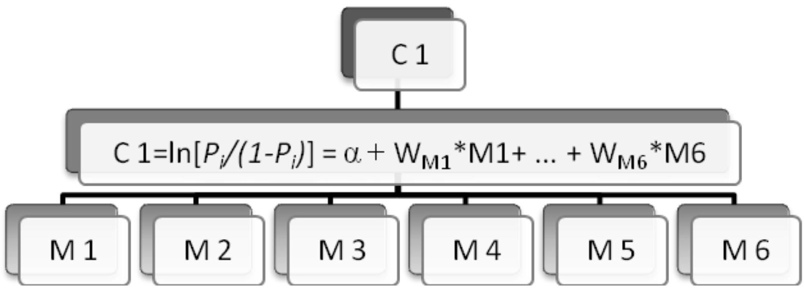
High levels of misclassification are of great concern when using probabilistic predictive models. This is especially the case when costly Type II errors occur and non-targets are predicted to be targets. Practical experience has shown that the best model in-sample might not be the more accurate when forecasting future values. This gives rise to the main aim of this study which is to introduce the concept of probability forecast combinations to predict takeover announcements. Although it has been proven to be an effective methodology in other forecast applications, to our knowledge it has not been used to date in the takeover prediction literature.

The methodology consists of combining the predictions obtained from different forecasting models using an aggregation function. The forecast combination system accounts for the diversity of the underlying forecasting models, instead of being focused on the narrow specification from one model. Timmermann (2006) documented that forecast combinations are often superior to their constituent forecasts. In our study, the combined forecast is the output of a function that gathers the results from a number of takeover prediction models using neural network and logistic modelling approaches as inputs. The advantage lies in the consideration of unique non-linear relationships between the takeover target and the explanatory variables found in each model and incorporated into the construction of the combination forecast.

Typically, binary models generate a probability as output. This, in turn, requires the specification of a threshold probability (cut-off) to assess the classification accuracy of the model. The prediction from each model is based on a cut-off probability that provides the highest proportion of correctly predicted targets in the estimation sample. The method of Maximum Chance Criterion, first used in Barnes (1999), is determined by dividing the number of correctly predicted targets by the population of predicted targets. The use of this rule implicitly recognizes that the penalty of misclassifying a non-target firm as a target (Type II error) is significantly larger than misclassifying a target as a non-target (Type I error). Deriving the cut-off probability using the Maximum Chance Criterion implicitly sets the threshold within the decision context of selecting a manageable number of predicted targets.

The established method of combining forecasts is the Weights Combination. It attributes weights to each of the models' forecasts and, in doing so, creates a combined vector of forecasts. Kamstra, Kennedy and Suan (2001) point out that the weights can show the contribution of each corresponding forecasting input to the final forecast. The key point in the determination of the weights is the choice of the combination function. In this study, a logistic regression, estimated by maximum likelihood, is used to determine the optimal weight for predictions from each of the models. The structure is based on the diverse aspects of the potential inputs and aggregation functions in the underlying predictive model. Figure 1 diagrammatically depicts the stages in the logistic regression where P_i is the probability of company i being taken over, α is the intercept, W_{M1} to W_{M6} are the maximum likelihood estimates of the weights for each model. The vectors M1 to M6 contain the probability forecasts from each specific model. The probabilities are then fed into the Weights Combination model, with the result the vector of combined forecasts, C1.

Figure 1: Weights Combination Model



Conceptual figure for the proposed model. C1= prediction from the weights combination model; ln[Pi/(1-Pi)] = logistic function; α is the constant; W_{M1} to W_{M6} are weights (coefficients) for the inputs M1 to M6 in the logistic regression. M1, M2 and M3 are the vectors of predicted probabilities from the single logistic models. M4, M5 and M6 are the vectors of predicted probabilities from each neural network model.

The classification accuracy is later assessed by selecting the best cut-off probability from the combined in-sample forecast.

6. Results

The results from this study are reported in two interrelated sections. The first section analyses the performance of the individual and combined forecasts at predicting takeover announcements. The second section is concerned with assessing the economic usefulness of portfolios made up of predicted targets from the single models and combined forecasts.

6.1 Performance Analysis

The accuracy rate is the only score rule used to measure the performance of predicting takeover targets from the individual classification models and the forecast combination method. It is calculated by taking the ratio of the number of correct predictions to the number of predicted takeover targets in the data set. The better the predictive power of a model, the higher is the ratio, given it estimates the percentage of observations that a model predicts correctly. Since we are interested in forecasting, we concentrate on both in-sample and out-of-sample results.[5]

Table 1 below shows the accuracy rate of the forecasts from each model in-sample and out-of-sample.

Table 1: Model's Accuracy In-sample and Out-of-sample

1999-2009	*Logistic Models*			*Neural Network Models*			*Combination*	Chance
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**C1**	
Out-of-sample (2009)								
Accuracy	**13.04%**	**14.29%**	**12.00%**	**7.69%**	**7.41%**	**13.33%**	**15.79%**	**2.93%**
Actual Targets	3	2	3	2	2	2	3	57
Predicted Targets	23	14	25	26	27	15	19	1948
In-sample (1999-2008)								
Accuracy	**41.05%**	**34.27%**	**33.69%**	**18.84%**	**21.77%**	**31.37%**	**38.07%**	**4.01%**
Actual Targets	78	98	220	26	32	16	174	566
Predicted Targets	190	286	653	138	147	51	457	14132

1999-2010	Logistic Models			Neural Network Models			Combination	Chance
	M1	M2	M3	M4	M5	M6	C1	
Out-of-sample (2010)								
Accuracy	**11.90%**	**6.38%**	**7.50%**	**10.00%**	**12.50%**	**11.11%**	**20.93%**	**3.90%**
Actual Targets	5	3	3	3	5	4	9	75
Predicted Targets	42	47	40	30	40	36	43	1924
In-sample (1999-2009)								
Accuracy	**37.14%**	**27.38%**	**29.06%**	**10.42%**	**13.49%**	**7.24%**	**39.04%**	**3.87%**
Actual Targets	117	230	342	20	51	21	146	623
Predicted Targets	315	840	1177	192	378	290	374	16080

1999-2011	Logistic Models			Neural Network Models			Combination	Chance
	M1	M2	M3	M4	M5	M6	C1	
Out-of-sample (2011)								
Accuracy	**11.76%**	**8.05%**	**7.23%**	**16.67%**	**18.18%**	**12.50%**	**33.33%**	**4.82%**
Actual Targets	4	7	12	7	6	5	6	94
Predicted Targets	34	87	166	42	33	40	18	1949
In-sample (1999-2010)								
Accuracy	**20.95%**	**22.75%**	**21.61%**	**8.27%**	**29.38%**	**11.31%**	**38.18%**	**3.88%**
Actual Targets	53	321	559	34	62	37	42	698
Predicted Targets	253	1411	2587	411	211	327	110	18004

The Table presents the accuracy in-sample and out-of-sample for the logistic models (M1 to M3), neural network models (M4 to M6), and the weights combination model (C1). The table also shows the total number of predicted targets and actual targets for each model in both samples. All seven models were estimated over three time periods to verify the model's stability over the years. The last column contains the number of observations and announcements for each sample and year and the probability of selecting a takeover target by chance.

For the group of logistic models (M1 to M3), we observe that an increase in model complexity does not necessarily result in better forecasts. In the first two in-sample estimation periods, the standard logistic specification (M1) has a greater level of accuracy than the more complex mixed and crossed effects models (M2 and M3, respectively). However, this characteristic is reversed somewhat in the third in-sample estimation period. The simplest model of all, the logistic regression (M1), was the more consistent out-of-sample and was more accurate for the financial years 2010 and 2011. For 2009, however, the mixed model, M2, with an accuracy rate of 14.29% was preferred. As expected, the levels of in-sample accuracy are reduced markedly for the logistic models in the out-of-sample periods.

In the neural network cases (M4 to M6), the three specifications that produced the best results in-sample were selected to predict one year ahead. The model that achieved the best result for the second and third in-sample and out-of-sample periods was M5. Recall it is a neural network model estimated with one layer containing three neurons and a tangent-sigmoid activation function. It had the highest level of accuracy of all the single models with third period rates of 18.18% out-of-sample, and 29.38% in-sample for the financial year 2011. In the first period, the M6 model with one hidden layer and four neurons performed best both in-sample and out-of-sample. Overall, all models produced forecasts considerably better than chance, with the neural network models outperforming the logistic models out-of-sample in most cases, especially following the financial crises that hit during the financial year 2009. In line with the empirical literature, the results confirm that the neural network models appear to have an advantage over the logistic models, but at the cost of more complexity.

While theory offers assistance in the choice of explanatory variables, no single forecasting method consistently dominates the takeover prediction literature. Given the same data set, each model has different underlying assumptions and, therefore, assigns different probability estimates to each company. What is investigated in this study is whether combining these different predictions can result in better forecasts than those offered by the individual models. The Weights Combination method takes into consideration the vector of predicted probabilities from each single model to estimate the combined forecast C1. Again, we use the best in-sample cut-off probability to derive the best out-of-sample forecast and the results are reported in the penultimate column of Table 1. It is clear that the combined forecasts outperform the single models by a considerable margin for all years and are more parsimonious in the portfolio selection.

Except for the logistic model M1 in the first estimation period, the in-sample estimation of C1 was better than the other logistic and the neural network models. It was stable over the years, with an accuracy rate of around 38% for the three in-sample periods. However, it was in the out-of-sample forecasts that the combined model particularly distinguished itself from the single models. Its forecast accuracy was constantly higher than any other model in the three periods.

Further, forecast combination resulted in better predictive accuracy out-of-sample than the single models in the first estimation period when the financial crisis had taken hold of the stock markets world-wide. Consistent with the literature, the forecast combination was generally more accurate than the single models both in-sample and out-of-sample across the different estimation periods.

These results suggest that the use of forecast combination is appropriate for the prediction of takeover targets in the Australian context. The Weights Combination model significantly outperformed the other models for predictive purposes, as well as being parsimonious with the number of predicted targets and, as a consequence, reducing the misclassification error. These results contest the claims of Barnes (1999) and Palepu (1986) that models cannot be implemented which achieved predictive accuracies greater than chance. On the other hand, they further confirm the results of studies such as Kamstra, Kennedy and Suan (2001) that propose forecast combination using weights enhances the performance of single models.

6.2 Economic Analysis

Although the above methodology provides us with a statistical assessment of model performance, it had nothing to say about the economic usefulness of the model. To make an assessment of the financial gains from our modelling approach, we use the predicted targets from the combined prediction models to create an equally weighted portfolio. Using this approach we are able to measure whether the Weights Combination model for predicting takeover targets wa The result of adopting a one year buy-and-hold strategy for the portfolio made up of the out-of-sample predictions from the combined model is contained in Table 2. The returns from the portfolio are calculated for the three out-of-sample years, financial years 2009, 2010 and 2011. s able to earn abnormal returns.

The columns in Table 2 include three benchmark indexes representing proxies for the market, plus the portfolio returns and the Cumulative Abnormal Return (CAR) since the first day of each financial year at monthly intervals. The three indexes are the All Ords[6], ASX200[7] and ASX300.

Table 2: Out-of-sample returns for the portfolios of predicted targets using the weights combination model and the market benchmark. (Buy-and-hold strategy)

2009	*Market Benchmark*			*Weights combination*	
	ALL ORDS	**ASX200**	**ASX300**	**C1**	**CAR**
Portfolio				**19 Companies**	
31-Jul-08	-5.26%	-4.56%	-4.70%	-2.50%	2.75%
31-Aug-08	-2.20%	-1.53%	-1.70%	-7.27%	-5.07%
30-Sep-08	-13.16%	-11.79%	-12.04%	-16.85%	-3.69%
31-Oct-08	-25.32%	-22.96%	-23.42%	-22.00%	3.32%
30-Nov-08	-31.13%	-28.24%	-28.73%	-29.46%	1.68%
31-Dec-08	-31.38%	-28.63%	-29.03%	-33.19%	-1.81%
31-Jan-09	-34.78%	-32.11%	-32.46%	-29.74%	5.04%
28-Feb-09	-38.18%	-35.87%	-36.19%	-32.52%	5.65%
31-Mar-09	-33.76%	-31.32%	-31.60%	-30.18%	3.59%
30-Apr-09	-29.78%	-27.51%	-27.72%	-29.75%	0.03%
31-May-09	-28.49%	-26.79%	-26.93%	-25.88%	2.62%
30-Jun-09	**-25.97%**	**-24.17%**	**-24.34%**	**-25.23%**	**0.74%**
2010	*Market Benchmark*			*Weights combination*	
	ALL ORDS	**ASX200**	**ASX300**	**C1**	**CAR**
Portfolio				**43 Companies**	
31-Jul-09	7.64%	7.31%	7.33%	7.61%	-0.03%
31-Aug-09	13.58%	13.25%	13.37%	18.06%	4.47%
30-Sep-09	20.05%	19.94%	20.09%	25.97%	5.92%
30-Oct-09	17.71%	17.40%	17.56%	31.92%	14.22%
30-Nov-09	19.45%	18.87%	19.07%	27.66%	8.22%
31-Dec-09	23.68%	23.15%	23.29%	29.20%	5.51%
29-Jan-10	16.44%	15.54%	15.68%	28.72%	12.28%
26-Feb-10	17.82%	17.27%	17.28%	24.11%	6.30%
31-Mar-10	23.94%	23.28%	23.29%	32.52%	8.57%
30-Apr-10	22.44%	21.55%	21.61%	36.12%	13.68%
31-May-10	12.81%	12.00%	12.02%	20.01%	7.20%
30-Jun-10	**9.55%**	**8.76%**	**8.72%**	**15.00%**	**5.45%**
2011	*Market Benchmark*			*Weights combination*	
	ALL ORDS	**ASX200**	**ASX300**	**C1**	**CAR**
Portfolio				**18 Companies**	
31-Jul-10	4.22%	4.46%	4.47%	3.99%	-0.24%
31-Aug-10	2.64%	2.39%	2.48%	4.72%	2.08%
30-Sep-10	7.22%	6.54%	6.81%	9.25%	2.03%
30-Oct-10	9.45%	8.37%	8.70%	17.31%	7.86%
30-Nov-10	8.13%	6.58%	7.03%	17.64%	9.51%
31-Dec-10	12.07%	10.32%	10.90%	18.18%	6.10%
29-Jan-11	12.14%	10.52%	11.01%	15.25%	3.10%

26-Feb-11	13.82%	12.32%	12.80%	23.83%	10.01%
31-Mar-11	13.96%	12.47%	12.97%	19.90%	5.94%
30-Apr-11	14.51%	13.29%	13.77%	16.60%	2.09%
31-May-11	10.73%	9.46%	9.87%	14.94%	4.20%
30-Jun-11	**7.75%**	**7.12%**	**7.34%**	**14.53%**	**6.79%**

The table provides the returns in each month since the first day of the financial year based on a buy-and-hold strategy. The penultimate column shows the returns for the portfolio of predicted target using the weights combination model. The numbers in the first three columns represent the market benchmark indexes' returns for the same period. The results in the last column represent the cumulative abnormal return of the portfolio relative to the market benchmark ALL ORDS.

During the financial year 2009 when the financial crisis impacted heavily the Australian Market, the returns of the predicted portfolios are similar to what the market experienced. At the end of the year there was virtually no abnormal return when compared to the All Ords Index. Compared to the results in Table 1, despite the higher predictive accuracy of the C1 model, losses in downturn periods are not necessarily reduced when compared to the benchmark indexes. Nonetheless, the results for the financial years 2010 and 2011 indicate that combining the predictions by Weights Combination, not only improves the forecast accuracy, but it almost doubles the average market return. The returns of the combination method are significantly higher than the market performance over the last two out-of-sample periods on a month-by-month basis. The final portfolio returns at the end of the financial years 2010 and 2011 were 15% and 14.53%, respectively. They represent an abnormal return of 5.45% for 2010 and 6.78% for 2011 when compared to the All Ords index.

Importantly, this positive economic result is achieved through the combination method resulting in reasonably sized portfolios. This has the added advantage of reducing the risk of investing in incorrectly predicted targets.

While impressive in themselves, it should be recognised that these results could have been potentially driven by actual non-target firms within the portfolio of predicted targets. This would suggest that the abnormal returns in 2010 and 2011 were partly the result of the selection of over-performing non-target firms, rather than an accurate selection of target firms. In spite of this, it is should be remembered that the portfolios have been formed by the use of models that are designed to predict companies with a minimal misclassification rate.

Overall, the combination of forecasts appears to be an efficient technique to both improve the accuracy of takeover prediction and to achieve abnormal returns. The Weights Combination method appears to be very stable the years and parsimonious for portfolio selection. The mix of panel data logistic and neural network models has proved to be a good choice to capture and combine information from different sources.

7. Conclusions

Forecasts of events based on economic and financial variables that take the form of probabilities are becoming increasingly common. Additionally, there is an extensive literature suggesting that forecast combination can improve on the best individual forecast. In this paper panel data logistic regressions and neural network models are used to predict takeover targets and to, subsequently, evaluate whether combining these methods forms a consensus forecast that improves prediction accuracy and generates abnormal returns from the portfolios comprised of the predicted targets. Weights Combination is the aggregation scheme used to combine the probability forecasts from six different non-linear models.

Two general conclusions are drawn from these results. Firstly, the combination methods outperform the single models and should be used to improve the prediction of takeover targets. In particular, the Weights Combination approach is a stable and efficient method for combining takeover target predictions in order to improve model accuracy and to achieve abnormal returns. Our combination results are consistent with those of other researchers in other applications who, in general, found that the combined forecasts outperformed the single input forecasts. Secondly, it has been demonstrated that an investment in the combined predicted targets in a regular year resulted in significant abnormal returns being made by an investor, in the order of up to two times the market benchmark return, in a portfolio of manageable size.

We believe our results provide evidence in favour of the proposition that abnormal returns can be made from an investment in predicted takeover targets from logistic and neural network models, and that these results can be significantly improved by using a combination of forecasts to achieve better returns with lower misclassification risk.

8. References

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Footnotes

[1] The ASX 300 index is a market-capitalisation weighted and float-adjusted stock market index of Australian stocks listed on the Australian Securities Exchange from Standard & Poors. The index incorporates all of the companies in the top 200, the ASX 200 index, and an additional 100 smaller companies, making a total of about 300 components.

[2] The financial year in Australia extends from July 1 of the previous year until June 30 of the current year under consideration. For example, the financial year 2009 includes the period from 01/07/2008 to 30/06/2009. In the case of the financial year 2011, the data set is truncated after 31/3/2011.

[3] Descriptive statistics of all the variables used in this study can be found in Appendix A-1.

[4] For this reason it is referred to as unobserved heterogeneity, or company effect, that represents all factors affecting the takeover announcements that do not change over time.

[5] Model estimations for the logistic-based models M1, M2 and M3, along with the Weights Combination model, C1, are reported in the Appendix A-2. Specific details for the neural network models are available from the authors by request.

[6] The All Ordinaries (All Ords) Index contains nearly all ordinary shares listed on the Australian Securities Exchange. The market capitalization of the companies included in the All Ords index amounts to over 95% of the value of all shares listed on the ASX.

[7] The ASX 200 index is a market-capitalization weighted and float-adjusted stock market index of the top 200 Australian stocks listed on the ASX from Standard & Poors.

Appendix

A-1 - Variables' descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
year	19951	2004.93	3.45	1999.00	2010.00
tkvr	19951	0.04	0.19	0.00	1.00
V1	19951	-0.93	83.74	-11773.00	242.41
V2	19951	-103.95	14584.37	-2060000	221.09
V3	19951	-137.35	3395.01	-269000	18251.00
V4	19951	-0.03	0.17	-9.30	4.96
V5	19951	0.73	10.58	-6.60	1367.10
V6	19951	5.28	375.74	-1.00	50928.00
V7	19951	0.18	0.85	-1.00	70.85
V8	19951	1.25	28.32	-1.00	1994.30
V9	19951	0.15	0.57	-1.00	18.91
V10	19951	0.58	41.35	-1359.10	4950.00
V11	19951	0.05	0.10	-0.11	0.97
V12	19951	3.14	460.73	-36.34	65077.00
V13	19951	3.14	186.92	-7636.70	24587.00

V14	19951	4.55	186.80	0.00	24587.00
V15	19951	-3.39	499.50	-64900.00	10800.00
V16	19951	57.25	4039.74	-1.00	534000.00
V17	19951	0.20	1.58	-1.00	52.62
V18	19951	76.74	3281.90	-1879.40	370000.00
V19	19951	248.66	13034.53	-109.06	1280000.00
V20	19951	5.61	204.26	-0.47	22465.00
V21	19951	79.91	6069.44	-20.79	623000.00
V22	19951	1.28	309.18	-19339.00	19343.00
V23	19951	0.25	1.31	0.00	145.00
V24	19951	0.56	27.41	-365.00	3554.00
V25	19951	0.56	27.41	-365.00	3554.00
V26	19951	5942034	235000000	-350000000	23300000000
V27	19951	112.34	13472.54	-72613.00	1860000.00
V28	19951	11.55	814.73	-1.00	109000.00
V29	19951	0.16	0.79	-1.00	34.12
V30	19951	32.71	1779.01	-50.46	233000.00
V31	19951	0.30	0.46	0.00	1.00
V32	19951	0.15	0.35	0.00	1.00
V33	19951	17.28	2.81	0.00	27.25
V34	19951	767000000	5730000000	0.00	244000000000
V35	19951	422000000	3710000000	-10800000	176000000000

A-2 - Models` Estimation Results.

2009 Models` Estimation Results:

M1 - LOGISTIC: 2009

Logistic regression Number of obs = 14132

LR chi2(13) = 233.92

Prob > chi2 = 0.0000

Log likelihood = -2258.7165 Pseudo R2 = 0.0492

tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.127	0.098	0.193
Market Capitalisation/ Total Assets	-0.055	0.027	0.042
Quick Assets	0.000	0.000	0.012
Dividend per share / Earnings per share	-0.009	0.006	0.104
Mining Industry Dummy	0.119	0.101	0.240
ASX300 Dummy	0.549	0.117	0.000
Log (Total Assets)	0.204	0.026	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-6.850	0.465	0.000

M2 - LOG. MIXED EFFECTS: 2009			
Mixed-effects logistic regression	Number of obs = 14132		
Group variable: id	Number of groups = 2516		
Obs per group: min = 1 avg = 5.6 max = 9			
Integration points = 7	Wald chi2(9) = .		
Log likelihood = -2255.4214	Prob > chi2 = .		
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.155	0.104	0.134
Quick Assets	0.000	0.000	0.017
Dividend per share / Earnings per share	-0.010	0.006	0.101
ASX300 Dummy	0.566	0.128	0.000
Log (Total Assets)	0.252	0.028	0.000
Market Capitalisation	0.000	0.000	0.001
_cons	-7.984	0.529	0.000
Random-effects Parameters	Estimate	Std. Err.	
id: Identity var(_cons)	0.678	0.215	
LR test vs. logistic regression: chibar2(01) = 13.63 Prob>=chibar2 = 0.00			

M3 - LOG. CROSSED EFF.: 2009			
Crossed-effects logistic regression	Number of obs = 14132		
No. of Group	Observations per Group Integration		
	Variable	Groups	Average
	_all	11	1284.7
	id	2516	5.6
Log likelihood = -2238.0709 Prob > chi2 = . Wald chi2(9) = .			
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.155	0.104	0.134
Quick Assets	0.000	0.000	0.016
Dividend per share / Earnings per share	-0.010	0.006	0.101
ASX300 Dummy	0.566	0.128	0.000
Log (Total Assets)	0.252	0.029	0.000
Market Capitalisation	0.000	0.000	0.001
_cons	-7.992	0.535	0.000
Random-effects Parameters		Estimate	Std. Err.
_all: Identity var(R.sector)		0.033	0.164
id: Identity var(_cons)		0.823	0.130
LR test vs. logistic regression: chi2(2) = 13.64 Prob > chi2 = 0.0011			

C1 - Weights Combination: 2009

Logistic regression	Number of obs = 14132		
LR chi2(6) = 1739.10			
Prob > chi2 = 0.0000			
Log likelihood = -1506.1223	Pseudo R2 = 0.3660		
tkvr	Coef.	Std. Err.	P>|z|
M1 - LOGISTIC REGRESSION	-2.429	8.393	0.772
M2 - LOG. MIXED EFFECTS	-67.509	13.330	0.000
M3 - LOG. HIERARCHICAL EFFECTS	73.173	6.325	0.000
M4 - NN: 1 LAYER; 10NEURONS, LOG.FUNC.	3.532	3.158	0.263
M5 - NN: 1 LAYER; 3NEURONS, TAN.FUNC.	-0.867	3.417	0.800
M6 - NN: 1 LAYER; 4NEURONS, TAN.FUNC.	9.115	3.647	0.012
_cons	-4.359	0.113	0.000

2010 Models` Estimation Results:

M1 - LOGISTIC: 2010

Logistic regression	Number of obs = 16080		
LR chi2(13) = 229.42			
Prob > chi2 = 0.0000			
Log likelihood = -2521.3028	Pseudo R2 = 0.0435		
tkvr	Coef.	Std. Err.	P>|z|
ROA	0.029	0.020	0.139
Growth of 3 year Total Assets	-0.143	0.092	0.118
Market Capitalisation/ Total Assets	-0.038	0.023	0.098
Quick Assets	0.000	0.000	0.012
Dividend per share / Earnings per share	-0.010	0.006	0.091
Mining Industry Dummy	0.126	0.095	0.186
ASX300 Dummy	0.520	0.113	0.000
Log (Total Assets)	0.196	0.025	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-6.738	0.449	0.000

M2 - LOG. MIXED EFFECTS: 2010

Mixed-effects logistic regression	Number of obs = 16080
Group variable: id	Number of groups = 2612
Obs per group: min = 1 avg = 6.2 max = 10	
Integration points = 7	Wald chi2(9) = .

Log likelihood = -2512.2731	Prob > chi2 = .		
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.170	0.098	0.083
Quick Assets	0.000	0.000	0.016
Dividend per share / Earnings per share	-0.011	0.007	0.088
ASX300 Dummy	0.560	0.126	0.000
Log (Total Assets)	0.248	0.028	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-7.983	0.516	0.000
Random-effects Parameters	Estimate	Std. Err.	
id: Identity var(_cons)	0.853	0.213	
LR test vs. logistic regression: chibar2(01) = 24.25 Prob>=chibar2 = 0.00			

M3 - LOG. CROSSED EFF.: 2010

Crossed-effects logistic regression Number of obs = 16080

No. of Group	Observations per Group	Integration Variable	Groups	Average
		_all	11	1461.8
		id	2612	6.2

Log likelihood = -2490.544 Prob > chi2 = . Wald chi2(9) = .

tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.170	0.098	0.082
Quick Assets	0.000	0.000	0.016
Dividend per share / Earnings per share	-0.011	0.006	0.088
ASX300 Dummy	0.559	0.126	0.000
Log (Total Assets)	0.249	0.028	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-8.005	0.526	0.000
Random-effects Parameters		Estimate	Std. Err.
_all: Identity var(R.sector)		0.047	0.111
id: Identity var(_cons)		0.922	0.115
LR test vs. logistic regression: chi2(2) = 24.30 Prob > chi2 = 0.0000			

C1 - Weights Combination: 2010

Logistic regression Number of obs = 16080

LR chi2(6) = 1910.28

Prob > chi2 = 0.0000

Log likelihood = -1680.873 Pseudo R2 = 0.3623

tkvr	Coef.	Std. Err.	P>|z|
M1 - LOGISTIC REGRESSION	4.871	6.828	0.476
M2 - LOG. MIXED EFFECTS	-96.505	12.813	0.000
M3 - LOG. HIERARCHICAL EFFECTS	92.607	7.115	0.000
M4 - NN: 1 LAYER; 10NEURONS, LOG.FUNC.	5.110	3.003	0.089
M5 - NN: 1 LAYER; 3NEURONS, TAN.FUNC.	8.363	9.478	0.378
M6 - NN: 1 LAYER; 4NEURONS, TAN.FUNC.	7.657	3.342	0.022
_cons	-4.755	0.298	0.000

2011 Models` Estimation Results:

M1 - LOGISTIC: 2011

Logistic regression Number of obs = 18004

LR chi2(13) = 236.25

Prob > chi2 = 0.0000

Log likelihood = -2834.7587 Pseudo R2 = 0.04

tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.135	0.085	0.113
Inventory/Working Capital	0.001	0.001	0.077
Market Capitalisation/ Total Assets	-0.032	0.021	0.129
Quick Assets	0.000	0.000	0.012
Dividend per share / Earnings per share	-0.010	0.006	0.082
Mining Industry Dummy	0.144	0.089	0.108
ASX300 Dummy	0.445	0.109	0.000
Log (Total Assets)	0.197	0.023	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-6.754	0.419	0.000

M2 - LOG. MIXED EFFECTS: 2011

Mixed-effects logistic regression Number of obs = 18004

Group variable: id Number of groups = 2674

Obs per group: min = 1 avg = 6.7 max = 11

Integration points = 7 Wald chi2(9) = .

Log likelihood = -2824.5732 Prob > chi2 = .

tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.165	0.091	0.071
Inventory/Working Capital	0.001	0.001	0.066
Quick Assets	0.000	0.000	0.017
ASX300 Dummy	0.496	0.121	0.000

Log (Total Assets)	0.243	0.026	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-7.891	0.486	0.000
Random-effects Parameters	Estimate	Std. Err.	
id: Identity var(_cons)	0.881	0.200	
LR test vs. logistic regression: chibar2(01) = 30.34 Prob>=chibar2 = 0.00			

M3 - LOG. CROSSED EFF.: 2011

Crossed-effects logistic regression	Number of obs = 18004		
No. of Group	Observations per Group Integration		
	Variable	Groups	Average
	_all	11	16080
	id	2612	6.2
Log likelihood = -2491.3354 Prob > chi2 = . Wald chi2(9) = .			
tkvr	Coef.	Std. Err.	P>|z|
ROA	0.009	0.009	0.296
Growth of 1 year Total Assets	-0.018	0.017	0.307
Inventory/Working Capital	0.001	0.001	0.068
Quick Assets	0.000	0.000	0.018
ASX300 Dummy	1.116	0.103	0.000
Market Capitalisation	0.000	0.000	0.261
_cons	-3.665	0.089	0.000
Random-effects Parameters		Estimate	Std. Err.
_all: Identity var(R.sector)		0.012	0.019
id: Identity var(_cons)		0.668	0.176
LR test vs. logistic regression: chi2(2) = 22.38 Prob > chi2 = 0.0000			

C1 - Weights Combination: 2011

Logistic regression	Number of obs = 18004		
LR chi2(6) = 1864.81			
Prob > chi2 = 0.0000			
Log likelihood = -2014.8145	Pseudo R2 = 0.3164		
tkvr	Coef.	Std. Err.	P>|z|
M1 - LOGISTIC REGRESSION	-39.025	5.677	0.000
M2 - LOG. MIXED EFFECTS	32.070	5.316	0.000
M3 - LOG. HIERARCHICAL EFFECTS	19.091	2.984	0.000
M4 - NN: 1 LAYER; 10NEURONS, LOG.FUNC.	-15.645	5.949	0.009
M5 - NN: 1 LAYER; 3NEURONS, TAN.FUNC.	6.888	0.847	0.000
M6 - NN: 1 LAYER; 4NEURONS, TAN.FUNC.	7.231	3.180	0.023

_cons	-3.945	0.098	0.000

Returns at the end of the year by company

FY 2009				
Predicted Targets 19 Companies		Buy and Hold Return	AVERAGE RETURN	Announcement
target	LST	-27.32%	-22.08%	24/06/2009
	QGC	7.08%		28/10/2008
	TPX	-46.00%		10/10/2008
non-target	BEN	-36.41%	-25.82%	
	CBH	-42.11%		
	CHQ	-44.79%		
	CIF	-45.45%		
	CNP	-62.04%		
	FLT	-48.11%		
	GPT	-21.17%		
	IPN	1.92%		
	MMX	-43.05%		
	NXS	-33.23%		
	QAN	-33.88%		
	REA	35.84%		
	SBM	-36.99%		
	SGB	2.18%		
	SST	27.12%		
	VBA	-32.98%		
Portfolio			-25.23%	

FY 2010				
Predicted Targets 40 Companies		Buy and Hold Return	AVERAGE RETURN	Announcement
target	AOE	36.62%	61.56%	22/03/2010
	CKT	154.88%		9/12/2009
	ERC	-52.40%		14/09/2009
	FLX	19.08%		14/08/2009
	LGL	46.10%		29/03/2010

	LLP	**231.52%**		28/09/2009
	PLI	**75.00%**		3/09/2009
	SSI	**-58.04%**		1/09/2009
	TKA	**101.28%**		8/02/2010
non-target	AAY	**-61.54%**	**1.48%**	
	AEM	**0.00%**		
	ANZ	**31.05%**		
	AQF	**21.60%**		
	AZO	**-4.24%**		
	CBZ	**-26.39%**		
	CDU	**82.17%**		
	CFE	**1.56%**		
	CSL	**1.34%**		
	CWK	**51.06%**		
	CXC	**18.26%**		
	EQX	**-22.22%**		
	HDI	**0.00%**		
	KMD	**-1.76%**		
	MDL	**51.61%**		
	MOO	**-8.33%**		
	MQA	**3.26%**		
	PTN	**-48.24%**		
	RMR	**40.00%**		
	ROB	**-46.15%**		
	RUL	**-23.08%**		
	RVE	**127.27%**		
	SHU	**-10.00%**		
	SNE	**-20.00%**		
	SOI	**-44.44%**		
	TBI	**-32.69%**		
	VGM	**-25.00%**		
	VIP	**0.00%**		
	WBC	**4.84%**		
	WCR	**-21.95%**		
	WIG	**8.02%**		
	Portfolio		**15.00%**	

FY 2011				
Predicted Targets 18 Companies		Buy and Hold Return	AVERAGE RETURN	Announcement
target	AKR	-6.33%	43.05%	22/11/2010
	ASX	4.42%		25/10/2010
	CRG	28.94%		15/12/2010
	DKN	41.07%		27/06/2011
	IIF	42.67%		23/12/2010
	JML	147.54%		9/02/2011
non-target	API	-28.21%	0.27%	
	CER	109.38%		
	CNP	-72.59%		
	DUE	5.26%		
	DXS	14.29%		
	EXT	19.08%		
	MDL	-39.57%		
	OMH	-37.20%		
	RIO	24.50%		
	SPN	23.53%		
	TAP	-2.92%		
	TPM	-12.24%		
Portfolio			14.53%	