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THE PREDICTION OF AUSTRALIAN TAKEOVER TARGETS: A BINOMIAL AND MULTINOMIAL LOGIT ANALYSIS

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Abstract

This thesis provides the first attempt to predict takeover targets in the Australian context using binomial and multinomial logit models, extending the relatively small amount of work focused in the United States, Canada, and the United Kingdom. Evidence is provided concerning eight main hypothesised motivations for takeovers. Our results confirm the contention that such motivations are inconsistent both throughout time and across economies. Application of models to a true ex-ante predictive sample suggests that individual models are quite inaccurate, but that the use of certain methodological improvements can produce relatively accurate predictive classifications. Multinomial logit models are also compared to binomial logit models to examine whether theoretical benefits exist from discrimination between types of targets. Evidence is provided suggesting that the binomial model is indeed misspecified, but that it is the most appropriate model if the purpose of prediction is investment. Our main empirical finding is that a significantly positive abnormal return of 23.37 percent (68.67 percent prior to robustness adjustments) may be made from an investment in the commonly predicted targets of logit based models. This contradicts the current belief within the extant literature that such returns cannot be achieved through the use of binomial logit models for true ex-ante prediction.

Introduction and Motivations

Academic research concerning the ability of discrete choice models to classify and predict targets of mergers and acquisitions is not a new phenomenon, as this fascination has a basic economic justification. Researchers such as Jensen and Ruback (1983) document that it is extremely difficult, if not impossible, for the market to predict future targets of mergers and acquisitions even three to six months prior to the bid. In addition, these researchers document evidence of the significant announcement period abnormal returns of 20 percent to 30 percent available to shareholders of firm's which are subject to takeover bids. Theoretically, if one were able to predict such events with accuracy greater than the market, then one would also be able to extract some of this abnormal return. In the words of Barnes (1999), if the stock market is a casino, then anyone who can predict takeover targets will surely break the bank. But the depth of research into takeover prediction has been minimal in comparison to the hundreds of published studies in the closely linked area of bankruptcy prediction, even though there is no real economic justification for such a fascination. Methodological improvements have also been slowly adapted from the bankruptcy prediction literature to the takeover prediction literature, and no direct tests have been conducted to examine the impact of these methodological changes. And although the argument for the availability of abnormal returns is an appealing one, the fact is that many of these studies are unable to predict takeovers with any accuracy greater than the market, as will be demonstrated by the following literature review.

The major objective of this paper will be to create and assess the ability of a discrete choice model to accurately classify and predict targets of mergers and acquisitions in the Australian context. This will be achieved through a modelling procedure known as the nominal logit model, and will be conducted in such a way as to replicate the problem faced by a practitioner attempting to predict such events in a future period. Financial and non-financial discriminators will be used. Only information available from a specific estimation period will be applied to a future prediction period to test the true ex-ante predictive accuracy of such models, rather than their ex-post classification abilities which have been heavily documented. Complementary to this major objective of the paper will be an assessment of the ability of the model predictions to earn the abnormal returns which are supposedly available through the reasoning explained above. This objective will also be assessed from the view of a practitioner attempting to predict such events. Many researchers have attempted this method but have failed to prove the availability of positive abnormal returns.

Such is the depth of the general mergers and acquisitions literature that no less than 15 theoretical motivations for takeover have been proposed within the corporate finance and strategic management literature (Trautwein, 1990). Additionally, researchers such as Walter (1994) have provided evidence that these motivations are inconsistent throughout time and across economies. Morck, Shleifer, and Vishny (1988) document that motivations are markedly different between hostile (disciplinary) and friendly (synergistic) takeovers. Based on this evidence, a minor objective of this thesis will be to examine the motivations for takeover in the Australian context. The purpose of this objective is to confirm or refute the select number of hypothesised motivations examined in the following literature review, which are based on well developed theoretical motivations from the extant mergers and acquisitions literature.

This thesis will proceed as follows. Section 1 will briefly examine the extant takeover prediction literature and highlight some of the basic methodological flaws of early research. Section 2 will focus on the general mergers and acquisitions literature to develop theoretical arguments for eight main motivations for takeovers, concluding with a small hypothesis development. Section 3 will document the methodological process of this paper, and the improvements which have been made relative to those studies within the extant literature. Section 4 will present the results of these analyses and attempt to synthesise these in comparison to the literature. Section 5 will conclude with an examination of the implications of the findings and possible avenues for future research within the realms of takeover prediction in the Australian context.

1. Literature Review

This literature review will begin with an examination of the takeover prediction literature to determine whether takeover prediction has been achieved with any robust level of accuracy. Following this will be an examination of the theoretical motivations for takeovers in Section 2. This will be undertaken from the perspective of both the general mergers and acquisitions literature and the takeover prediction literature. Such motivational development is a major requirement for the construction of a model with classification accuracy, as these theories allow us to discriminate between target and non-target firms on the basis of individual firm characteristics. Note that specific motivations for takeovers, such as the well acknowledged synergies theories, are not examined because we are unable to use such theories to discriminate between target and non-target firms. Section 2.8 will conclude the analysis of the literature by developing eight main motivational hypotheses to be examined by this thesis.

1.1 The Takeover Prediction Literature

Takeover prediction became popular within the finance literature in the early 1970's with published US research from Simkowitz and Monroe (1971) and Stevens (1973). Because of the close link to bankruptcy classification and prediction, the models of these researchers were based on the Multiple Discriminant Analysis (MDA) technique made popular by Altman (1968). Stevens (1973) coupled his MDA with a factor analysis to eliminate potential multicollinearity problems. Their models were based purely on financial ratios as discriminators between target and non-target firms, which conformed to groups such as liquidity, profitability, leverage and activity. Also, traditional holdout approaches were applied for predictive accuracy assessment, which involved splitting the sample in two – one portion was used to estimate the model and the remaining portion was used to assess the classification accuracy. Stevens (1973) reported a predictive accuracy[1] of some 67.5 percent under this methodology, suggesting that takeover prediction was viable. On the basis of these results, Belkaoui (1978) and Rege (1984) conducted similar analyses in Canada. Belkaoui (1978) confirmed the results of these earlier researchers, with a predictive accuracy of 85 percent reported from a similar holdout methodology as the US researchers. But concerns were raised by Rege (1984), who was unable to predict accurately. These concerns were confirmed by the research of Singh (1971), and Fogelberg, Laurent, and McCorkindale (1975).

A new wave of research methodology was adopted in the takeover prediction literature as a result of the research of Harris et al (1982). Their probit analysis began a trend in discrete choice modelling for takeover prediction which was based on the logit analysis of Ohlson (1980) in the

[1] Predictive accuracy refers to the proportion of targets correctly classified as targets by the model.

bankruptcy prediction literature. These researchers presented evidence that the model had extremely high explanatory power, but was unable to discriminate between target and non-target firms with any degree of accuracy. Dietrich and Sorensen (1984) continued this early work and, utilising a logit model, presented evidence of a classification accuracy rate of some 90 percent. Their results represent the highest predictive accuracy reported by any published takeover prediction study, suggesting that takeover prediction was indeed viable.

But there were some obvious methodological limitations within this early literature. The use of holdout samples indicated ex-post classification ability rather than ex-ante predictive ability. Many other problems were highlighted by the influential paper of Palepu (1986) which utilised the logit model. He proposed that the use of state-based prediction samples, where a number of targets were matched with non-targets for the same sample period, exaggerated predictive accuracies[2]. This was based on the contention that estimated error rates from such samples were not indicative of their occurrence in the population. He also proposed the use of an optimal cutoff point derivation which considered the decision problem, payoff function, and prior state probabilities. The purpose of this was to overcome the use of arbitrary cutoff points[3] by prior research which made the interpretation of reported accuracies meaningless. Using rectified methodology and an extremely large US data set, Palepu (1986) provided evidence that the ability of the logit model was no better than a chance selection of target and non-target firms. He also utilised an ingenious equally weighted portfolio approach, a variation of which will be

[2] For a mathematical proof of the bias impounded into reported accuracies because of the use of state based prediction samples, see page 10 of Palepu (1986).

[3] The significance of the derivation of the cutoff point will be examined in the methodological section of this paper. Essentially, the cutoff point is used to classify predicted probabilities of acquisition into predictions that the firm will or will not become a takeover target during the sample period.

presented in this thesis, to assess whether the predictions of his model were able to earn abnormal returns. This provided no evidence that abnormal returns could be made, consistent with an inability to predict these events with accuracy greater than the market. Methodological improvements were furthered by Barnes (1999), who shifted focus from accurately predicting targets to maximising the number of actual targets in the portfolio of predicted targets. This maximised returns from a portfolio investment. Although implementing the best methodology available, his model was unable to predict any takeover targets – one of the poorest results of any published study. Powell (2001) improved this accuracy with another UK analysis, but confirmed that abnormal returns were unavailable from application of the binomial model. Wansley et al (1983) contradicted this evidence using a state based prediction sample, but as acknowledged by Palepu (1986) such methodologies are flawed.

All of the cited literature to this point has been based on financial ratios derived from historical cost data, but many researchers have advocated the use of current cost data for the calculation of financial ratios. This argument is based on the fact that historical cost data inaccurately proxies for undervaluation or overvaluation of a firm, which has been proposed as an important motivation for takeover and subsequently an important discriminating variable. Walter (1994) made a comparison of current and historical cost models, providing evidence that the inclusion of current cost variables improved explanatory power. Although the historical cost model exhibited predictive accuracies greater than chance, the current cost model made higher, but not positive, returns. Bartley and Boardman (1990) also utilised current cost financial ratios in their models, reporting an accuracy of some 82.5 percent. However, this result was problematic as this study utilised state-based sampling which exaggerated their reported accuracies. Note that

Bartley and Boardman (1990) actually utilised the MDA methodology like the early researchers. Zanakis and Zopounidis (1997) also utilised the MDA methodology for the classification of Greek targets and non-targets. Their research indicated classification accuracies significantly better than chance for the MDA models although their logit model was unable to achieve such accuracies. Barnes (1990) confirmed the accuracy of this technique, providing further evidence that the MDA methodology could be utilised to predict with accuracy greater than chance.

The most recent research has been conducted by Powell (1997, 2004) within a UK dataset spanning from 1986 to 1995. He utilised a multinomial specification of the logit model which attempted to discriminate between non-targets and hostile and friendly targets individually. Powell (2004) demonstrates that the prediction of hostile takeover targets alone allows one to earn a significantly positive abnormal return of 17 percent over a three year holding period. Although a significant result, the portfolio of 117 predicted targets contained only 7 firms which were actually taken over. The significantly positive returns to the 7 actual targets would likely be washed out by the average zero abnormal returns on the 110 non-target firms in this portfolio of predicted targets. This suggests that the result is driven by a chance selection of outperforming non-target firms rather than an accurate selection of targets. It is our contention that the result of Powell (2004) is spurious.

Two main conclusions can be drawn from the extant takeover prediction literature. Firstly, where it has been demonstrated that predictive accuracy greater than chance can be achieved, as in the case of Walter (1994), these studies have employed samples which are not representative of the population of firms. Secondly, where papers have demonstrated the ability to earn significantly positive abnormal returns, such as in Wansley et al (1983) and Powell (2004), the results are either based on problematic sampling methodology or are a potentially spurious result. The conclusion drawn from the literature is that we are unable to predict takeover targets with accuracy greater than chance, and that we are unable to use the predictions of such models to earn abnormal returns[4].

1.2 Implications for Market Efficiency

Because of the polarised nature of the market efficiency debate, some researchers have attempted to relate this argument to the takeover prediction literature. Rege (1984) proposes that an ability to accurately predict takeover targets based on purely financial information constitutes an infringement of semi-strong market efficiency. His justification is that semi-strong form efficiency stipulates that all publicly available information is impounded into the current price of a security, suggesting that any implied probability of takeover should be impounded into the current price of a stock. His proposal is that if we are able to provide evidence that an abnormal return can be made from an investment in predicted targets, then we have evidenced a violation of semi-strong form market efficiency. Barnes (1990) furthers this in the context of the random walk hypothesis (weak form efficient markets hypothesis); suggesting that future price changes should not be able to be forecasted from past price changes and existing information. Although this is a theoretically appealing argument against market efficiency, most researchers have neglected to draw such conclusions. This is based on the belief of researchers such as Fama (1998) that market efficiency tests of this from are joint tests of the applicability of the returns model used to calculate abnormal returns, making it extremely difficult to prove market

[4] Inability to earn abnormal returns implies an inability to predict takeovers more accurately than the market, which is based on the reasoning of Palepu (1986).

inefficiency. Fama (1998) also argues that there must be consistent evidence of an ability to earn significantly positive abnormal returns to prove the existence of an anomaly.

2. Hypothesised Motivations for Mergers and Acquisitions

2.1 The Inefficient Management Hypothesis and the Market for Corporate Control

Explanation of the inefficient management hypothesis requires acknowledgement of the corporate structure of the modern firm. As management are generally not majority shareholders in these firms, Jensen and Meckling (1976) suggest this causes an agency problem as decision making and risk bearing are separated between management and stakeholders[5]. Although a principal-agent problem may exist, Fama (1980) and Manne (1965) theorised that a mechanism existed which ensured that management acted in the interests of the vast number of small non-controlling shareholders[6]. They proposed that a market for corporate control existed in which alternative management teams competed for the rights to control corporate assets. This is based on the premise that the threat of acquisition would align management objectives with those of stakeholders as management would surely be terminated in the event of an acquisition for inefficient management of the firm's assets. Although Fama (1980) proposes that this is an effective mechanism to ensure that target management act in the best interests of shareholders, Martin and McConnell (1991) and Manne (1965) propose that deviations from efficient management provide an effective motivation for takeovers. This contention is confirmed by Jensen and Ruback (1983), who suggest that both capital gains and increased dividends are available to an acquirer who can eliminate the inefficiencies created by target management, with the attractiveness of the firm for takeover increasing with the level of inefficiency. Manne (1965)

[5] Stakeholders are generally considered to be both stock and bond holders of a corporation.

[6] We take the interests of shareholders to be in the maximization of the present value of the firm.

contends that the stock price of a firm must be positively related to the efficiency of the firm for this to occur, providing capital gains to those able to eliminate inefficiencies. This disciplinary motivation for takeovers suggests that inefficiently managed firms are acquired by management teams who believe that they can more efficiently employ the assets of the firm (Fama, 1980).

Accordingly, the takeover prediction literature has attempted to utilise the inefficient management hypothesis to discriminate between target and non-target firms. Three main groups of financial ratios have been utilised as proxies for management efficiency. The use of proxies is based on the contention of Manne (1965) that the true efficiency of the firm is only observable by internal parties. These include operating performance, stock price performance, and activity performance. Early research by Stevens (1973) and Simkowitz and Monroe (1971) pioneered the use of profitability ratios, usually based on variables such as EBIT and scaled by net assets or total assets, to proxy for management efficiency. Palepu (1986) utilised a ROE measurement, and Walter utilised a ROA measurement, both of which were found to be insignificant in explaining acquisition likelihood. Barnes (1999) contradicted these early researchers and the inefficient management hypothesis, providing evidence that higher profitability increased acquisition likelihood. As noted, appropriate operation of the market for corporate control requires a positive relationship between management efficiency and the market value of the firm. Based on this reasoning, Palepu (1986) utilised a Cumulative Abnormal Return variable. He provided evidence that this was significantly negatively related to acquisition likelihood, confirming the inefficient management hypothesis as inefficiently managed firms had higher estimated acquisition likelihoods. Researchers such as Barnes (1999) and Dietrich and Sorensen (1984) utilised activity ratios as proxies for management efficiency, as they indicate the ability of assets to generate revenue[7]. Both documented that such measurements were significantly negatively related to acquisition likelihood. Mixed evidence for the inefficient management hypothesis has been confirmed by the general merger and acquisitions literature. Researchers such as Martin and McConnell (1991) have provided significant evidence in favour of this hypothesis, but researchers such as Agrawal and Jaffe (2003) have provided contradictory evidence using similar operating and stock price performance measurements. Contradictory evidence has been confirmed in the Australian context by Bugeja and Walter (1995) and McDougall and Round (1986). Although inefficient management is commonly accepted as a strong theoretical motivation for takeovers, the empirical evidence is mixed.

2.2 The Market for Corporate Control and the Undervaluation Hypotheses

2.2.1 Market to Book Hypothesis

The Market to Book Hypothesis was developed on the basis of the Market for Corporate Control and the Inefficient Management Hypothesis. Manne (1965) proposes that a deflated stock price is indicative of the markets belief that an alternative management team exists who could more efficiently employ the firms' assets, providing an opportunity for realisation of capital gains. But Palepu (1986) suggests an alternative explanation, like Ravenscraft and Scherer (1987) and Bradley, Desai, and Kim (1983), that undervaluation simply measures the potential economic gain available to an acquirer who is able to change the markets perception concerning the true value of the firm's assets. Eddey (1991) furthers this contention, suggesting that undervalued firms are more attractive for takeovers as they allow immediate economic gains to be realised

[7] Activity ratios such as the Operating Revenue/Total Assets variable utilised by most researchers are extremely informative as they indicate the efficiency of management in generating revenue for a given level of assets.

through the process of asset stripping. Although the above researchers propose competing explanations, they all suggest that the attractiveness for takeover will increase with the level of undervaluation of the firm. Golbe and White (1988) document that aggregate merger and acquisition activity increases in period of low Q ratios[8], providing general evidence consistent with this contention. The takeover prediction literature has also attempted to utilise these variables to explain acquisition likelihood. Walter (1994) and Bartley and Boardman (1990) provided evidence that acquisition likelihood is negatively related to such variables, confirming that undervalued firms have a higher likelihood of acquisition. Other studies which do not have access to current cost data utilise a close proxy for this value, being the market to book ratio. This variable is an inefficient proxy of the Q ratio because net assets, as a historical cost, are a poor measurement of the replacement value of assets[9]. Palepu (1986) and Barnes (1999) provided evidence that the M/B ratio is insignificant in the discrimination between target and non-target firms, a result most likely driven by the empirical limitations of this variable. Although undervaluation is a theoretically appealing motivation for takeovers, studies employing variables based on historical costs have been unable to document it as a significant motivation for takeovers.

2.2.2 Price to Earnings Hypothesis

The P/E ratio has also been proposed as an explanatory variable in takeover prediction studies, as some researchers believe that it is a measurement of both management efficiency and relative

[8] Note that Q ratios in this context measure the ratio of the market value of assets to the replacement value of assets.

[9] The M/B ratio should be a more accurate representation of the Q ratio in the Australian context because companies are regularly required to update the book value of their assets, making the value of net assets more representative of their true replacement values.

valuation. Barnes (1999) utilises the modern interpretation of this variable, suggesting that it indicates the markets expectation of the profitability of the firm in the short to medium term future. Powell (1997) suggests that this variable indicates the markets expectation of management's ability to achieve earnings growth into the future, as high (low) values indicate higher (lower) expectations for earnings growth. One could also make a comparison to the M/B ratio, as some believe that the P/E ratio measures the relative valuation of the firm's earnings, which is entirely consistent with the other explanations. But Palepu (1986) offers an alternative explanation which is a little more illogical than that of Barnes (1999). He suggests that a firm with a low P/E multiple will be a likely acquisition target for an acquirer with a high P/E ratio because the earnings of the acquired firm will be valued at the multiple of the acquirer, allowing an immediate capital gain to be realised by the acquirer. Although plausible, most researchers take the first explanation as the basis for the inclusion of this variable for discrimination between target and non-target firms. Empirically, all takeover prediction studies cited since the earliest study of Stevens (1973) have documented that this variable is insignificant in explaining acquisition likelihood. As for the M/B hypothesis, the empirical evidence in favour of the P/E hypothesis is weak.

2.3 Managerial Behaviour and the Growth-Resource Mismatch Hypothesis

This hypothesis is based on two commonly accepted resource allocation problems:

2.3.1 Agency Costs of Free Cash Flow

Jensen (1986) furthers the examination of the principal-agent problem explored within the inefficient management hypothesis to incorporate arguments concerning the level of free cash flow that a firm possesses[10]. His analysis focuses on firms which have achieved high levels of growth in recent periods, and have a high level of free cash flow, but no profitable investment opportunities. The proposal is that management will be reluctant to return excess funds to shareholders, as this would reduce assets under management and subsequently the value of management to shareholders along with their remuneration. This argument is based on the theoretical and empirical evidence of Marris (1963), which suggests that management are more concerned with the size of their firms than shareholder welfare maximisation as their pecuniary and non-pecuniary numeration is more heavily related to size. Such agency hypotheses suggest that even though these firms have no profitable investment opportunities available, they will still invest in negative Net Present Value (NPV) projects, which constitutes a resource misallocation. Jensen (1986) suggests that the market value of the firm is discounted by the expected agency costs of free cash flow, which can be rectified through merger or acquisition with a growing firm which requires the use of these excess funds.

2.3.2 Corporate Decisions under Information Asymmetry

Myers and Majluf (1984) analyse the opposite situation, where a firm has profitable investment opportunities but has no financial slack available and must issue stock to raise the required capital. Their model assumes that information asymmetry exists between stockholders and management, as management is unable to convey the true profitability of the investment opportunity to shareholders. In such a case, the issuance of stock results in a negative stock price reaction for the issuing firm, resulting in a large cost for existing shareholders. In the case that the loss in value for the existing shareholders outweighs the positive NPV of the project,

[10] We take the definition of free cash flow to be cash flows in excess of those required for positive NPV investment opportunities and normal levels of financial slack.

management of the firm will not undertake the issuance of stock or investment. A reverse resource misallocation problem exists to that proposed by Jensen (1986), as these researchers propose that an underinvestment in positive NPV projects occurs. Myers and Majluf (1984) provide evidence that the elimination of such misallocations, through merger or acquisition, can result in a positive value impact.

2.3.3 Growth Resource Mismatch as a Motivation for Takeovers

Smith and Kim (1994) combine these two resource allocation problems to create a theoretically strong motivation for takeovers. They propose that a combination of these firms through merger or acquisition, the “slack-poor” and the “slack-rich” firm, will be an optimal solution to the two respective resource allocation problems. The slack-poor firm proposed by Myers and Majluf (1984) will have the required funds to invest in the positive NPV project, whilst the slack-rich firm proposed by Jensen (1986) will have no longer have the incentive to invest in negative NPV projects as the size of the firm has been dramatically increased. The result should be a market value for the combined entity which exceeds the sum of the individual values, suggesting a synergistic type of benefit. Smith and Kim (1994) subsequently provide empirical evidence that the merger of a slack-poor and slack-rich firm creates more value than that of two similar firms where the merger is believed to simply exacerbate the resource misallocation problem.

The takeover prediction literature has attempted to utilise this motivational hypothesis to differentiate between target and non-target firms. Researchers such as Barnes (1999), Palepu (1986), and Powell (2001) hypothesise that firms which possess high growth opportunities / low resources, or low growth opportunities / high resources, are more likely to be acquisition targets.

Inefficient proxies have been used by these researchers for future growth rates, such as current growth rates, as we are unable to accurately observe these variables. Barnes (1999) utilised a capital expenditure variable to more appropriately measure growth opportunities. Financial resource availability has generally been measured through variables such as current liquidity and leverage. The problem with these measurements is that they focus only on the attributes of potential targets, and are unable to compare these to characteristics of potential acquirers, contradicting the combinational nature of the theory. Even so, empirical evidence has strongly confirmed the growth-resource mismatch hypothesis. Palepu (1986) utilised a dummy and a set of continuous variables which indicated significance for this hypothesis. This method was replicated by the analysis of Barnes (1999) with continuous variables and Powell (2001) with dummy and continuous variables. Both of these researchers documented significant growth-resource imbalances for targets. Walter (1994) and Bartley and Boardman (1990) contradicted them, providing no evidence of statistical significance. Powell (1997, 2001) also included a Free Cash Flow measurement to examine for an agency cost of free cash flow problem individually, but documented insignificance[11].

2.3.4 Dividend Payout Hypothesis

As suggested, past growth ratios are an inefficient measurement of future growth opportunities. Stevens (1973) and Harris et al (1982) utilised the dividend payout ratio as a more appropriate proxy for the true investment opportunities available for a firm. This is based on the theory of Myers and Majluf (1984), which suggests that it is optimal for firms to hold adequate financial slack for investment opportunities, rather than distributing it to shareholders as stock issuance

[11] We believe that the FCF variable is more applicable as a measurement of profitability under the inefficient management hypothesis.

results in a large cost for existing investors. Interpretation of this theory suggests that firms which are paying out less of their earnings are aggregating financial slack to exploit future investment opportunities which they believe exist. This theory exploits observed managerial behaviour to extract information concerning the future opportunities of the firm. Empirically, Harris (1982) and Stevens (1973) found the dividend payout ratio to be insignificant in discriminating between target and non-target firms. But Dietrich and Sorensen (1984) documented a significant negative relationship between the payout ratio and acquisition likelihood. More recent research by Barnes (1999), Palepu (1986) and Powell (1997) has neglected to include the payout ratio as a discriminatory variable. Overall, the theoretical and empirical evidence is quite strongly in favour of the growth resource mismatch hypothesis, although evidence in favour of the dividend payout hypothesis is generally weaker.

2.4 Capital Structure and the Inefficient Financial Structure Hypothesis

Lewellen (1971) believes that an alternative exists to operational synergies as a motivation for takeovers, suggesting that financial synergies may have been a motivation for conglomerate US mergers of the 1960's. His analysis is based on the traditional model of capital structure, which suggests that increases in debt to reasonable levels will not dramatically increase the required return on equity. He suggests increases in debt in such firms should increase the residual equity value of the company, as high return demanding equity is replaced with low coupon debt. The implication of this traditional theory is that, if a merger partner is not utilising its latent debt capacity, then a combination with a firm which utilises this capacity will realise a valuation gain known as a financial synergy. Such a financial synergy can also be explained within the well known Miller and Modigliani (1964) model, but in it's cum corporate taxes form. M&M suggest that increases in debt to reasonable levels will increase the residual equity value of the firm. Such an outcome confirms that a merger of firms where either is not utilising their latent debt capacity will result in a financial synergy being realised. Note that existence of financial synergies of this form requires that the existing suboptimal capital structure of a merger partner is unable to be eliminated without effecting the merger or acquisition. This could result from such things as management incompetence in capital structure planning, or an inability to gain access to the required debt facilities.

But Barnes (1999) suggests that potential financial synergies may exist from combining two firms where one of these firms has higher than optimal levels of debt in their capital structure. According to the traditional theory presented in Brealey, Myers, and Allen (2005), an optimal capital structure exists at a medium debt capacity, as increases in debt past these levels will be extremely costly because of increased risk. This conforms to the view of Jensen (1986), that an optimal capital structure exists which equates the marginal costs and marginal benefits of debt. This suggests than an equivalent financial synergy may be made available when a potential merger partner has an over-levered position. The rectification of such problems through merger will result in an increase in the residual equity valuation. To understand this from a different perspective, we must realise that high levels of leverage make firms Earnings per Share (EPS) extremely volatile. This volatility significantly reduces EPS in times of recession, flowing on into market values and increasing the vulnerability of the firm for bankruptcy or takeover. The proposition of Barnes (1999) is that during recessions, acquisition of a firm which is experiencing issues from an extremely levered position, and rectifying this deficiency, will result in a financial synergy.

On the basis of these theories, Leverage has been included as an explanatory variable in many models of takeover prediction. The early models of Stevens (1973) examined whether this was a significant motivational factor, with mixed success in discriminating between target and non-target firms. Barnes (1999), Walter (1994), and Powell (1997) have deemed this variable to be insignificant for discrimination. However, Dietrich and Sorensen (1984) and Palepu (1986) found that leverage is significantly negatively related to acquisition likelihood, consistent with the interpretation of Lewellen (1971). Powell (2001) believed that this variable could also be used to measure financial resource availability for the purposes of the growth-resource mismatch hypothesis, as under-utilised debt capacity could suggest excess financial slack. Although the theoretical argument for inefficient financial structure as a motivation for takeovers is strong, the empirical evidence for such a financial motivation for mergers is mixed.

2.5 Takeover Activity Waves and the Industry Disturbance Hypothesis

Since the earliest mergers and acquisitions literature, researchers have acknowledged that takeovers occur in distinct waves which cluster both throughout time and across industries. Gort (1969) was one of the first to explore the concept that industry disturbances created such wave activity. He postulated that economic shocks (such as deregulation, changes in input and output prices, etc) caused expectations concerning future cash flows to become more variable, increasing the likelihood that a potential acquirer would value the target shares at a higher level than their current holders and resulting in a takeover. Mitchell and Mulherin (1996) provided significant empirical evidence of this through analysis of the US experience during the 1980's, suggesting that such events cluster by industry throughout time. But they believe that the waves result from the fact that mergers, acquisitions, and leveraged buyouts are the least cost method for response to economic shocks. This reasoning is confirmed by Andrade, Mitchell, and Stafford (2001). Either way, both theories suggest that mergers occur in distinct waves as a result of economic shocks.

But Rhodes-Kropf and Viswanathan (2004) believe that such waves may exist even without economic shocks as the "trigger". Their theoretical second price auction framework suggests that merger waves may simply result from overvaluation[12] in the general market place, and that market undervaluation may halt such waves. This is based on the contention that during periods of market overvaluation, the estimation error associated with synergy valuation is high; leading to more bid proposals and acceptances as targets will more readily accept takeover bids. This confirms the general evidence of Jovanovic and Rousseau (2002) that such waves occur in periods of market overvaluation, and similar behavioural explanations proposed by Gugler, Mueller, and Yurtoglu (2005). Whichever theoretical cause of industry takeover activity one chooses to support, all theories and empirical evidence support the contention that takeover activity clusters both throughout time and within industries.

Although a widely accepted motivational factor in the general literature, the takeover prediction studies have generally neglected this variable. Walter (1994) suggested that such variables are of the upmost importance, as they create a form of control variable for differential acquisition rates across industries. Palepu (1986) created an extremely simplistic dummy variable which indicated whether a bid had been made within the firm's industry within the past twelve month period,

[12] In this case, overvaluation refers to the ratio of the market value of assets to the replacement value of assets, or the Q ratio.

which was indicated to be significantly positively related to acquisition likelihood. The problem with this variable is that it accounts for a continuous variable with a dichotomous variable, creating a specification error which may have led to inaccuracy. Walter (1994) was the only other published researcher to utilise such a variable. He included a categorical variable relating merger and acquisition activity in an industry to the average level for all industries. This was also found to be a significant discriminating variable. The advantage of the variable of Walter (1994) is that it accounted for differences in the number of firms within each industry, which is an important consideration as firms are disproportionately distributed across industry classifications. But the problem with this variable is that it does not account for different “normal” levels of takeover activity between industries, as heavily regulated industries would expect to have lower acquisition frequencies than other lightly regulated industries. Overall, the evidence is significantly in favour of the industry disturbance hypothesis as a determinant of acquisition likelihood. Ignorance of this variable by many researchers may have contributed to their inabilities to predict with any degree of accuracy.

2.6 Growth Maximisation and Size Hypotheses

The takeover prediction literature has also developed a distinct hypothesis which related the probability of acquisition to the size of the potential target firm. Barnes (1999) explains this relationship through the Growth Maximisation hypothesis of Marris (1963). He proposes that management are more concerned with the size of their firm than in maximising shareholder welfare, as their pecuniary and non-pecuniary remuneration is more closely related to size than performance. This explanation is extremely similar to the agency cost of free cash flow argument forwarded by Jensen (1986) in Section 2.3.1. This hypothesis suggests a positive relationship between the size of a firm and its acquisition likelihood, as management should be attempting to maximise the size of their firm through the acquisition of the largest potential targets.

An alternative argument has been proposed within the takeover prediction literature by Palepu (1986) and Walter (1994). Palepu (1986) contends that as the size of the target becomes larger; the transaction and integration costs of the deal will become larger, reducing the viability of the transaction to the acquirer. Larger target firms may also attempt to defend themselves, which can be extremely costly for the acquirer in terms of transactions costs and the actual price paid for the target. Walter (1994) relies on a probability argument, suggesting that the number of potential acquirers of a target firm is reduced with the size of the firm because larger targets demand larger acquirers with the resources to enact the transaction. Both of these studies theorise that a negative relationship should exist between acquisition likelihood and the size of a firm, which suggests that targets are smaller than their non-target counterparts. Empirically, Walter (1994), Palepu (1986), Harris et al (1982), Dietrich and Sorensen (1984) and Powell (2001) have provided significant evidence that acquisition likelihood is negatively related to size[13]. As many general merger and acquisition studies have also confirmed this negative relationship, the conclusion is that size is a significant motivation for takeovers, with smaller size increasing acquisition likelihood.

2.7 Differential Motivations for Hostile and Friendly Takeovers

It has become widely acknowledged through research by Morck, Shleifer, and Vishny (1988) that significant motivational differences exist between hostile and friendly takeovers. Their

[13] Note that size has been measured in the takeover prediction literature through variables such as Net Assets, the log of Net Assets, and Market Capitalisation.

analysis suggested that hostile takeovers are enacted for disciplinary reasons, as described within the inefficient management hypothesis, but that friendly takeovers are enacted more regularly to exploit potential synergistic benefits. Bradley, Desai, and Kim (1983) have confirmed such contentions, providing evidence that friendly takeovers are enacted for synergistic reasons rather than disciplinary ones. Although most takeover prediction studies have grouped all targets into a single category within a binomial model, Powell (1997) attempted to discriminate between the targets of friendly and hostile takeovers with a multinomial logit model. Targets of hostile takeovers were found to be generally larger (older), have lower levels of leverage, and inefficient managed (underperforming) relative to their friendly counterparts. Targets of friendly takeovers generally exhibit a growth resource mismatch, which suggests a synergistic motivation for takeover of such firms. These results are confirmed in the subsequent study of Powell (2004), and suggest that the inability of some binomial models to provide evidence of the inefficient management hypothesis may simply be a result of model misspecification. Powell (2004) also attempted to predict targets of hostile takeovers, rather than targets of hostile and friendly takeovers. He provided evidence that an abnormal return of 17 percent could be made over a three year holding period, a result we believe is spurious for reasons outlined in Section 1.1. Overall, this evidence suggests that care must be taken when analysing the results of binomial studies which group takeover targets into a single category, as heterogeneous motivational factors for different groups of targets may lead to spurious and inconsistent results. The theoretical and empirical limitations of non discrimination between these categories will be discussed further in Section 3.14 of this thesis.

2.8 Motivational Hypotheses

As the literature review demonstrates, there exists considerable ambiguity as to the motivations for mergers and acquisitions. Even though these motivational theories are inconsistently examined in the literature, they provide a clear theoretical base on which to build takeover prediction models. Eight main hypotheses are proposed, the significance of which will be examined within the methodologies outlined in this paper.

The first, and probably most commonly accepted motivational theory for takeovers is the *inefficient management hypothesis*. Also known as the disciplinary motivation for takeovers, this theory has been disguised in many forms since its initial proposal by Manne (1965). The suggestion of the inefficient management hypothesis is that inefficiently managed firms are acquired by more efficiently managed firms, and forms the first hypothesis of this thesis:

H_1: Greater inefficiency of management will lead to an increased likelihood of acquisition.

A number of different roles have been proposed for undervaluation within the realms of acquisition likelihood. Some believe that this simply indicates the value of gains to be made by an acquirer upon market revaluation of acquired assets, whilst the more traditional theorists suggest close links to the inefficient management hypothesis. Although these are competing explanations, they suggest a consistent impact of undervaluation on acquisition likelihood, leading to the second hypothesis known as the *undervaluation hypothesis*:

H_2: Greater undervaluation of the firm will lead to an increased likelihood of acquisition.

As suggested, the P/E ratio is closely linked to this undervaluation hypothesis. Although alternative explanations have also been proposed for the impact of P/E on acquisition likelihood, the directional impact proposed by these competing theories is consistent, leading to the third hypothesis of this thesis which will be referred to as the *P/E hypothesis*:

H_3: Greater Price to Earnings Ratios will lead to a decreased likelihood of acquisition.

Unlike the above hypotheses, the *growth resource mismatch hypothesis* has had only one distinct line of reasoning proposed. This constitutes the fourth hypothesis of this thesis, but note that the variables used to examine this hypothesis separately capture growth and resource availability:

H_4: Firms which possess low growth / high resource combinations or high growth / low resource combinations will have an increased likelihood of acquisition.

Although the growth resource mismatch hypothesis has not been challenged from a theoretical perspective, many researchers have attempted to improve the measurement of this theory by utilising different proxies for the future growth prospects of a firm. From this literature the *dividend payout hypothesis* was created, which suggests that firms which payout less of their earnings are doing so to maintain enough financial slack to exploit future growth opportunities expected to arise:

H_5: Greater payout ratios will lead to a decreased likelihood of acquisition.

Capital structure has played such a major part in the financial theory of a firm, and thus plays a major part in the main creative and destructive forces in the market for corporate control – mergers and acquisitions. Some disagreement exists as to the impact of high and low leverage on acquisition likelihood. This paper proposes a hypothesis consistent with the general takeover and takeover prediction literature, forming the sixth hypothesis known as the *inefficient financial structure hypothesis*:

H_6: Greater leverage will lead to a decreased likelihood of acquisition.

Recent interest in the mergers and acquisitions literature has shifted focus to the analysis of waves of activity both across economies and within specific industries. These M&A activity wave theories have a consistent implication for takeover prediction studies, which creates the *industry disturbance hypothesis* as the seventh hypothesised determinant of acquisition likelihood:

H_7: Greater industry merger and acquisition activity will lead to an increased likelihood of acquisition.

The final hypothesised motivation for takeovers is unique to the takeover prediction studies. It is obvious that size will have an impact on acquisition likelihood, although competing theories concerning this impact have been proposed. It seems more plausible from a probability perspective that smaller firms will have a greater likelihood of acquisition, which is confirmed by a significant amount of empirical literature. The proposition of this paper forms the following *size hypothesis*:

H_8: Greater size of a specific firm will lead to a decreased likelihood of acquisition.

3. Methodology

3.1 Discriminating Variables

For each of the eight hypothesised motivations for takeover developed in Section 2.8, a number of explanatory variables have been proposed by the literature. Aggregation of all of the financial discriminators proposed in bankruptcy and takeover prediction studies would indicate that more than 100 of these ratios exist (Barnes, 1999). Many of these variables are likely to be collinear, which can make examination of the motivation hypotheses extremely difficult as estimators will be inefficient. The aim of our variable selection is to maintain a complete representation of the hypothesised motivations for takeovers, whilst attempting to eliminate the bulk of the multicollinearity problem. This is achieved by removing any variables which have similar numerators or denominators, as this is generally the cause of the collinearity problem.

Dependent Variable
1 – Firm became a target during the sample period (including all unsuccessful/withdrawn and successful takeover bids announced during these periods).
0 – Firm did not become a takeover target during the sample period.

Inefficient Management Hypothesis
1. ROA (EBIT/Total Assets – Outside Equity Interests)
2. ROE (NPAT/Shareholders Equity – Outside Equity Interests)
3. EBIT Margin (EBIT/Operating Revenue)
4. EBIT/Shareholders Equity
5. FCF/Total Assets
6. Dividend/Shareholders Equity
7. Growth in EBIT over past year

Activity Ratio
8. Asset Turnover (Net Sales/Total Assets)

Undervaluation Hypothesis
9. Market to book ratio (Market Value of Securities/Net Assets)

P/E Hypothesis
10. Price/Earnings Ratio

Growth Resource Mismatch Hypothesis
11. Growth in Sales (Operating Revenue) over past year
12. Capital Expenditure/Total Assets
13. Current Ratio (Current Assets/Current Liabilities)
14. (Current Assets – Current Liabilities)/Total Assets
15. Quick Assets/Current Liabilities (Current Assets – Inventory)/Current Liabilities

Dividend Payout Hypothesis
16. Dividend Payout Ratio

Inefficient Financial Structure
17. Net Gearing (Short Term Debt + Long Term Debt)/Shareholders Equity
18. Net Interest Cover (EBIT/Interest Expense)
19. Total Liabilities/Total Assets
20. Long Term Debt/Total Assets

Industry Disturbance Hypothesis
21. It is proposed that an industry specific ratio of takeover activity is used. The numerator will be the total bids launched in a given year for a specific industry, whilst the denominator will be the average number of bids launched in that industry for the prior four years. Both the numerator and denominator will be calculated by dividing the total number of bids announced in an industry by the number of firms in that industry. This will create a relative value for industry takeover activity that accounts for different levels of "normal" merger and acquisition activity between industries.

Firm Size Hypothesis
22. Ln (Total Assets)
23. Net Assets

3.2 The Logistic Regression Model

$$L_i = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_k x_{ki} = z_i \qquad [1]$$

$$where\ p_i = \Pr\,(\mathrm{y_i} = 1)$$

$$p_i = \Pr\,(y_i = 1|z_i) = \frac{1}{1+e^{-z_i}} \qquad [2]$$

To model the discrete outcomes of bid or no bid proposed by the variable list in Section 3.1, we require a discrete choice modelling procedure which is able to overcome specific problems relating to the dichotomous nature of the dependent variable. A logistic regression model is used by this thesis because of a number of theoretical advantages over alternative models. The logit (L_i) is estimated according to Equation 1 using a set of quantitative variables (z_i) as discriminators between target and non-target firms, as listed in Section 3.1. Consistent with the literature, this thesis designates the dependent variable (y_i) as one if the firm was bid for during the sample period, and zero otherwise. This means that the estimated event probability (p_i) of the logit model in Equation 2 is an estimated probability of acquisition for an individual firm. This method can be applied to a future set of explanatory variables, in a similar way to a linear regression model, to estimate acquisition probabilities for future periods. To classify these estimated acquisition probabilities into predictions that firms will or will not be taken over, we must use a cutoff probability methodology explained in Section 3.10.

$$\frac{\partial p_i}{\partial x_i} = \beta p_i(1 - p_i) \qquad [3]$$

The logit model has a number of inherent advantages over the Linear Probability Model (LPM), which is equivalent to Ordinary Linear Regression with a discrete dependent variable. In the presence of a binary dependent variable, the logit is able to estimate unbiased, efficient, and consistent parameters, whilst the estimators of the LPM will be inconsistent and inefficient. This is caused by the binary dependent variable, which causes the error term to follow a binary distribution – violating a major assumption of linear regression. One of the major disadvantages of the LPM is that it stipulates a linear relationship between acquisition likelihood and the explanatory variables. The logit model stipulates a linear relationship between the log odds of acquisition (the logit, L_i) and the explanatory variables, suggesting a non-linear relationship between acquisition probability and the explanatory variables determined by the logit. Equation 3 highlights the advantages of this relationship. This partial derivative indicates the impact of a change in the explanatory variable on acquisition likelihood. At high and low acquisition probabilities, the effect of an explanatory variable on acquisition probability (measured by β) is reduced as $p_i(1-p_i)$ is reduced relative to where $p_i = 0.5$. If a firm is clearly defined as a target or non-target and thus has a high or low p_i, a larger change in the explanatory variables is required to change the classification of this firm. Conversely, the LPM stipulates that the partial derivative is always equal to β, suggesting a linear relationship. The log odds ratio of the logit also stipulates that estimated acquisition probabilities remain between the logical bounds of 0 and 1, which is not achievable by the linear form of the LPM.

Anyone with knowledge of the takeover prediction literature will recognise that MDA is the dominant discrete choice model employed by early studies. Barnes (1990) and Zanakis and

Zopounidis (1997) have also provided favourable results for this technique in comparison to the logit model, as documented in Section 1.1. But the logit has a number of inherent advantages over this technique as well. The factor loadings estimated within the MDA technique have no logical interpretation, but the parameters in the logit model have logical interpretations which are similar to coefficient estimates in the linear regression model. Also, MDA models are based on the strict assumptions of multivariate normality. Given that financial ratios are now acknowledged to be anything but multivariate normally distributed (Zanakis and Zopounidis, 1997), MDA models are likely to be problematic. Barnes (1999) acknowledges this problem himself, even though his earlier work utilised the MDA methodology (Barnes, 1990). The logit model requires no distributive assumptions concerning the explanatory variables, and is also able to examine multiple discrete outcomes, rather than simple binary outcomes. For these reasons, the nominal logit model to has been employed for the purposes of this study.

3.3 Explanation of Estimation and Prediction Sample Construction

Two samples will be required to perform the analysis in a way that mimics the problem faced by a practitioner attempting to predict these events into the future. Our samples are constructed such that targets and non-targets from calendar years 2003 and 2004 will be used to estimate a model which predicts targets and non-targets for the 2005 and 2006 calendar years. The first sample will be used to estimate the models parameters, and will subsequently be referred to as the estimation sample. Four different models will be estimated to examine different methodologies, all of which utilise the calendar years of 2003 and 2004 to designate target and non-target firms.

Table One – Explanation of the Estimation Sample

Estimation Model Description	Estimation Sample Financial Data	Target/Non-target Designation Period	Industry Adjustment
Single Raw	2002	2003 and 2004	No
Single Adjusted	2002	2003 and 2004	Yes
Combined Raw	Average (2001, 2002)	2003 and 2004	No
Combined Adjusted	Average (2001, 2002)	2003 and 2004	Yes

The single models in Table One will utilise only one year of pre-sample financial data to estimate the model, that is, only 2002 financials. The combined models will utilise an average of the two years of pre-sample financial data, that is, the average of 2001 and 2002[14]. The purpose of these averages is to remove any random fluctuation in the variables and provide clear indications of the condition of the firm. Walter (1994) proposed that such practices increase the predictive accuracy of the models. The raw models will use unadjusted (raw) financial ratios, as were utilised by many of the earlier researchers, whilst the adjusted models will utilise industry adjusted financial ratios. Such practices have been implemented since the study of Palepu (1986), who began a trend in the takeover prediction literature by introducing population scaling. Platt and Platt (1990) propose that such scaling may increase the predictive accuracy of such models as it should enable the model to make more accurate predictions both across industries and through time where raw ratios would be meaningless. The first reason is that average financial ratios are inconsistent across industries, as they reflect the relative efficiencies of production commonly employed in those industries. The second reason is that average financial ratios are inconsistent throughout time, as performance will vary throughout time with economic conditions and other factors.

[14] Note that variables 9 (M/B) and 10 (P/E) will always be measured in the final year of pre sample data, regardless of whether the model is of the combined form or of the single form. This is consistent with the methodology of Walter (1994) who utilised the average of two years or pre-sample financial ratios.

Table Two – Explanation of the Prediction Sample

Prediction Model Description	Prediction Sample Financial Data	Target/Non-target Designation Period	Industry Adjustment
Single Raw	2004	2005 and 2006	No
Single Adjusted	2004	2005 and 2006	Yes
Combined Raw	Average (2003, 2004)	2005 and 2006	No
Combined Adjusted	Average (2003, 2004)	2005 and 2006	Yes

The second sample will be used to assess the ex-ante predictive accuracy of the four models estimated from the estimation sample, and will subsequently referred to as the prediction sample. The models estimated within the estimation sample will be applied to classify firms in the prediction period presented in Table Two. The prediction sample can be explained in an identical manner to the estimation sample. The only difference between the prediction sample and the estimation sample is that measurement and designation of firms as targets and non-targets is moved two years forward. The single models utilise only 2004 financial data, whilst the combined models utilise the average of 2003 and 2004 financial data. Firms are classified as targets and non-targets using calendar years 2005 and 2006 for all models.

Note that for all models the classification period for targets and non-targets refers to calendar years, whilst the measurement of financial data refers to financial years. This lag between measurement and classification is to allow the timely release of financial data into the public arena and to allow those companies whose balance dates fall after 30th June to report their financials. Measurement of financial data before the designation of firms as targets and non-targets allows us to predict in a true ex-ante fashion. This is because we only use financial variables from a period before prediction of targets and non-targets, which allows us to invest in the predictions of the model.

For the estimation of the model, we propose a technique known as *state-based sampling* in conjunction with Maximum Likelihood estimation available through SAS[15]. This is achieved by including all target firms in the estimation sample, along with an equal number of randomly selected non-target firms for the same period. Allison (2006) proposes that the use of such state-based sampling, where the dependent variable states are unequally distributed in the population, increases the precision of the estimated parameters (reduces the standard error of the estimated parameters). Unequally distributed states are an evident problem in this study, as less than 7 percent (11 percent) of firms actually become targets in the estimation (prediction) samples. Targets from the estimation sample will be paired with a *random sample* of non-target firms from the same period. Although Hosmer and Lemeshow (1989) provide evidence that this method biases the estimated intercept term, model classifications remain accurate as estimated acquisition probabilities for targets and non-targets are equally biased.

3.4 Advantages of Sample and Model Construction

The sampling methodology explained in Section 3.3 has a number of obvious differences to that commonly employed in the takeover prediction literature. Firstly, researchers such as Barnes (1990, 1999) match targets and non-targets on the basis of size and/or industry participation, creating an estimation sample which is essentially non-random. Although this creates an unbiased and accurate estimation of the theorised model, this is generally applied to a prediction sample where classification outcomes are not known and targets cannot be matched to non-

[15] SAS is extremely useful for the purposes of logistic regression as it allows the estimation of models and prediction within future sample periods. It also allows the estimation of multinomial models and provides many extremely valuable model options, which are essential for the methodologies explained in this section of the thesis.

targets. For this reason, randomly selected non-target firms will be used for the state-based estimation sample.

Secondly, researchers such as Powell (2001) and Palepu (1986) randomly assign years of measurement for non-target variables. Although industry adjustment goes some way to improve comparability across time periods, this adjustment is not perfect, and may cause biases and inconsistencies in the estimated model. This thesis will make all measurements for target and non-target firms over identical periods.

Thirdly, researchers such as Powell (2001) and Palepu (1986) utilise estimation samples which are some 10 years in length. Powell himself, and others such as Walter (1994), have provided significant evidence that the motivations for takeover are highly unstable throughout time. Motivations for takeover estimated from such long samples may not be applicable to a future prediction sample. A short two year estimation sample will be used to predict in a short two year prediction period to maximise the potential predictive accuracy of the model.

Fourthly, many studies do not account for survivorship bias, which is particularly prevalent in financial ratios constructed from Datastream as only live firms are included in the construction of industry averages. Non-inclusion of dead firms may create an upward bias in estimated industry averages, which could result in skewness across industries and lead to inaccurate predictions. Only Powell (2001) has explicitly accounted for this by reconstructing the full sample of listed firms for measurement years by including dead firms. This study will account for potential survivorship biases by reconstructing the industry averages for the estimation and prediction samples on the basis of all live firms with available accounting data.

3.5 Accurate Calculation of Industry Relative Ratios

As suggested, most researchers attempting to predict takeover targets since the paper of Palepu (1986) have utilised a common form of industry relative ratios, which are generally calculated by scaling the firms' financial ratio by the industry average as shown by Equation 4.

$$Industry\ Relative\ Ratio = \frac{x}{I} \qquad [4]$$

$$where\ x = individual\ firm\ financial\ ratio$$

$$I = industry\ average\ financial\ ratio$$

Under this procedure all financial ratios are standardised to one, with industry relative ratios above one indicating outperformance of the industry and those below indicating underperformance of the industry for a ratio such as ROA or ROE. But a problem is encountered when the industry average is a negative value. In this case, those firms which underperform the industry average are also given industry relative ratios which are greater than one, as a large negative number will be divided by a smaller negative number. A firm which outperforms a negative industry average but retains a negative ratio will be assigned a variable less than one, which suggests underperformance. The existence of some industries with negative industry averages and some with positive ones exacerbates the problem, resulting in meaningless financial ratios. Such problems may have contributed to the inability of the Barnes (1999) model to predict any takeover targets at all.

$$Industry\ Relative\ Ratio = \frac{x-I}{|I|} \qquad [5]$$

Examination of the variables constructed from Section 3.1 indicates that many industries have negative averages, whilst some have positive averages. We propose the use of a new calculation which was implemented for our two models which utilised industry adjustment. Equation 5 utilises the difference between the individual firm's ratio and the industry average ratio, which is divided by the absolute value of the industry average ratio. This standardises all financial ratios to an industry average of 0 whilst correcting problems relating to the sign of the ratio by taking the absolute value. Using a variable such as ROA, underperformance of the industry results in an industry relative ratio which is less than zero, whilst outperformance of the industry results in an industry relative ratio which is greater than zero. Even if some industries have negative averages, and some have positive averages, this ratio will still be meaningful. Note that all industry adjustments are made on the basis of the old ASX coding system, rather than the new GICS codes, as this system provides a more specific differentiation between industries with 24 industry codes. Industry averages in this thesis will be calculated on an equally-weighted basis, consistent with the bulk of the takeover prediction literature. Researchers such as Powell (2001) have used different approaches, using value-weighted calculations. Variables in both models which utilised industry adjustment were calculated according to this methodology, resulting in improved explanatory power and markedly different parameter estimates.

3.6 Data Requirements

To construct the financial variables required for the construction of the logit model, accounting data was required for all ASX listed companies for the financial years of 2001 to 2004. This information was sourced from the AspectHuntley database, which provided us with standardised access to financial statement data for all ASX listed companies between 1995 and 2004. Such a wide sample was a requirement for the construction of industry relative ratios, which were used in the construction of the adjusted models. To construct the M/B (9) and P/E (10) variables, stock prices from the relevant balance dates were required for all of these listed companies. These were sourced from the AspectHuntley online database, the SIRCA Core Price Data Set, and Yahoo! Finance as a last resort. Additionally, lists of takeover bids and their announcement dates were required for the construction of the dependent variables from 2003 to 2006. These were sourced from AspectHuntley and Connect 4.

Additionally, target statements were required for all targets to ascertain whether the bid was hostile or friendly. This was required for the multinomial models to be explained in Section 3.14. Stock price data was also required for the construction of portfolios to be explained in Section 3.12. This comprised daily price data for these stocks for the calendar years 2004, 2005 and 2006. This data was sourced from the AspectHuntley online database, whilst the required ASX200 index levels were sourced from Yahoo! Finance. Data concerning the interest rate for 90 Day Bank Accepted Bills was collected from the RBA website for the same period.

3.7 Data Limitations and Filtering Procedures

Note that for the purposes of our analysis four industries were eliminated, as measurements of financial performance in these industries are dissimilar to traditional measurements of profitability and performance in other industries. These included Banks and Finance (16), Insurance (17), Investment and Financial Services (19), and Property Trusts (20). This resulted in

20 of 24 industries being available for the final four models. Problems with the calculation of three variables were encountered, which led us to eliminate these from the model. Due to the insufficient data regarding operating revenue and interest expense, variables 3, 11 and 18 were eliminated as their calculation resulted in many undefined variable observations. Some firms were missing balance date prices, negating the calculation of the M/B (9) and P/E (10) variables. Additionally, some firms were missing statement lines for EBIT and NPAT, although we reconstructed many of these from other statement lines in the database. A filtering process was then undertaken to remove any firm observations which did not have complete variables, as application of the model to these firm observations would cause estimated acquisition probabilities for these firms to be biased. This process, and the elimination of the four problematic industries, resulted in the initial sample of approximately 1500 firms being reduced to estimation and prediction samples which held 1060 and 1054 firms respectively. This is adequately representative of all ASX listed firms, and compares favourably to the largest study of Palepu (1986) which utilised 1087 firms for similar classifications.

Some preliminary outlier elimination was also conducted. Powell (1997) eliminated all firms with any financial ratios which exceeded three standard deviations of their mean. Powell (2001) utilised a similar technique, but instead of eliminating these outlier variables, he winsorized them to lie within three standard deviations of their means. We undertook a much more simple procedure, as it may be these outliers which allow us to achieve accurate classifications of targets and non-targets. Firms were only eliminated if one or more of their financial ratios exceeded three standard deviations of the mean, and if this was obviously impacting on the industry average financial ratio. This resulted in a different number of observations for the four different models in both the estimation and prediction samples. Differences in sample sizes between models also resulted from different data availabilities.

3.8 Multicollinearity Elimination Process

It has been widely acknowledged within the takeover and bankruptcy prediction literature that the financial variables used to proxy for the motivational hypotheses are highly collinear (Barnes, 1999). This results from the use of common denominators such as net assets, total assets, and shareholders equity. As in the Classical Linear Regression Model (CLRM), multicollinearity causes a number of problems for estimated models. Parameters are inefficiently estimated, leading to high standard errors and imprecise estimators, and to many insignificant variables in a model which may have high explanatory power. Stevens (1973) overcame these problems by using a factor analysis within his discriminant model to create uncorrelated factors. Palepu (1986), Walter (1994), and Powell (2001) utilised a different technique within their logit models, selecting only one variable for each of the hypothesised motivations for takeover. Although effective from a multicollinearity perspective, this may have also caused another problem known as the omission of relevant explanatory variables. Econometricians such as Gujarati (2003) suggest that this violates the unbiased and consistent nature of estimated coefficients. Such problems may have been a contributing factor to the poor predictive accuracies reported in these studies.

This thesis will not employ this multicollinearity elimination methodology, but will attempt to eliminate multicollinearity from the variable list in Section 3.1 to create an appropriately specified model. All four models will first be estimated with all of the explanatory variables to examine whether any problems are evident and to compare the explanatory power of models. Two different procedures will be utilised to examine for the presence of multicollinearity. The first procedure available in SAS is the calculation of the correlation matrix for all explanatory variables. The problem with this procedure is that it only examines first order correlations between two explanatory variables. Because multicollinearity may be caused by higher order correlations, examination of correlations alone may lead to an ineffective elimination of multicollinearity. SAS will be used to calculate Tolerance and Variance Inflation Factors, which are based on R_x^2 from a regression of one of the individual explanatory variables on all other explanatory variables in the model. A variable will be deemed as problematic and eliminated if its correlation coefficient with another variable exceeds 0.8 or if its Variance Inflation Factor exceeds a value of 10.

3.9 Examination of Motivational Hypotheses

The next step after the elimination of multicollinearity is to examine the significant motivations for takeovers. This will be firstly achieved with a univariate comparison of means between target and non-target firms using a t-test methodology. This is equivalent to the use of a one-way Analysis-of-Variance (ANOVA) table, which is also equivalent to some forms of the CLRM. As logistic regression also has links to linear regression, any significant differences should be indicative of the significant parameters from the subsequent logit estimation. A positive (negative) and significant t value indicates that the mean financial ratio of targets is statistically greater (smaller) than the mean financial ratio for non-targets at the designated level of significance.

H$_0$: Means are not statistically different ($\bar{X}_T - \bar{X}_{NT} = 0$)

H$_1$: Means are statistically different ($\bar{X}_T - \bar{X}_{NT} \neq 0$)

$$t = \frac{\bar{X}_T - \bar{X}_{NT}}{s.e(\bar{X}_T - \bar{X}_{NT})} \quad [6]$$

$$where\ s.e(\bar{X}_T - \bar{X}_{NT}) = \sqrt{\frac{VAR_T}{N_T} + \frac{VAR_{NT}}{N_{NT}}} \quad [7]$$

The logit models will be estimated after this univariate comparison. A *backward stepwise regression* will be utilised to retain only those variables which are significant in explaining acquisition likelihood across all four models estimated. On the basis of the univariate and stepwise regression results, an examination of the hypothesised motivations for takeover in the Australian context will be made and compared to results from the extant literature. Note that although the backward stepwise model is useful for examination of motivational hypotheses, the full complement of variables will be included for the purposes of prediction. This is based on the contention of researchers such as Barnes (1999) that complex relationships between explanatory variables may allow us to differentiate between target and non-target firms at a level which cannot be achieved with only significant discriminatory variables.

3.10 Classification and Alternative Optimal Cutoff Calculations

When we implement the ordinary linear regression model for prediction, the explanatory variables for future periods are used as inputs into the model, which results in a predicted value for the dependent variable. This is simple, as the predicted value simply forms the prediction. In the case of the logit model, the output of a prediction based on the input of explanatory variables is a predicted probability of acquisition estimated according to Equation 2. But the outcome that we want is a prediction of whether the firm will or will not become a target during the future period. Two methodologies, known as optimal cutoff calculations, have been proposed to accurately classify these probabilities as predicted targets and non-targets. Firms with predicted probabilities of acquisition above these cutoffs are classified as predicted targets and those with predicted probabilities of acquisition below these cutoffs are classified as predicted non-targets.

Table Three – Classification and Prediction Outcome Matrix

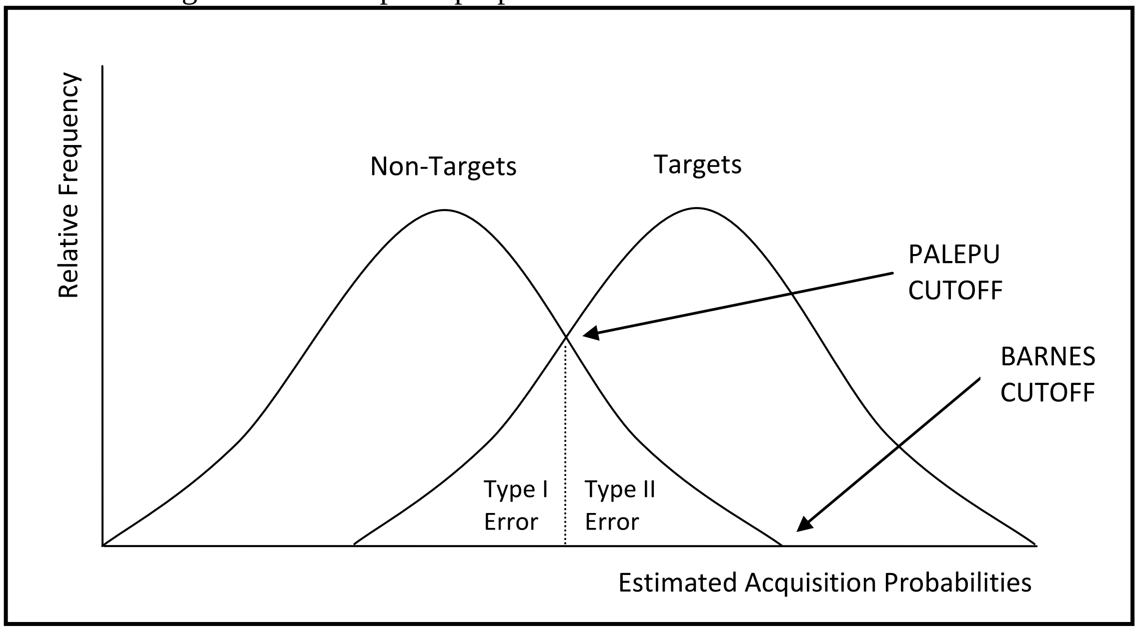
	Predicted Outcome		
Actual Outcome	Non-Target (0)	Target (1)	***Total***
Non-Target (0)	A_{00}	A_{01} (Type II Error)	$\mathbf{T_{A0}}$
Target (1)	A_{10} (Type I Error)	A_{11}	$\mathbf{T_{A1}}$
Total	$\mathbf{T_{P0}}$	$\mathbf{T_{P1}}$	**T**

$$Concentration\ Ratio = A_{11}/T_{P1}$$

3.10.1 Minimisation of Total Error Probabilities (Palepu, 1986)

To understand the calculation of the optimal cutoff probability, an understanding of Type I and Type II errors must first be reached. A Type I error occurs when a firm is predicted to become a takeover target and does not (outcome A_{01} in Table Three), whilst a Type II error occurs when a firm is predicted not to become a target but actually becomes a target (outcome A_{10}). The methodology of Palepu (1986) assumes that the cost of these two types of errors is identical to an investor in the predicted targets of the model. To calculate the optimal cutoff probability in this case, we simply use a histogram to plot the frequencies of estimated probabilities of acquisition for targets and non-targets separately on the same graph as demonstrated by Figure One. The optimal cutoff probability which minimises the total probabilities of these errors occurs at the intersection of these two conditional distributions – where the two conditional marginal densities are equal. Such a methodology allows for equal occurrences of Type I and Type II errors.

Figure One – Graph of proposed Alternative Cutoff Calculations



3.10.2 Minimisation of Total Error Costs (Barnes, 1999)

The problem with the methodology of Palepu (1986) is that it assumes that the costs of the two types of errors are identical. Particularly in bankruptcy prediction, researchers such as Heish (1993) have concluded that the costs of these types of errors are not identical. If the objective of prediction is returns maximisation from investment in predicted targets, the cost of investing in the equity of a firm which doesn't become a takeover target (Type II error) is greater than the cost of not investing in the equity of a firm that becomes a takeover target (Type I error) as we do not invest in predicted non-targets. To maximise returns, Barnes (1999) suggests that we must maximise the concentration ratio of Powell (2001) – the number of actual targets in the portfolio of predicted targets (A_{11} to T_{P1} in Table Three). This minimises the occurrence of Type II errors, as demonstrated by Figure One, as no actual non-target firms are classified as targets. But note that this dramatically increases the occurrence of the non-costly Type I error (A_{10}). This optimal cutoff calculation is based on the rationale that targets should earn significantly positive abnormal returns, and to maximise returns we must maximise the concentration of actual targets in the portfolio of predicted targets. To calculate the optimal cutoff probability for this method, we manually change the cutoff probability from 0 to 1 by an increment of 0.025. For each cutoff, we calculate the concentration ratio. The optimal cutoff is chosen which maximises the concentration ratio. This methodology is also similar to that of Powell (2001). Note that references to accuracy from this point will be referring to the concentration ratio rather than the proportion of targets accurately predicted, as this theoretically maximises returns.

3.10.3 Optimal Cutoff Calculation Methodology

Note that to calculate the optimal cutoff probability accurately for the *prediction* sample; we require knowledge of the actual outcomes for the period. As the purpose of this paper is to implement the model in such a way which replicates the problem faced by a practitioner, we are unable to utilise the actual outcomes of bid or no bid in the prediction period to calculate the optimal cutoff. We must use a cutoff point estimated from the estimation sample. Many researchers cited in this paper (such as Walter, 1994) use a cutoff point derived from the prediction period, which does not indicate the true predictive accuracy of the model implemented by a practitioner for prediction. It most likely inflates the accuracies reported in these studies. On the basis of these cutoff probabilities, a comparison will be made concerning their accuracies to conclude whether the Barnes (1999) methodology improves classification accuracy in the estimation and prediction samples relative to the Palepu (1986) methodology. If the parameters describing the distributions of estimated acquisition probabilities for targets and non-targets individually are stable over time, then the Barnes (1999) methodology should improve predictive accuracy for all models within the prediction sample. If stability is not maintained, then the results may not indicate superiority of this methodology. Such instability is confirmed by the results of Powell (2001) who demonstrates that the optimal cutoff derived from an estimation sample does not maximise the concentration ratio in a predictive sample.

3.11 Assessing the Predictive Accuracy of the Logit Model

SAS provides a number of statistics which allow us to assess the explanatory power of our estimated models. The likelihood ratio and likelihood score are both identical to the F test in a linear regression, and examine whether all coefficients are equal to zero. Jennings (1986) proposes that the likelihood score is more appropriate in small samples, which is relevant to this study given that we are not estimating with an entire sample but a smaller state-based sample. Additionally, a traditional R-squared statistic and a Maximum Rescaled R-square statistic can be used to estimate predictive power of the models. The Maximum Rescaled version accounts for the fact that a perfect fit is not available in a dichotomous choice model by rescaling with a value less than 100 percent. But the problem with these statistics is that they do not examine the true classification accuracy of such models, which is a major objective of this thesis. Walter (1994), Zanakis and Zopounidis (1997), and Barnes (1999) utilised an ingenious technique which assesses whether predictions of the model are significantly greater than a chance selection[16]. Our model will predict a number of actual targets and non-targets with errors in both predictions. We must be able to compare these accuracies to some benchmark, such as a chance selection. The Proportional Chance Criterion and the Maximum Chance Criterion were developed by Morrison (1969) to compare the predictions of discriminant models to chance. They are applicable in this situation as we face a similar discrete choice problem.

[16] If we were to predict a portfolio of targets with chance accuracy, we would expect an occurrence of targets in this portfolio equal to their frequency of occurrence in the population of listed firms.

3.11.1 Proportional Chance Criterion

To assess the predictive power and classification abilities of the estimated models, a proportional chance criterion statistic can be calculated to compare the models predictive accuracy to that expected under chance. This statistic assesses whether the overall classifications of the model are better than that expected under chance, as the statistic is based on the correct classification of targets and non-targets jointly. Although this does not indicate the source of the classification accuracy of the model, that is whether the model accurately predicts either targets or non-targets individually, it is an important statistic with which to assess alternative models.

H_0: $P \leq$ Chance (Model is unable to classify targets and non-targets jointly better than chance)

H_1: $P >$ Chance (Model is able to classify targets and non-targets jointly better than chance)

$$Z = \frac{P_C - C_{PRO}}{\sqrt{\frac{C_{PRO}(1-C_{PRO})}{n}}} \qquad [8]$$

$$\begin{gathered} where\ C_{PRO} = p \propto +(1-p)(1-\propto) \\ p = percentage\ of\ targets\ in\ sample\ (T_{A1}/T\ \ from\ \ Table\ Three) \\ \propto = percentage\ of\ firms\ classified\ as\ targets\ by\ model\ (T_{P1}/T) \\ P_C = percentage\ of\ total\ correct\ classifications\ ((A_{00}+A_{11})/T) \\ n = total\ observations\ (T) \end{gathered}$$

The simple Z calculation in Equation 8 tests the hypothesis that the accuracy of the model is worse than or equal to chance against the alternative hypothesis that the accuracy of the model is greater than chance. Note that under a chance selection, we would select a proportion of targets and non-targets equal to their occurrence in the population under consideration. If the calculated

Z statistic in Equation 8 is significant, we are able to reject the null hypothesis and conclude that the model can classify target and non-target firms jointly better than expected under chance.

3.11.2 Maximum Chance Criterion

Although the above proportional chance criterion statistic may indicate that the model can classify firms better than chance, it does not indicate the specific source of this accuracy, that is whether the model is accurately classifying target or non-target firms individually. Based on a similar Z statistic calculation and hypotheses, a significant value for the Maximum Chance Criterion statistic indicates that the model has power significantly greater than chance in classifying target or not target firms individually, whichever is the accuracy of interest.

H_0: P ≤ Chance (Model is unable to classify targets/non-targets individually better than chance)

H_1: P > Chance (Model is able to classify targets/non-targets individually better than chance)

$$Z = \frac{Obs_{CC} - C_{MAX}}{\sqrt{\frac{C_{MAX}(1-C_{MAX})}{n}}} \qquad [9]$$

$$Obs_{CC} = observed\ correct\ classification\ (A_{11}/T_{A1}\ from\ \ Table\ Three)$$
$$C_{MAX} = maximum\ potential\ chance\ correct\ classification\ (T_{A1}/T)$$
$$n = total\ number\ of\ actual\ targets\ \ (T_{A1})$$

If the calculated Z statistic in Equation 9 is significant, we can conclude that the prediction of targets/non-targets individually is greater than chance. To assess the classification accuracy of the models in both the estimation and prediction samples, these two statistics will be utilised to compare the accuracies of competing models and also compare the accuracies of our models to those in the extant literature. Note that our focus is on the maximum chance criterion for targets, as under the reasoning of Barnes (1999) the accurate prediction of targets is the main objective of the model, rather than the accurate prediction of target and non-target firms. This is because the accurate prediction of targets should maximise the concentration ratio and also the returns from an investment in the portfolio of predicted targets (Powell, 2001).

3.12 Assessing Profitability of Common Predictions

Although the Proportional and Maximum Chance Criterions provide us with a statistical assessment of the predictive accuracies of our models, we require an economic quantification of the potential investment returns from the portfolio of predicted targets. Palepu (1986) contends that we may be able to predict with high accuracies, but that the probability of takeover may already be impounded into the price of a stock, negating the ability to earn significant abnormal returns from an investment in predicted targets. Palepu (1986), Walter (1994), Wansley et al (1983) and Powell (2001) all analysed returns from an investment in an equally weighted portfolio of predicted targets. Only Wansley et al (1983) was able to provide evidence of the ability to earn significantly positive abnormal returns, but this was based on the flawed state-based prediction sample explained in Section 1.1. The conclusion to be drawn from these studies is that significant positive abnormal returns cannot be made from an investment in predicted targets of the models. Also, the portfolios of predicted targets in these studies were unrealistically large. Walter predicted 91 firms to become targets, Palepu predicted 625, and Powell predicted 96. A sensible practitioner would limit their investment to a portfolio of 10 to 15 stocks as the transactions costs associated with a portfolio larger than this would erode any potential profit opportunity. To overcome this problem, only the commonly predicted targets across all models were retained. This also served the purpose of increasing the concentration of actual targets in the portfolio of predicted targets.

The equally weighted portfolio approach was applied to these commonly predicted targets rather than the predictions of a single model, and the portfolio was held for the entire prediction period of 2005 and 2006. Note that this approach has one severe limitation, being that a practitioner with such information is unlikely to simply take a long position in these stocks. They are more likely to take a leveraged position through options. Even so, this approach provides a similar abnormal return measurement to those employed in the extant literature so that accurate comparisons can be drawn.

$$r_{it} = r_{ft} + \beta_i(r_{mt} - r_{ft}) \qquad [10]$$

$$E(r_{it}) = r_{ft} + b_i(r_{mt} - r_{ft}) \qquad [11]$$

The benchmark return used for risk adjustment was the Capital Asset Pricing Model (CAPM) demonstrated in Equation 10. This differs from the methodologies of Walter (1994) and Palepu (1986), who utilised the market model and decile portfolios respectively for benchmark returns. The relevant parameters for the calculation of benchmark returns were estimated from 252 trading days in the 2004 calendar year according to Equation 11. Note that the market return was taken to be the return on the ASX 200 Index, whilst the risk free return was taken to be the interest rate on 90 Day Bank Accepted Bills.

$$AR_{it} = r_{it} - E(r_{it}) \qquad [12]$$

To calculate the abnormal return for each of the stocks during the prediction period, the expected return calculated according to the estimated CAPM of Equation 11 is taken from the actual return as demonstrated by Equation 12.

$$AAR_t = \frac{\sum_{i=1}^{n} AR_{it}}{n} \tag{13}$$

$$CAAR_t = \sum_{t=1}^{k} AAR_t \tag{14}$$

The idea of the equally weighted portfolio approach is to have an equal weight in each predicted target. To calculate the Average Abnormal Return (AAR) from such a portfolio, we simply take the average of each stocks abnormal return according to Equation 13. Note that the number of stocks in this portfolio (n) changes during the prediction period as successfully acquired firms are delisted. To calculate the statistic of interest, the Cumulative Average Abnormal Return (CAAR) for the prediction period, we simply sum the AAR of the portfolio over the days which the portfolio is active according to Equation 14. To assess the significance of this outcome, we require an appropriate test statistic. Walter (1994) proposed the relatively simple t statistic calculation presented in Equation 15, which will be utilised by this study[17].

H_0: CAAR is not significantly different from zero

H_1: CAAR is significantly different from zero

$$t = \frac{CAAR_t}{(s.e.)(504)^{0.5}} \tag{15}$$

[17] The standard error in this equation is the estimated standard error from the 2004 calendar year, and 504 represents the number of trading days over which significance is being assessed.

Fama (1998) highlights an obvious problem with this test statistic, as abnormal returns may be correlated across stocks due to common event waves, and the standard error of the portfolio will change with the construction of the portfolio (heteroskedasticity).

$$SAR_t = \frac{\sum_{i=1}^{n} AR_{it}}{SD_t} \qquad [16]$$

$$t = \frac{\sum_{i=1}^{k} SAR_t}{\sqrt{k}} \qquad [17]$$

$$where\ k = number\ of\ days\ of\ cumulation$$

Jaffe (1974) and Mandelker (1974) proposed that the abnormal return on the equally weighted portfolio be divided by an estimate of the standard deviation of that portfolio on a daily basis, creating what has become known as a Standardised Abnormal Return (SAR) of Equation 16. Palepu (1986) utilised this technique within his takeover prediction study as a result of the influential study of Brown and Warner (1985) whose techniques are still utilised today for the assessment of abnormal returns on a daily basis. The test statistic in Equation 17 accounts for the potential problems highlighted by the above researchers, and accumulates the SAR for the period over which the significance of the CAAR is being assessed. By not enacting this procedure, our estimated t statistic may be exaggerated, which may lead to inaccurate inferences being made because as the null hypothesis of no significant CAAR would be more readily rejected.

A number of robustness checks will be undertaken to ensure that any abnormal return to our portfolio is consistent. A positive return may be driven by a chance selection of non-target firms in the portfolio of predicted targets which simply outperform the market, which we believe is driving the results of Powell (2004). In this case, a significant CAAR would be attributable to chance rather than accuracy of the model, as sometimes we may select highly performing non-target stocks but in other times we might select poorly performing non-target stocks. But if the returns are driven by the predicted targets which actually become targets, then we can be certain that any positive CAAR is a result of the accuracy of the model rather than a chance selection.

3.13 Justification of CAR Methodology for Return Metric

Recently, researchers such as Lyon and Barber (1997) and Kothari and Warner (1997) have proposed the use of Buy and Hold Returns (BHAR's) rather than CAR's for the measurement of abnormal performance. They propose that in volatile markets, CAR's are positively biased predictors of BAHR's, which may lead to inaccurate statistical inferences being drawn, with the use of asset pricing models leading to problematic biases in such studies. Fama (1998) has refuted this evidence. He cites evidence of the skewness issues created by BAHR's as they compound short period returns and their inability to overcome cross-correlation problems which have been accounted for within the SAR methodology. Our contention is that the CAAR methodology, coupled with the appropriate SAR methodology of Brown and Warner (1985) which accounts for potential heteroskedasticity and cross-correlation, is the most appropriate statistic to assess abnormal returns on a daily basis. And even though the CAPM has come under some recent scrutiny, researchers such as Fama (1998) still believe that calculated abnormal returns are extremely accurate using such a benchmark return.

3.14 Multinomial Logit Models – Methodology and Justification

The methodology to this point of the thesis has focused on the binomial model which aggregates all types of targets into a single category. This is consistent with the bulk of the extant literature.

Allison (2006) and Powell (2004) suggest that the aggregation of multinomial categories into a binomial model can lead to a misspecified model in which parameter estimates are uninterpretable as the groups of interest are not clearly defined. On the basis of this evidence, an attempt will be made to differentiate between certain categories of targets. The first differentiation will be between targets of successful and unsuccessful takeover bids[18]. Most researchers do not indicate whether their binomial models include all successful and unsuccessful takeovers. Barnes (1999) denominates both successful and unsuccessful takeover targets as targets in his binomial model, but Powell (2001) denominates only targets of successful takeovers as targets. Our discrimination is based on a basic economic argument rather than empirical evidence which documenting differences between these two groups of targets. Jensen and Ruback (1983) document no significant abnormal returns for shareholders of target firms where the bid fails, contrasting significant abnormal returns of 20 percent to 30 percent in the case of successful takeovers. This is confirmed by Bradley, Desai, and Kim (1983), who document that all positive abnormal returns made around the bid announcement dissipate if the bid fails and another bid is not expected. Based on this reasoning, if one is able to differentiate between targets of successful and unsuccessful takeovers, one should be able to utilise the multinomial model to predict targets of successful takeovers only. This should theoretically lead to increased abnormal returns from portfolio investment.

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[18] If a target receives more than a single bid during the sample period, then the takeover will be considered successful if one of the bids is successful. Otherwise the bid will be classified as unsuccessful. Note that success as defined by this thesis requires that the bidder has achieved enough acceptances to assure compulsory acquisition of remaining shares.

The second differentiation will be made between targets of hostile and friendly takeovers[19]. This is based on both the empirical evidence of differential characteristics between these groups of targets, and a similar economic justification. Morck Shleifer and Vishny (1988) provide general evidence that significant differences in motivations exist between hostile (disciplinary) and friendly (synergistic) takeovers. These differences are confirmed by the multinomial models of Powell (1997, 2004), providing significant evidence that the binomial model is misspecified. Economically, Jensen and Ruback (1983) provide evidence that abnormal returns to shareholders of targets of hostile takeovers are 10 percent larger than those to shareholders of friendly takeovers (30 percent versus 20 percent abnormal announcement period returns). Franks and Harris (1989) confirm this evidence, but believe that this differential may be larger at some 14 percent. Based on this reasoning, we should be able to use the multinomial model to predict targets of hostile acquisitions only. This should theoretically increase the abnormal returns from a portfolio investment as in the case of the prediction of successful targets only.

Multinomial logit models require the estimation of K-1 equations, essentially similar to the binomial model presented in Equation 1, where K represents the number of categories being modelled. Each multinomial model will therefore require the estimation of two equations, which indicate the probability of becoming successful or unsuccessful takeover targets, or hostile or friendly takeover targets. A third equation is able to be estimated in multinomial models to examine whether any significant differences exist between types of takeover targets. These will be utilised to examine whether any significant differences exist between the characteristics of

[19] Takeovers will be considered to be hostile in nature if the independent target report contains a director's recommendation to reject the proposed bid. In the case that a number of bids are launched during the sample period, a firm will be classified as a hostile takeover target if at least one of the bids is rejected by target management.

these types of target firms to determine whether the binomial model is misspecified. In the case that the binomial model is misspecified, our estimated parameters will need to be reinterpreted in the context of the multinomial model. Robustness checks will also be made using the univariate comparison of means explained in Section 3.9, which should be indicative of the estimated parameters of the multinomial model. Classification within the estimation and prediction samples will also be extended to classification of successful and hostile takeovers individually, as the above economic reasoning suggests that investment in these types of takeover targets should increase abnormal returns from a portfolio investment. These classification results will be compared to those of the binomial model to examine whether any benefit exists from the application of the multinomial model to single out these categories.

3.15 Methodological Hypotheses

This methodological section of this thesis has provided theoretical evidence suggesting that a number of methodological improvements will improve the predictive accuracy of the model. Platt and Platt (1990) provided evidence that the use of industry relative ratios improved predictive accuracy within bankruptcy prediction studies, but this has not been empirically confirmed within the takeover prediction literature. Additionally, Barnes (1999) was unable to demonstrate that his derivation of the optimal cutoff point resulted in increases in predictive accuracy. And although the study of Walter (1994) indicated that the combination of two years of pre-sample financial data improved predictive accuracy, no direct comparisons were made. Also, Powell (2004) provided weak evidence that the use of multinomial logit models to predict hostile takeover targets individually increased the accuracy of the model in predicting these events. On the basis of these arguments, four hypotheses relating to methodological improvements are proposed. These will be tested through a comparison of the predictive accuracies of the four proposed models from Tables One and Two.

H_9: Use of the average of two years of pre-sample financial data will result in an improvement in predictive accuracy over the use of only a single years' pre-sample financial data.

H_{10}: Use of industry relative ratios will result in an increase in predictive accuracy over models which employ raw financial ratios.

H_{11}: Use of the Barnes (1999) derived cutoff point will result in an increase in predictive accuracy over the use of the Palepu (1986) derived cutoff point.

H_{12}: Use of multinomial logit models for the prediction of successful and hostile takeover targets individually will result in improved accuracies for prediction of these events compared to those of the binomial model.

4. Results

4.1 Initial Estimation

Table Four presents the results of the initial estimation of all four models, which was undertaken to examine for the presence of multicollinearity and to compare the explanatory power of competing models. This was based on a final state-based estimation sample of 125 firms, consisting of 62 targets and 63 non-targets.

Table Four – Initial Estimation of all models

	Single Raw Model		Single Adjusted Model		Combined Raw Model		Combined Adjusted Model	
Variables	Est	Prob > Chi Sq	Est	Prob > Chi Sq	Est	Prob > Chi Sq	Est	Prob > Chi Sq
Intercept	**-14.61**	**(<0.01)**	-0.19	(0.65)	**-15.64**	**(<0.01)**	-0.06	(0.89)
1 – ROA	2.14	(0.41)	-0.11	(0.49)	4.30	(0.13)	0.19	(0.42)
2 – ROE	-6.55	(0.16)	0.04	(0.32)	-6.16	(0.11)	0.02	(0.87)
4 – EBIT/SE	6.96	(0.17)	0.01	(0.70)	5.68	(0.13)	-0.01	(0.92)
5 – FCF/TA	3.91	(0.25)	-0.05	(0.60)	2.92	(0.31)	0.03	(0.80)
6 – DIV/SE	2.97	(0.74)	0.18	(0.46)	-2.67	(0.74)	0.18	(0.44)
7 – EBIT GWTH	0.00	(0.98)	-0.02	(0.58)	0.08	(0.47)	-0.02	(0.60)
8 – ACTIVITY	-0.26	(0.54)	**-0.70**	**(0.05)**	-0.19	(0.61)	-0.52	(0.15)
9 – M/B	-0.02	(0.32)	0.19	(0.31)	-0.01	(0.53)	0.08	(0.68)
10 – P/E	2.00	(0.13)	0.02	(0.25)	0.59	(0.48)	0.03	(0.36)
12 – CAPEX/TA	4.00	(0.46)	0.32	(0.16)	6.35	(0.22)	**0.67**	**(0.02)**
13 – CURRENT	0.07	(0.87)	0.35	(0.71)	-0.41	(0.58)	1.36	(0.35)
14 – (CA-CL)/TA	**-3.64**	**(0.05)**	-0.02	(0.68)	-2.14	(0.15)	**-0.21**	**(0.07)**
15 – QCK ASSETS	-0.01	(0.98)	0.01	(0.99)	0.52	(0.48)	-0.13	(0.92)
16 – PAYOUT	**-4.07**	**(<0.01)**	**-0.26**	**(0.09)**	**-2.75**	**(0.01)**	**-0.51**	**(0.04)**
17 – NET GEAR	-0.24	(0.42)	-0.14	(0.28)	**-1.06**	**(0.04)**	-0.11	(0.18)
19 – TL/TA	-2.94	(0.16)	-0.17	(0.78)	-1.21	(0.44)	-1.08	(0.12)
20 – LT DEBT/TA	-1.41	(0.62)	-0.09	(0.63)	-0.43	(0.86)	-0.07	(0.78)
21 – INDUSTRY	-0.10	(0.79)	-0.31	(0.31)	-0.02	(0.94)	-0.52	(0.18)
22 – Ln (TA)	**0.95**	**(<0.01)**	**12.53**	**(<0.01)**	**0.95**	**(<0.01)**	**15.88**	**(<0.01)**
23 – NET ASSETS	**0.00**	**(0.01)**	-0.22	(0.11)	**0.00**	**(0.01)**	**-0.27**	**(0.04)**
Model Statistics								
Likelihood Ratio	79.90	(<.0001)	54.01	(<.0001)	74.92	(<.0001)	67.88	(<.0001)
Likelihood Score	53.42	(<.0001)	41.70	(0.003)	54.19	(<.0001)	51.86	(<.0001)
R-Square	0.47		0.35		0.45		0.42	
Max Rescaled R-Square	0.63		0.47		0.60		0.56	

Note: Estimated parameters in bold type represent those variables which are significant in explaining acquisition likelihood at the 10 percent level. A Chi-square statistic is used to assess the significance of each variable, which is the most appropriate test statistic for logistic regressions.

Note that interpretation of estimated coefficients in the case of the logit model is not identical to parameter interpretation in the linear regression model. In the CLRM, a one unit change in the explanatory variable corresponds to an x unit change in the dependent variable, x representing the estimated coefficient. But in the logit model, a one unit change in the explanatory variable corresponds to an x unit change in the log odds of event probability, which in the case of this thesis is acquisition probability. The non-linear relationship between acquisition probability and the explanatory variables means that we cannot interpret the exact impact of a change in an explanatory variable on acquisition probability without the use of a reference point, as demonstrated by the explanation of Equation 3 in Section 3.2. Even so, the sign and significance of estimated parameters can be interpreted in an identical manner to the CLRM.

Examination of Table Four indicates some interesting preliminary results. The likelihood and R-squared statistics seem to suggest that the models which utilise a single year of pre-sample financial data have a higher level of explanatory power and predictive accuracy than those models which utilise an average of two years of pre-sample financial data. This contradicts Hypothesis 9 of this thesis. These statistics also suggest that the models which utilise the unadjusted (raw) financial ratios have a higher level of explanatory power and predictive accuracy than those models which utilise adjusted financial ratios. This contradicts Hypothesis 10 of this thesis. Additionally, there is no clear consensus as to the significant motivations for takeovers across the estimated models, even though the models have significant explanatory power beyond the 1 percent level. This is an obvious sign of multicollinearity, as standard errors will be inflated leading to inefficient parameter estimates which are also shown to be insignificant. Even so, all models suggest a positive relationship between variable 22 (Ln (TA)) and acquisition likelihood. This relationship contradicts the size hypothesis which suggests a negative relationship between this variable and acquisition likelihood. All models also suggest negative relationship between variable 16 (PAYOUT) and acquisition likelihood, which confirms the hypothesised sign of the dividend payout hypothesis.

4.2 Multicollinearity Analysis

The next step of the analysis is to eliminate multicollinearity from the four models to be estimated for significant parameter interpretation. Our analysis will focus on only one of the models from this point forward as reporting statistics for all models would not be feasible[20]. As the combined adjusted model theoretically has the highest predictive accuracy, our focus will be on this model. Appendix A reports the two sets of multicollinearity statistics for the combined adjusted model. Table A.1 presents the correlation matrix, which does not indicate that any extreme multicollinearity problems exist. Note that all correlations greater than 0.8 are presented in bold type. Examination of Table A.2, the Variance Inflation Factors, indicates a more widespread problem. Five variables in this figure exhibit Variance Inflation Factors which are extremely high. On the basis of these two figures, it was decided to eliminate five problematic variables – 2 (Return on Equity), 5 (FCF/TA), 13 (Current Ratio), 14 (Current Assets – Current Liabilities/Total Assets), and 19 (Total Liabilities/Total Assets). These variables either had a correlation coefficient with another explanatory variable greater than 0.8 or a VIF greater than 10, and their elimination caused all statistics to return to normal levels. This process was repeated for the remaining three models. Appendix B lists the variables eliminated from these models, which range from three to five variables and generally conform to the same variable groups eliminated from the combined adjusted model. These models, which are theoretically free

[20] Detailed results for the remaining models are available on request from the author. Many of these are presented in the accompanying appendices of this thesis.

from multicollinearity, were used as a basis for the univariate comparison of means and the backward stepwise logistic regression.

4.3 Univariate Comparison of Means

Before the process of backward stepwise regression was conducted, a simpler methodology was employed to examine whether any significant differences existed between the means of targets and non-targets which may be indicative of the parameters to be estimated.

Table Five – Univariate Comparison of Means for the Combined Adjusted Model.

Variable	**Non-Target Mean**	**Target Mean**	**t-statistic**
1 – ROA	-0.06	1.47	**3.97**
4 – EBIT/SE	-0.94	1.71	2.04
6 – DIV/SE	-0.57	0.20	1.84
7 – EBIT GWTH	-0.37	0.04	0.28
8 – ACTIVITY	0.09	-0.58	**-3.18**
9 – M/B	0.11	-0.04	-0.10
10 – P/E	-1.47	2.10	1.14
12 – CAPEX/TA	-0.27	0.36	**3.38**
15 – QCK ASSETS	0.06	-0.26	-1.15
16 – PAYOUT	-0.10	-0.70	-2.14
17 – NET GEAR	-0.12	0.43	0.96
20 – LT DEBT/TA	-0.25	0.11	1.60
21 – INDUSTRY	0.93	0.97	0.28
22 – Ln (TA)	0.00	0.07	**3.55**
23 – NET ASSETS	1.43	0.61	-0.61

Note: Reported t-statistics in bold type indicate that the mean values are significantly different between target and non-target firms at the 1 percent level of significance. A significantly positive (negative) t statistic suggests that the mean financial ratio for targets is significantly greater (smaller) than the mean financial ratio for non-targets. These statistics were generated from the same observations used for the estimation sample, containing 62 target and 63 non-target observations.

Table Five presents the results of this comparison of means. Significant differences exist between the means of targets and non-targets for four of the variables which will be included in the backward stepwise regression, providing evidence for four of the eight hypothesised motivations for takeover. This provides significant evidence against the results of Zanakis and Zopounidis (1997), which suggested that financial profiles of targets and non-targets were extremely similar. Variable one (ROA) suggests that targets outperform their non-target counterparts in terms of profitability, whilst variable eight (ACTIVITY) suggests that targets underperform in terms of revenue generating abilities. Variable twelve (CAPEX/TA) indicates that targets are spending a higher amount on capital expenditure, which implies large future growth opportunities relative to non-target firms. And, as in the initial estimation of all models, this comparison suggests that target firms are indeed larger than their non-target counterparts according to variable twenty two (Ln (TA)).

4.4 Backward Stepwise Regression Results and Interpretation

Using the same variables, a backward stepwise regression was performed with the purpose of retaining only those variables which are significant in explaining acquisition likelihood. The significance level for retention of variables in the analysis was set at 0.15 through the available SAS options, consistent with the methodology of Walter (1994). This was performed for all four models, as was the multicollinearity analysis, although the results for the remaining three models are reported in Appendix B. The backward stepwise analysis for the combined adjusted model eliminated six insignificant variables from a starting number of 15 variables, retaining nine significant variables as reported in Table Six below. These results are quite robust, as re-examination of the comparison of means indicates that most of the significant variables from the backward stepwise regression are confirmed. Additionally, many of the confirmed variables for the combined adjusted model presented here are confirmed by a similar process for the remaining three models presented in Tables B.1, B.2 and B.3. Note that the industry disturbance hypothesis (21) is not confirmed by the remaining three models, nor is it confirmed by the comparison of means, suggesting that the significance of this variable may be a spurious result. Additionally, the significance of variables for the inefficient financial structure hypothesis (17-20) are not confirmed by the univariate comparison of means, but are confirmed by two of the remaining three backward stepwise logistic regressions, highlighting the robustness of the significance of variable 20.

Table Six – Backward Stepwise Results for the Combined Adjusted Model

Variable	**Parameter Estimate**	**Prob > Chi Sq**
Intercept	-0.04	(0.92)
1 – ROA	0.28	(0.09)
8 – ACTIVITY	-0.54	(0.05)
12 – CAPEX/TA	0.69	(<0.01)
15 – QCK ASSETS	0.93	(0.02)
16 – PAYOUT	-0.34	(0.02)
20 – LT DEBT/TA	-0.32	(0.07)
21 – INDUSTRY	-0.59	(0.06)
22 – LN (TA)	13.34	(<0.01)
23 – NET ASSETS	-0.21	(0.07)

The first of the confirmed hypotheses is the inefficient management hypothesis, which is analysed by variables one to eight, although some of these were excluded due to multicollinearity and incomplete data. The positive coefficient estimate for variable one (ROA) indicates that an increase in operating performance increases the log odds of acquisition for a firm, which contradicts our a priori expectation for the sign of the estimated coefficient as we expect targets to underperform relative to industry averages. This contradicts the results of both Palepu (1986) and Walter (1994) who documented insignificance, but confirms the same result found by Barnes (1999) is his UK analysis of takeovers. This suggests that target firms have underlying businesses which are essentially profitable. The estimated coefficient for variable eight (ACTIVITY) suggests that a poor sales generating ability increases the log odds of acquisition, providing evidence in favour of the inefficient management hypothesis and confirming the results of Dietrich and Sorensen (1984) and Barnes (1999). Taken together, these two variables suggest that targets are essentially profitable firms which are unable to generate the sales revenue to be competitive in their industries. Although this confirms the results of Barnes (1999), this thesis will provide evidence that outperformance of the industry in terms of ROA results from targets of friendly takeovers only, the significance of which will be discussed in Section 4.11. Relying solely on the binomial evidence at this point, one could conclude that targets are essentially profitable businesses with poor revenue generating abilities relative to their industries.

The results for the growth resource mismatch hypothesis are somewhat more reliable. The estimated coefficient for variable twelve (CAPEX/TA) is significantly positive, which indicates that firms which have a relatively higher level of capital expenditure have higher log odds of acquisition. This leads to the conclusion that targets have higher future growth opportunities than non-target firms, but contradicts the growth variable of Palepu (1986) which indicated a negative relationship. Variable sixteen (PAYOUT) provides further evidence for this contention, as the negative coefficient indicates that firms which have higher payout ratios will generally have a lower log odds of acquisition. This suggests that firms which are paying out less of their earnings, and aggregating financial slack to exploit profitable future investment opportunities, are more likely to be acquired. These results provide strong evidence for the dividend payout hypothesis, which is surprising given that only Dietrich and Sorensen (1984) found it to be significant, and most other researchers have neglected to include it as an explanatory variable.

The growth variable results are confirmed by variable fifteen (QCK ASSETS). Its positive estimated coefficient suggests that firms with a higher level of current financial slack are more likely to be acquired. Taken together with variables twelve and sixteen, they suggest that targets are aggregating financial slack to exploit potentially profitable investment opportunities in the future. But it really does not provide any evidence for either of the forms of the growth resource mismatch hypotheses, which suggests that targets are suffering from an imbalance which must be rectified by an acquirer[21]. This contradicts the evidence of Palepu (1986) and Powell (2004), who document severe growth resource imbalances for target firms, although they disagree on the form of the imbalance. Our conclusion is that targets do not suffer from a growth resource imbalance, but are actually growing firms which seem to have the resources to exploit such opportunities without the help of an acquiring firm. This refutes the claim of these researchers that mergers and acquisitions are enacted to remove such imbalances.

The results for the inefficient financial structure hypothesis are clearer. The negative coefficient estimate for variable twenty (LT DEBT/TA) confirms the results of Dietrich and Sorensen (1984) and Palepu (1986). Interpretation of this coefficient indicates that target firms are under levered relative to other firms in their industry, as lower leverage results in higher log odds of acquisition. This result confirms the first interpretation of the inefficient financial structure hypothesis, as it seems that acquirers are attempting to exploit the underutilisation of debt by target management as proposed by Lewellen (1971). This contradicts the second interpretation of this hypothesis, as otherwise over-levered firms should have higher log odds of acquisition.

[21] Note that these variables are only significant within the adjusted models, as demonstrated in Appendix A. This suggests that the measurement of growth prospects and current liquidity must be made in an industry specific context.

There may be a number of reasons for this observation. As the Australian economy was in a period of expansion during the estimation period of 2003 and 2004, it is likely that acquirers were looking to acquire firms with what is the sole purpose of exploiting the benefits from a levered position[22]. Also, Private Equity Firms and many Investment Banks have been acquiring firms with what seems to be the sole purpose of loading them with an inconceivable level of debt. If they were maximising the potential returns from such a strategy, they would target relatively under levered firms. Our analysis seems to confirm such theories. These results would probably not hold in periods of recession or economic contraction. During such times, high levels of leverage can significantly decrease EPS, placing such over-levered firms in financial distress and most likely increasing their likelihood of acquisition. Our conclusion is that targets underutilise their debt capacity relative to their industry.

Close inspection of the results would indicate that the estimated coefficient for variable twenty one (INDUSTRY) has the opposite sign to the hypothesised sign of this thesis. Both Palepu (1986) and Walter (1994) provided evidence of a positive relationship. Such significance may be a spurious result, as it is unconfirmed by the remaining three models presented in Appendix B and the univariate comparison of means in Table Five. Our hypothesis suggests that an industry which has been subject to some form of economic disturbance will have an abnormally high level of merger and acquisition activity which will persist for a wave period. But our result suggests the converse, indicating that firms in an industry which is in a wave period will have lower log odds of acquisition. To understand this result, we must acknowledge that the measurement of industry activity is made in the two years before firms are designated as target

[22] During periods of economic expansion, firms may substantially increase their EPS by increasing their leverage.

and non-target firms. The problem stems from the fact that periods of wave activity generally last no longer than two to three years (Mitchell and Mulherin, 1996). This may allow the wave of activity to have passed before the designation of target and non-target firms within industries, which suggests that industries may have reached the bottom of the activity cycle by the time that firms are designated. Our conclusion is that the result is consistent with the notion of merger and acquisition waves, but that such waves have lives of no more than two years.

Close inspection will also reveal that the estimated coefficient for the size variable (22) is of the opposite sign to that expected a priori. Note that if we eliminate variable twenty three (NET ASSETS) from the analysis, as its estimated coefficient is economically insignificant, the estimated coefficient for variable twenty two (Ln (TA)) remains positive and significant. This is consistent across all four models. Only variable twenty two is confirmed by the univariate comparison of means. The positive coefficient indicates that larger firms have higher log odds of acquisition, which contradicts the reasoning and results of both Palepu (1986) and Walter (1994) which hypothesises a negative relationship. This result provides confirmation for the growth maximisation hypothesis of Marris (1963), which suggests that management of acquiring firms are more concerned with maximising the size of their firm than maximising shareholder welfare, as this maximises their pecuniary and non-pecuniary rewards. Also supported is the agency hypothesis of Jensen (1986), which suggests that management will retain excess cash flows and invest them in negative NPV projects rather than returning them to shareholders with the purpose of maximising their value to shareholders. These results suggest that management are attempting to acquire larger targets because they are acting in their own self interests rather than the interests of shareholder welfare. This provides significant evidence in favour of the growth maximisation hypothesis, which severely contradicts the results of many researchers who rely on the size hypothesis.

It is obvious from an examination of the results that the two valuation ratios, variables nine (M/B) and ten (P/E), are insignificant in explaining acquisition likelihood. This is unlikely to be a spurious result, as this insignificance is confirmed across every single model estimated for the purposes of this study and by the univariate comparison of means. Insignificance of the M/B ratio confirms the experience of the extant literature, as no published study has shown this ratio to be significant in explaining acquisition likelihood. Note that both Walter (1994) and Bartley and Boardman (1990) found the current cost version of this variable, the Q ratio, to be one of the most significant discriminatory variables in their models. This confirms that the M/B ratio is an extremely inefficient proxy for the Q ratio, even though Australian companies are more regularly required to update the reported book values of assets. The insignificance of the P/E ratio is not surprising either, given that every published study cited in this paper has documented this variable to be insignificant in explaining acquisition likelihood. On the basis of these results, we conclude that undervaluation was not a motivation factor for takeovers during the sample period of 2003 and 2004 in the Australian context.

4.5 Classification in the Estimation Period

Figures Two and Three present the results of an estimation of the Palepu (1986) derived cutoff point for the combined adjusted model only. Using different bin ranges for their construction; both indicate that an optimal cutoff point exists at 0.675, which is the highest intersection of the estimated acquisition probabilities for targets and non-targets.

Figure Two – Cutoff Calculations using the Palepu (1986) Methodology and 0.10 bin increments.

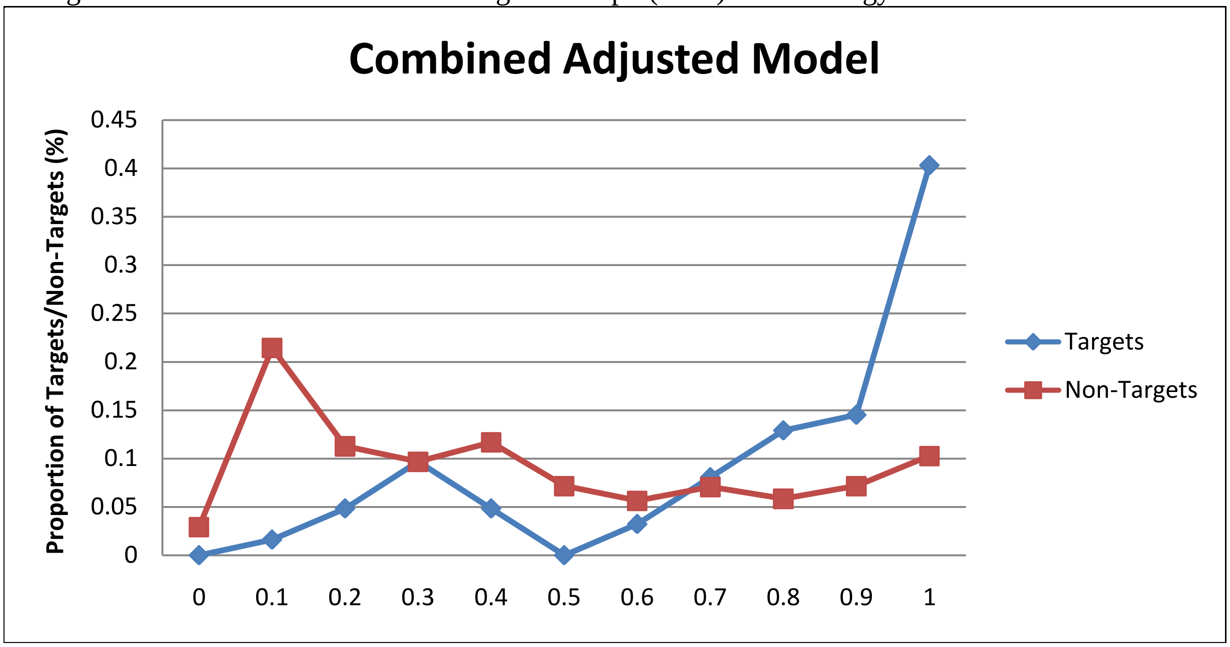
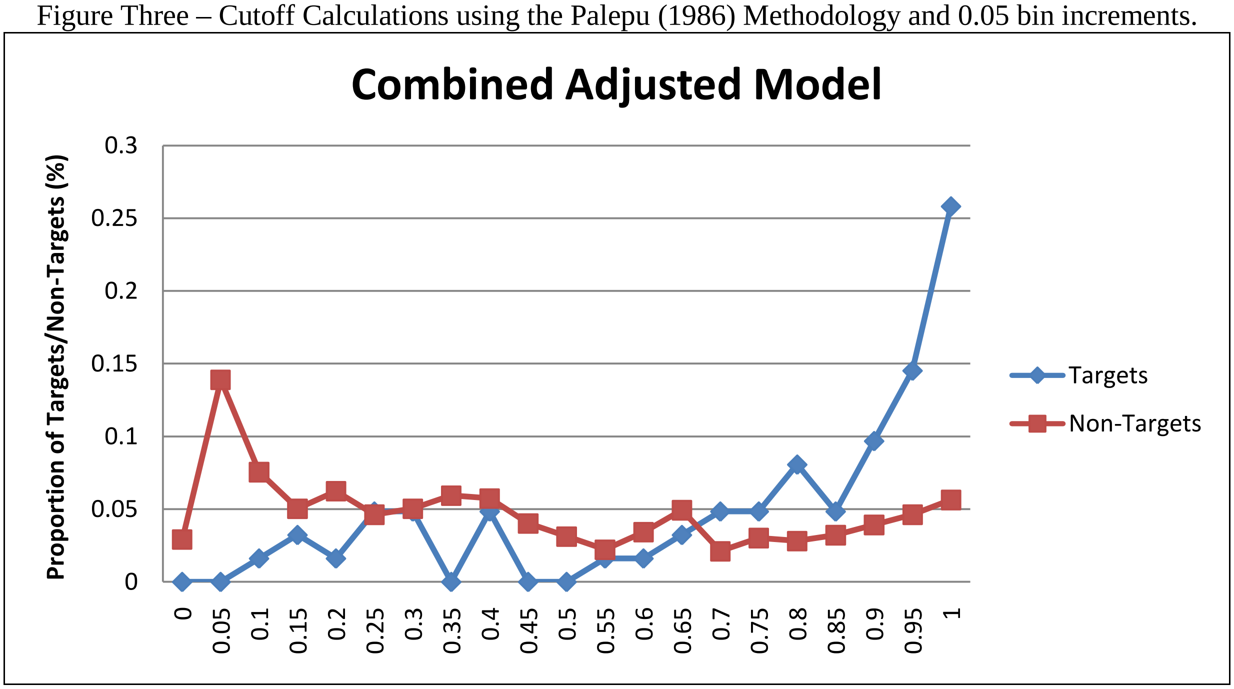


Figure Three – Cutoff Calculations using the Palepu (1986) Methodology and 0.05 bin increments.



Examination of these graphs indicates that the distribution of acquisition probabilities are not as clean as suggested in the methodological explanation of their derivation in Section 3.10. This results in a number of intersections for the distributions. The highest of these is selected as the optimal cutoff point, as Barnes (1999) concluded that these lower potential cutoff probabilities had significantly lower predictive accuracies. This was also confirmed by this thesis, although no results are reported as the comparison of interest is between the two optimal cutoff derivations. This methodology was replicated for the remaining three models, the results of which are presented in Table Seven.

Table Seven – Calculated Cutoff Probabilities for both Methodologies

Optimal Cutoff Probabilities	**Methodology** Palepu	**Barnes**
Single Raw Model	0.725	0.850
Single Adjusted Model	0.725	0.900
Combined Raw Model	0.850	0.950
Combined Adjusted Model	0.675	0.950

Table Seven also reports the results from the calculation of the Barnes (1999) optimal cutoffs. Examination of these results indicates that the cutoff points derived under the Barnes (1999) methodology are significantly higher than those derived under the Palepu (1986) methodology, consistent with the outcomes of Powell (2001) and Barnes (1999). We would expect both smaller portfolios of predicted targets and higher concentration ratios under the former methodology. To examine the classification accuracy of these models, these cutoff points were utilised to classify all estimation sample firms. The estimation sample consisted of 1060 firms, of which 62 became targets during the sample period[23]. Classification results from an application of the Barnes (1999) derived cutoff point are presented in Table Eight, whilst identical results for the Palepu (1986) derived cutoff are presented in Appendix C. This allows us to make a comparison of these methodologies, as the inaccuracy of the Barnes (1999) models was such that neither methodology predicted any takeover targets accurately.

[23] Note that the number of sample firms differs between models because of reasons outlined in Section 3.7.

Table Eight – Estimation Sample Classifications using Barnes (1999) Optimal Cutoff

Single Raw Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	874	124	998
Target	27	35	62
Total	901	159	1060
Concentration Ratio		22.01%	
Relative to Chance		276.34%*	

Single Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	906	88	994
Target	36	26	62
Total	942	114	1056
Concentration Ratio		22.81%	
Relative to Chance		288.46%*	

Combined Raw Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	935	61	996
Target	43	19	62
Total	978	80	1058
Concentration Ratio		23.75%	
Relative to Chance		305.28%*	

Combined Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	938	56	994
Target	46	16	62
Total	984	72	1056
Concentration Ratio		22.22%	
Relative to Chance		278.49%*	

^ Indicates that the overall predictions of the model are significantly better than chance at the 1 percent level of significance according to the Proportional Chance Criterion.

’ Indicates that the overall predictions of the model are significantly better than chance at the 5 percent level of significance according to the Proportional Chance Criterion.

* Indicates that the prediction of targets individually is significantly greater than a chance selection at the 1 percent level of significance according to the Maximum Chance Criterion.

~ Indicates that the prediction of targets individually is significantly greater than a chance selection at the 5 percent level of significance according to the Maximum Chance Criterion.

Table Eight provides outcome matrices for all of the models which are identical to the outcome matrix presented in Table Three. A number of important statistics can be readily generated from these results. All models exhibit significant values for the Proportional Chance Criterion, suggesting that they are all able to classify targets and non-targets jointly better than chance. All models also exhibit significant values for the Maximum Chance Criterion, suggesting that they are all able to classify target firms better than chance. Such accuracies are expected within the estimation sample, as all targets from this sample are used to estimate the models parameters. The most important statistic is the concentration ratio of Powell (2001), which is the ratio of actual targets in the portfolio of predicted targets (A_{11}/T_{P1} from Table Three). Under a chance selection, one would expect to select a number of targets equal to their frequency of occurrence in the population of listed firms (T_{A1}/T). To compare the concentration ratio to the chance benchmark, we simply divide the former ratio by the latter and minus one. A quick examination of these statistics indicates that the combined raw model provides the most accurate classifications within the estimation sample. Of the 80 firms that this model predicts to become takeover targets in the estimation period, 19 actually become targets, representing a concentration ratio (accuracy) of 23.75 percent. When taken relative to chance, this accuracy exceeds the benchmark by 305 percent. These results confirm the high within-sample classification accuracies reported by researchers such as Powell (2001) and Walter (1994).

Examination of Table C.1 in comparison to Table Eight highlights some interesting results for our methodological hypotheses. For all of the estimated models, use of the Palepu (1986) derived cutoff probability significantly increases the proportion of targets accurately classified as targets (A_{11}/T_{A1} from Table Three). The problem stems from the fact that this is also accompanied by an increase in the number of non-target firms incorrectly classified as targets by the models (A_{01}, the Type II Error). This in turn significantly reduces the concentration ratio. As we are concerned with the concentration ratio for investment purposes, rather than the accurate classification of targets as targets, this reduces the theoretical accuracy of the model. This result stems from the different perspectives taken by these cutoff calculation methodologies. The Barnes (1999) methodology focuses on increasing results from a portfolio investment, and readily achieves this, providing evidence in favour of Hypothesis 11 of this thesis.

4.6 Classification in the Prediction Period

The estimated models were then extended to classification within the prediction period, as our interest is in the ex-ante predictive ability of the models rather than their ex-post classification abilities. Of 1054 firms in this sample, 108 actually became takeover targets during the sample period. This occurrence of targets is significantly larger than in the estimation sample (108 vs. 62), suggesting a wave period during the prediction sample. Table Nine presents identical classification results to those presented in Table Eight, but for the prediction sample. Similar results for the Palepu derived cutoff point are presented in Appendix D.

Calculation of the Proportional Chance Criterion suggests that only the combined adjusted model is able to predict targets and non-targets jointly better than chance. All models are able to predict targets individually greater than chance according to the Maximum Chance Criterion, which suggests significant accuracy. Comparison of models indicates that the combined adjusted model is the clear winner, as it has the highest concentration ratio, confirming our hypotheses.

Table Nine – Prediction Sample Outcomes using Barnes (1999) Optimal Cutoff

Single Raw Model	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	856	90	946
Target	92	16	108
Total	948	106	1054
Concentration Ratio		15.09%	
Relative to Chance		47.31%~	

Single Adjusted Model	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	816	128	944
Target	84	24	108
Total	900	152	1052
Concentration Ratio		15.79%	
Relative to Chance		53.80%~	

Combined Raw Model	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	890	56	946
Target	96	12	108
Total	986	68	1054
Concentration Ratio		17.65%	
Relative to Chance		72.22%*	

Combined Adjusted Model’	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	841	100	941
Target	83	25	108
Total	924	125	1049
Concentration Ratio		20.00%	
Relative to Chance		94.26%*	

^ Indicates that the overall predictions of the model are significantly better than chance at the 1 percent level of significance according to the Proportional Chance Criterion.
’ Indicates that the overall predictions of the model are significantly better than chance at the 5 percent level of significance according to the Proportional Chance Criterion.
* Indicates that the prediction of targets individually is significantly greater than a chance selection at the 1 percent level of significance according to the Maximum Chance Criterion.
~ Indicates that the prediction of targets individually is significantly greater than a chance selection at the 5 percent level of significance according to the Maximum Chance Criterion.

Of the 125 firms predicted to become takeover targets by the combined adjusted model, 25 actually do, suggesting an accuracy of 20 percent. Taken relative to chance, this exceeds the benchmark by some 94.26 percent. This predictive accuracy is comparable to the highest reported accuracies in the takeover prediction literature. Walter (1994) was able to predict some 102 percent better than chance, but his sample was limited to firms which reported current cost data. Thus our study confirms this result in a larger sample, and refutes studies such as Palepu (1986) and Barnes (1999) that were unable to predict better than chance.

The fact that the combined adjusted model reports the highest predictive accuracy confirms a number of the methodological hypotheses. Industry adjustment significantly increases predictive accuracy for both the single and combined models, confirming the stability argument of Platt and Platt (1990). The average of two years of pre-sample financial data also improves predictive accuracy, suggesting that such practices eliminate meaningless fluctuations in financial ratios to improve predictive accuracies. Hypotheses 9 and 10 are confirmed with significant strength. Examination of the results for Hypothesis 11 is not as clear. The predictive outcomes for the models based on the Palepu (1986) derived cutoff in Table D.1 indicate that this methodology increases the concentration ratio for the first three models, but reduces it for the combined adjusted models. This confirms the contention of Barnes (1999) that his derivation of the optimal cutoff point will only improve predictive accuracy where the distributions of estimated acquisition probabilities for targets and non-targets are stable over time. As the accuracy of the best model of this thesis are increased by the use of the Barnes (1999) derived cutoff point, and this methodology has theoretical strengths, we conclude in favour of Hypothesis 11 of this thesis. Our contention is that further research should implement only the Barnes (1999) derived cutoff methodology. Future research should also examine methodologies to improve the stability of this optimal cutoff probability derivation.

4.7 Elimination of Problematic Variables

On the basis of these results, a number of different models were implemented to improve the accuracy of the two best predictive models – the combined raw model and the combined adjusted model. This was undertaken to improve accuracy in the estimation sample, replicating the problem faced by a practitioner. Our concerns were based on variables 9 (M/B) and 10 (P/E), the valuations ratios, as they were indicated to be insignificant in explaining acquisition likelihood in every model estimated to this point of the thesis and by the univariate comparison of means. Additionally, variable 7 (Sales Growth) seemed to be causing problems because it estimated growth over only a single year, making it extremely volatile.

Table Ten – Application of improved models to Estimation Sample.

Combined Raw Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	941	55	996
Target	44	18	62
Total	985	73	1058
Concentration Ratio		24.66%	
Relative to Chance		320.77%*	

Combined Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	951	43	994
Target	48	14	62
Total	999	57	1056
Concentration Ratio		24.56%	
Relative to Chance		318.34%*	

Table Eleven – Application of improved models to Prediction Sample.

Combined Raw Model	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	899	47	946
Target	98	10	108
Total	997	57	1054
Concentration Ratio		17.54%	
Relative to Chance		71.22%*	

Combined Adjusted Model	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	865	76	941
Target	86	22	108
Total	951	98	1049
Concentration Ratio		22.45%	
Relative to Chance		118.05%*	

^ Indicates that the overall predictions of the model are significantly better than chance at the 1 percent level of significance according to the Proportional Chance Criterion.
' Indicates that the overall predictions of the model are significantly better than chance at the 5 percent level of significance according to the Proportional Chance Criterion.
* Indicates that the prediction of targets individually is significantly greater than a chance selection at the 1 percent level of significance according to the Maximum Chance Criterion.
~ Indicates that the prediction of targets individually is significantly greater than a chance selection at the 5 percent level of significance according to the Maximum Chance Criterion.

The Sales Growth and P/E variables were eliminated from the combined raw model, and the Sales Growth, M/B and P/E variables were eliminated from the combined adjusted model. Elimination of these variables resulted in significant improvements in classification accuracy presented in Table Ten, with the concentration ratio for both models exceeding a chance selection by more than 300 percent. This accuracy was held into the prediction sample, the results of which are presented in Table Eleven. The accuracy of the combined adjusted model, at 118 percent greater than chance, represents the highest accuracy reported by any published takeover prediction study. This is achieved by the prediction of 98 firms to become takeover targets, of which 22 actually become targets, providing a concentration ratio of 22.45 percent. These results strongly refute the claims of Barnes (1999) and Palepu (1986) which suggest that such models cannot be implemented to achieve predictive accuracies greater than chance, and improves the reported accuracy of Walter (1994) in a wider sample of firms.

Note that the combined adjusted model significantly outperforms all other models for predictive purposes, confirming that this is the most appropriate model for the application of logit models for the prediction of takeover targets in the Australian context. This provides further evidence in favour of Hypotheses 9 and 10 of this thesis. Our results suggest that inclusion of more than one variable for each of the hypothesised motivations for takeovers can significantly improve predictive accuracy, but that rejection of some variables where poor significance is consistently demonstrated can also improve predictive accuracy.

4.8 Combination of Model Predictions

Although the concentration ratio of the combined adjusted model is quite high, the occurrence of actual targets in the portfolio of predicted targets at a rate of only 22.45 percent is not feasible from an investment perspective. And a portfolio of 98 stocks is also still to large from an investment perspective. For a practitioner with limited funds, the transactions costs associated with any investment in such portfolios would erode any potential profit opportunity made available through the accuracy of the model. Only the commonly predicted targets across all six models estimated to this point were retained. This provided 14 predicted targets which are listed in Appendix E, Table E.1. One of these firms was actually delisted prior to the prediction sample, reducing the portfolio to only 13 firms[24]. Of these predicted targets, 5 actually became targets during the sample period, suggesting a concentration ratio of some 38.46 percent. This

[24] This occurred because all firms with accounting data were included in the samples to avoid survivorship bias in the calculation of industry relative ratios.

significantly outperforms the best single model which has a concentration ratio of only 22.45 percent (the combined adjusted model in Table Eleven). Taken relative to chance, this exceeds the benchmark by some 274 percent, which is comparable to a single model classifying in the estimation period. This suggests that combinations of predictions across different methodologies can significantly improve concentration for investment purposes.

4.9 Analysis of Cumulative Abnormal Returns from Portfolio Investment

The next stage of the process is to economically quantify the benefit from an investment in these predicted targets. If, according to Palepu (1986), the probability of takeover is impounded into the price of a stock, we should be unable to earn significantly positive abnormal returns from an investment in the predicted targets. The equally weighted portfolio approach was applied to these 13 commonly predicted targets for the 2005 and 2006 calendar years. Table Twelve presents the results of this analysis over intervals of 20 days throughout this 504 trading day period. The first column, labelled Portfolio, presents the CAAR results for the full portfolio of 13 stocks. Over the entire prediction period, this portfolio earns a significantly positive abnormal return of 68.67 percent. Such a result significantly exceeds any expectations for the abnormal performance of this portfolio.

Table Twelve – Cumulative Average Abnormal Returns for portfolios during 2005 and 2006.

Day	**Portfolio (13)** *CAAR (%)*	**Actual Targets (5)** *CAAR (%)*	**Robust Portfolio** *CAAR (%)*
20	1.38%	5.36%	1.58%
40	2.84%	10.50%	3.13%
60	-1.98%	5.58%	1.69%
80	-2.53%	6.11%	0.88%
100	-5.52%	-1.15%	-1.86%
120	4.40%	25.16%	8.35%
140	3.06%	17.83%	7.23%
160	4.38%	20.70%	8.77%
180	5.51%	24.79%	10.10%
200	9.90%	34.82%	14.24%
220	7.51%	34.87%	12.16%
240	6.40%	29.31%	11.00%
260	5.04%	27.71%	10.18%
280	4.77%	29.64%	9.87%
300	4.67%	32.47%	10.05%
320	3.08%	33.53%	8.94%
340	0.73%	31.96%	6.93%
360	2.89%	26.62%	8.19%
380	5.28%	33.72%	11.05%
400	6.99%	32.02%	12.41%
420	9.78%	37.43%	15.48%
440	11.33%	40.22%	17.15%
460	57.44%	46.00%	20.33%
480	58.38%	47.27%	21.50%
500	68.90%	52.12%	23.41%
503	**68.67%**	**50.86%**	**23.37%**
SAR t-statistic	21.82	4.85	9.17
Significance Level	*(<0.01)*	*(<0.01)*	*(<0.01)*
Walter t-statistic	43.75	22.73	14.89
Significance Level	*(<0.01)*	*(<0.01)*	*(<0.01)*

Note: The second column of this figure presents the CAAR at 20 day intervals for the equally weighted portfolio of 13 stocks which were commonly predicted by the models. The third column presents identically calculated results for only the five actual targets within this portfolio, whilst the final column presents identical results to the second other than that the daily abnormal return to the stock ATM is set to zero.

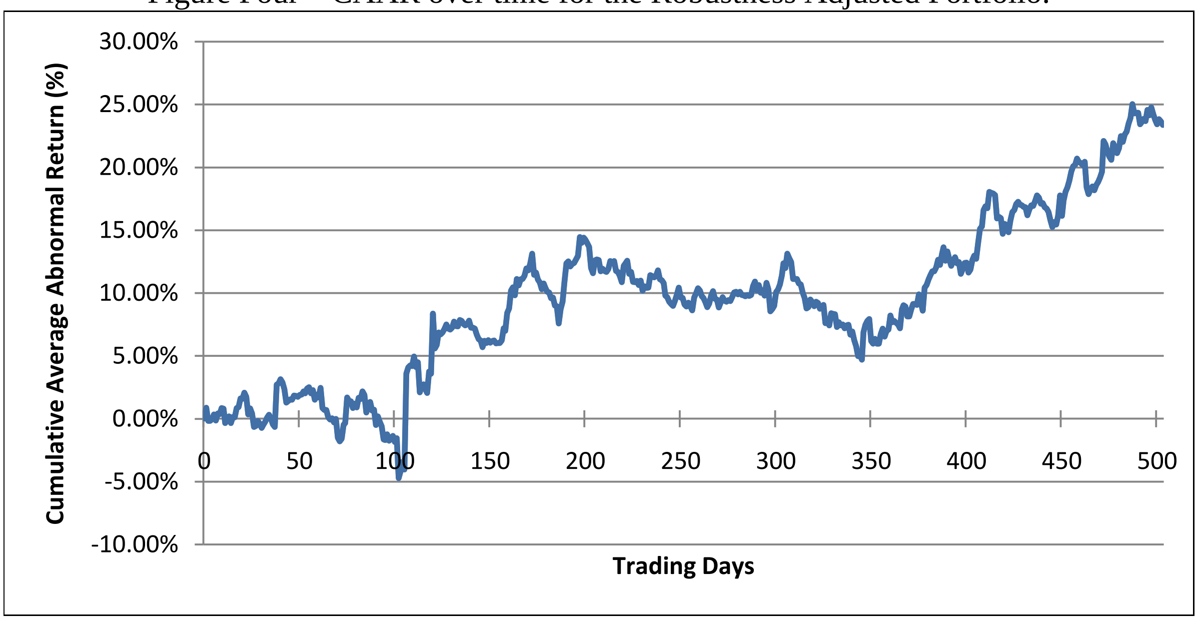
To confirm that this is driven by actual targets in the portfolio of predicted targets, the methodology is repeated for only the 5 actual targets in this portfolio. This provides evidence of a significant abnormal return of 50.86 percent for the entire prediction period, confirming somewhat that the results are driven by the outperformance of actual targets[25]. But the CAAR of the portfolio is larger than the CAAR of the targets, suggesting that some actual non-targets in this portfolio significantly outperformed the benchmark. Examination of the individual stock CAR's for the period indicates that the infrequently traded ATM is driving these significantly positive abnormal returns for the entire portfolio, especially between days 440 and 460 when the portfolio CAAR jumps from 11.33 percent to 57.44 percent. Throughout the prediction period, this stock had a CAR of some 422 percent. For the purposes of robustness, the daily abnormal returns of ATM were set to zero for the entire prediction period. Reapplication of the CAAR approach to the entire portfolio subsequent to this change provided the results in the final column of Table Twelve. This robustness adjusted portfolio reported a CAAR of 23.37 percent for the entire prediction period. Note that all reported CAAR's were significantly greater than zero at the 1 percent level of significance under both methodologies.

The abnormal performance of this robustness adjusted portfolio confirms to our chance expectations. If we assume that all targets outperform over the period by the 50.86 percent reported, and assume that on average non-targets in this portfolio perform with daily abnormal returns indifferent from zero, then we can calculate the expected abnormal return on the portfolio. Our calculations suggest an expected abnormal return of approximately 20 percent (38.46 percent multiplied by 50.86 percent). Even if the actual targets in this portfolio of predicted targets made a smaller abnormal return, say the 30 percent estimated by Jensen and Ruback (1983), we would still expect the portfolio abnormal return to be significantly positive at

[25] Announcement period abnormal returns of 50% are confirmed in the paper of Franks and Harris (1989), suggesting that our abnormal return results for targets are at the higher end of the range suggested by the literature.

12 percent (38.46 percent multiplied by 30 percent). Based on this reasoning, we believe that the calculated CAAR of 23.37 percent for the robustness adjusted portfolio is extremely accurate. A graphical representation of this result is presented in Figure Four. Examination of this suggests that the portfolio must be held for the entire prediction period. If one were to exit the portfolio at approximately day 350, one would have made returns insignificantly different from zero. These results also confirm that our results contain an element of chance. There is always the possibility that the non-targets in the portfolio will perform poorly enough to erode any profitability from an accurate selection of actual targets. Without perfect accuracy we cannot guarantee that application of the model for prediction will result in positive abnormal returns being made, but we believe that positive abnormal returns should be available with such accuracy on average.

Figure Four – CAAR over time for the Robustness Adjusted Portfolio.



Researchers such as Powell (2001) have launched specific attacks on the use of the CAPM as a returns benchmark on the basis of the size argument of Bansz (1981) and the fact that most targets are smaller than their non-target counterparts. They propose that the CAPM overestimates abnormal returns in such situations. But this paper has documented that targets are larger than non-targets, which would suggest that the CAPM underestimates abnormal returns rather than overestimates. M/B ratios are also not significantly different between target and non-target firms, negating arguments put forward by researchers such as Fama and French (1993) concerning the applicability of the CAPM. This suggests that our estimated abnormal returns are extremely robust. Confirmation by a logical interpretation of the accuracy of the model confirms this robustness. Our conclusion is that significantly positive abnormal returns may be made from an investment in the commonly predicted targets of binomial logit models.

The ability to earn significantly positive abnormal returns from the application of binomial models is a significant contradiction to the belief expressed in the extant literature. Palepu (1986), Walter (1994), and Powell (2001) all provide evidence that investment in predicted targets results in portfolio abnormal returns indistinguishable from zero. Barnes (1999) reinforced this, as his inability to predict any targets at all would result in the inability to make significant abnormal returns. Our results confirm the belief of Jensen and Ruback (1983) that the market is unable to predict such events with any accuracy in the months leading up to their announcement. They also suggest that the accuracy of the model is greater than that of the market in predicting these events, strongly refuting the beliefs expressed in the extant literature especially by researchers such as Palepu (1986) who contend that the probability of takeover is accurately impounded into the firm’s market value.

4.10 Multinomial Logit Analysis – Successful and Unsuccessful Takeovers

To examine whether such predictive accuracies can be improved, the multinomial models were estimated. Table Thirteen presents the results of a differentiation between successful and unsuccessful takeovers and non-targets using the multinomial logit model. This model was based on the same 62 target observations, split into 45 successful and 17 unsuccessful takeovers.

Table Thirteen – Results from estimation of the multinomial logit model within the combined adjusted model framework.

Variable	Parameter Estimates: Successful Target vs. Non-Target	Unsuccessful Target vs. Non-Target	Successful Target vs. Unsuccessful Target
Intercept	**-1.62**	**-1.67**	0.06
1 – ROA	0.23	**0.93**	**-0.70**
4 – EBIT/SE	0.06	-0.02	0.09
6 – DIV/SE	0.58	-0.44	1.02
7 – EBIT GWTH	-0.03	-0.02	-0.01
8 – ACTIVITY	**-2.24**	-0.09	**-2.15**
9 – M/B	-0.01	0.00	-0.01
10 – P/E	0.03	0.03	0.00
12 – CAPEX/TA	**0.86**	0.51	0.36
15 – QCK ASSETS	-0.01	0.01	-0.02
16 – PAYOUT	-0.34	-0.24	-0.11
17 – NET GEAR	0.01	0.01	0.00
20 – LT DEBT/TA	0.01	-0.25	0.26
21 – INDUSTRY	-0.45	-0.77	0.32
22 – Ln (TA)	**13.62**	4.32	**9.29**
23 – NET ASSETS	-0.24	-0.14	-0.10
Likelihood Ratio	133.22	Likelihood Deviance	0.49
Pr > Chi Sq	0.0000	Pr > Chi Sq	0.0006

Note: Coefficients in bold type indicate significance at the 10 percent level. The likelihood deviance statistic indicates whether all coefficients are identical between successful and unsuccessful targets, with a significant value indicating a significant difference in determination factors for each category and a conclusion that the binomial model is misspecified.

The likelihood deviance statistic is significant beyond the 1 percent level, suggesting that significant differences exist between the characteristics of successful and unsuccessful takeover targets. This is confirmed by the likelihood ratio of the multinomial model (133.22), which is significantly larger than the likelihood ratio of the binomial model in Table Four (67.88), suggesting increased explanatory power for the multinomial model. Note that the estimated parameters indicate the impact of a change in the explanatory variable on the log odds of becoming a successful and unsuccessful takeover target respectively (in columns one and two). The final column indicates whether any significant differences exist between these discriminating factors of successful and unsuccessful takeover targets.

Examination of the multinomial results indicates that targets of successful targets have significantly lower activity (8) than non-targets, whilst unsuccessful targets do not. Targets of unsuccessful bids actually outperform in terms of profitability (1), whilst successful targets do not. Taken together, these results suggest that it is the targets of successful takeovers which are inefficiently managed, and that targets of unsuccessful takeovers are driving the high profitability performance of targets suggested by the binomial model. To interpret this result, it could be that the acquirer, through their due diligence, realises that the efficiency of the target is not poor enough to allow capital gains or increased dividends to be realised through takeover. This would result in an unsuccessful takeover bid. It could also be that target shareholders in unsuccessful bids do not accept the bid because they believe that their management team is performing adequately, which is confirmed by the results. The results also indicate that successful targets are significantly larger (22) than non-targets, although unsuccessful targets are not. To understand this result, we must realise that the size of a firm is a close proxy for the age of the firm (Barnes, 1990). A potential acquirer may launch a bid for a small (young) target, but subsequently realise that the track record of the target is insufficient to allow proper examination of the firm. This could lead them to withdraw their bid. A univariate comparison of mean financial ratios between successful targets/non-targets and unsuccessful targets/non-targets is presented in Appendix F. These results should be indicative of the estimated parameters determining the likelihood of these events in the multinomial model. Examination of these results indicate that every one of the significant factors in the multinomial model are confirmed, highlighting the robustness of the reported results. Overall, the results suggest that the binomial model is misspecified for the purposes of parameter interpretation.

Table Fourteen – Application of the Multinomial Model within the Combined Adjusted Framework for the prediction of successful takeover targets only.

ESTIMATION SAMPLE	Predicted Outcome		
Actual Outcome	Non-Target/Unsuccessful	Successful Target	Total
Non-Target	879	115	994
Unsuccessful Target	13	4	17
Successful Target	19	26	45
Total	911	145	1056
Concentration Ratio		20.69%*	
Successful Target Concentration Ratio		17.93%	

PREDICTION SAMPLE	Predicted Outcome		
Actual Outcome	Non-Target/Unsuccessful	Successful Target	Total
Non-Target	804	137	941
Unsuccessful Target	14	8	22
Successful Target	66	20	86
Total	884	165	1049
Concentration Ratio		16.97%~	
Successful Target Concentration Ratio		12.12%	

BINOMIAL MODEL	Predicted Outcome		
Actual Outcome	Non-Target/Unsuccessful	Successful Target	Total
Non-Target	865	76	941
Unsuccessful Target	14	8	22
Successful Target	72	14	86
Total	951	98	1049
Concentration Ratio		22.45%*	
Successful Target Concentration Ratio		14.29%	

* Indicates that the prediction of successful and unsuccessful targets jointly is significantly greater than chance at the 1 percent level of significance according to the Maximum Chance Criterion.
~ Indicates that the prediction of successful and unsuccessful targets jointly is significantly greater than chance at the 5 percent level of significance according to the Maximum Chance Criterion.
^ Indicates that the prediction of successful targets individually is greater than chance at the 1 percent level of significance according to the Maximum Chance Criterion.

On the basis of this estimated model, the multinomial framework was extended to classify targets of successful takeovers individually, as this has been suggested to increase abnormal returns from a portfolio investment. Results from the application of this model to the estimation and prediction samples are presented in Table Fourteen, along with identical results for the binomial model from the prediction period. Our best binomial model, the combined adjusted model, reports a concentration ratio of 22.45 percent, whilst the multinomial prediction of successful targets has a concentration ratio of only 16.97 percent. We expect a trade-off in this situation – attempting to increase the proportion of successful targets in the portfolio of predicted targets (which should theoretically increase abnormal returns) should also reduce our overall predictive accuracy measured by the concentration ratio (which should theoretically decrease abnormal returns). But an analysis of the tables indicates that the multinomial model predicts a smaller concentration ratio of successful targets than the binomial model (12.12 percent versus 14.29 percent). A smaller concentration ratio and an inability to predict a higher proportion of successful targets lead us to the conclusion that the application of the multinomial model will not improve abnormal returns. Although our results suggest that the binomial model is misspecified relative to the multinomial model, they also indicate that the binomial framework is the most appropriate to predict takeover targets for investment purposes.

4.11 Multinomial Logit Analysis – Hostile and Friendly Takeovers

Table Fifteen presents the results of a similarly estimated multinomial model which attempts to discriminate between hostile and friendly takeover targets and non-targets. The 62 targets from the initial estimation sample were split into 21 hostile and 41 friendly targets. Significance of the likelihood deviance statistic at the 2 percent level again suggests that the binomial model is misspecified. Examination of the likelihood ratio for the multinomial model (159.38), versus the likelihood ratio for the binomial model in Table Four (67.88), suggests that the multinomial model has a higher level of explanatory power.

Table Fifteen – Results from the estimation of the multinomial logit within the combined adjusted framework to differentiate between targets of hostile and friendly takeovers.

	Parameter Estimates		
Variable	**Hostile Target vs. Non-Target**	**Friendly Target vs. Non-Target**	**Hostile Target vs. Friendly Target**
Intercept	**-1.35**	**-1.75**	0.39
1 – ROA	0.41	**0.74**	-0.32
4 – EBIT/SE	-0.04	0.04	-0.08
6 – DIV/SE	0.37	0.19	0.19
7 – EBIT GWTH	-0.01	-0.04	0.03
8 – ACTIVITY	**-1.55**	-0.26	**-1.29**
9 – M/B	0.09	0.02	0.07
10 – P/E	0.08	0.03	0.05
12 – CAPEX/TA	**0.87**	**0.73**	0.14
15 – QCK ASSETS	0.09	-0.49	0.58
16 – PAYOUT	-0.22	**-1.18**	0.96
17 – NET GEAR	0.04	0.03	0.01
20 – LT DEBT/TA	-0.40	0.20	-0.60
21 – INDUSTRY	-0.40	**-0.84**	0.44
22 – Ln (TA)	**14.62**	3.76	**10.85**
23 – NET ASSETS	-0.27	-0.10	-0.17
Likelihood Ratio	159.39	Likelihood Deviance	-0.33
Pr > Chi Sq	0.0011	Pr > Chi Sq	0.0127

Note: Coefficients in bold type indicate significance at the 10 percent level. The likelihood deviance statistic indicates whether all coefficients are identical between hostile and friendly targets, with a significant value indicating a significant difference in determination factors for each category and a conclusion that the binomial model is misspecified.

The estimated coefficients suggest that poor activity performance (8) is a characteristic of hostile targets, and not of friendly targets. This confirms the belief of Morck, Shleifer, and Vishny (1988) that hostile takeovers are enacted to discipline target management. The results also suggest that outperformance in profitability terms (1) is the result of friendly targets and not hostile targets. This confirms the contention of Bradley, Desai, and Kim (1983) that friendly takeovers are enacted more for the synergistic benefits available from takeovers, as this suggests that they are not undertaken to discipline target management for poor performance. These results are quite consistent with the multinomial results of Powell (1997, 2004). Hostile targets are also significantly larger (22) than non-targets, whilst friendly targets are not. This confirms the results of Powell (1997), who also suggests that targets of hostile takeovers are significantly larger than targets of friendly takeovers. Also confirmed is the Australian evidence of Eddey (1991), which suggested that the targets of corporate raiders were significantly larger than targets of other takeovers. His reasoning was that such corporate raiders were attempting some sort of empire building exercise. It may be that hostile acquirers are also attempting a similar form of empire building, which would be consistent with the growth maximisation and agency costs of free cash flow arguments presented in the literature review and documented in the binomial model. These results suggest that acquirers in friendly acquisitions do not suffer from the same behavioural biases.

A univariate comparison of mean financial ratios for hostile targets/non-targets and friendly targets/non-targets is presented in Appendix G. Significant differences in mean financial ratios should be indicative of the significant parameters estimated in the multinomial model. But unlike the two uses of such univariate comparisons earlier in the thesis, these results are different to the model they are providing robustness checks for. The results suggest outcomes more consistent with the binomial model, as the characteristics of hostile and friendly targets are similar. Such contradictory evidence is surprising, and may result from the small number of hostile targets included in this analysis. Zanakis and Zopounidis (1997) also suggest that this may result from the non-normality of financial ratios utilised for comparison, which invalidates the t test methodology in serious cases. We are inclined to the robustness of the multinomial logit results as they do not require such assumptions of normality, and conclude that significant differences exist between the characteristics of hostile and friendly takeover targets.

Table Sixteen – Application of the Multinomial Model within the Combined Adjusted Framework for the prediction targets of hostile takeovers only.

ESTIMATION SAMPLE	Predicted Outcome		
Actual Outcome	Non-Target/Friendly	Hostile Target	Total
Non-Target	909	85	994
Friendly Target	33	8	41
Hostile Target	15	6	21
Total	957	99	1056
Concentration Ratio		14.14%~	
Hostile Target Concentration Ratio		6.06%	

PREDICTION SAMPLE	Predicted Outcome		
Actual Outcome	Non-Target/Friendly	Hostile Target	Total
Non-Target	771	170	941
Friendly Target	58	23	81
Hostile Target	21	6	27
Total	850	199	1049
Concentration Ratio		14.57%~	
Hostile Target Concentration Ratio		3.02%	

BINOMIAL MODEL	Predicted Outcome		
Actual Outcome	Non-Target/Friendly	Hostile Target	Total
Non-Target	865	76	941
Friendly Target	66	15	81
Hostile Target	20	7	27
Total	951	98	1049
Concentration Ratio		22.45%~	
Hostile Target Concentration Ratio		7.14%	

* Indicates that the prediction of successful and unsuccessful targets jointly is significantly greater than chance at the 1 percent level of significance according to the Maximum Chance Criterion.
~ Indicates that the prediction of successful and unsuccessful targets jointly is significantly greater than chance at the 5 percent level of significance according to the Maximum Chance Criterion.
^ Indicates that the prediction of successful targets individually is greater than chance at the 1 percent level of significance according to the Maximum Chance Criterion.

As in the case of successful takeovers, the multinomial model was applied to select only targets of hostile takeovers, the results of which are presented in Table Sixteen with identical prediction results for the binomial model. Again we expect that an identical trade-off will exist – although the multinomial model may sacrifice concentration of all types of targets in the portfolio of predicted targets (which should theoretically reduce abnormal returns), one would expect it to increase the concentration of hostile takeover targets in this portfolio (which should theoretically increase abnormal returns). But examination of the portfolios of predicted targets indicates that the binomial model has a higher concentration ratio for hostile takeover targets (7.14 percent for the binomial model and 3.02 percent for the multinomial model). This, combined with a decreased general concentration ratio (14.57 percent for the multinomial model versus 22.45 percent for the binomial model), suggests that returns from investment in predicted hostile targets will be smaller than an investment in the predicted targets of the binomial model. This inaccuracy probably results from only 21 hostile takeovers being included in the estimation sample. We could possibly increase the length of the estimation sample to include more hostile target observations. But this may reduce the currency of the estimated parameters, which we believe is integral to the high predictive accuracies reported by this thesis. Based on these two multinomial models, it is obvious that the binomial model is superior if purpose of prediction is investment in predicted targets. This contradicts the proposal of Hypothesis 12 which suggests that implementation of the multinomial model should improve the concentrations of successful and hostile takeover targets in the portfolios of predicted targets. It also contradicts the results of Powell (2004), which suggested that an investment in predicted hostile targets improved returns significantly over an investment in predictions of the binomial model.

5. Conclusions

This thesis has extended the takeover prediction literature in a number of key areas. Firstly, an analysis of the hypothesised motivations for takeover provided evidence of six of the eight hypothesised motivations developed in our literature review. Targets are profitable but have poor revenue generating abilities. They are aggregating financial slack by paying out less of their earnings and investing a high level of this aggregated slack in future growth projects. They are underutilising their debt capacity. They are part of industries which have experienced high levels of takeover activity. And they are generally larger than their non-target counterparts. Significant evidence was also provided suggesting that significant motivational differences exist between successful and unsuccessful takeovers, and between hostile and friendly takeovers. Hostile takeovers are demonstrated to be undertaken for disciplinary reasons, whilst friendly takeovers are demonstrated to be undertaken for synergistic benefits. Successful takeovers are made for targets which seem to be underperforming and have profitable future investment opportunities, whilst unsuccessful takeover bids are made for targets which seem to be efficiently managed. This evidence confirms recent contentions that the binomial model is misspecified; suggesting that disaggregation of the target category must be undertaken to allow appropriate parameter interpretation.

Secondly, empirical application of binomial models for classification and prediction suggests that they can be implemented with accuracy significantly greater than chance. The best individual model, the combined adjusted model, is able to predict targets with accuracy some 118 percent better than chance. This outcome refutes the conclusions of the extant literature, whilst furthering similar small sample results of Walter (1994). This accuracy is achieved whilst exploring the most appropriate methodology for prediction. Our results confirm that the binomial model which utilises industry adjustment and averages of pre-sample financial data significantly outperforms the predictive accuracy of alternative model methodologies. Evidence also suggests that the application of the Barnes (1999) derived optimal cutoff point is empirically problematic.

Thirdly, the paper indicates that selecting only commonly predicted targets across a number of methodologies can significantly improve predictive accuracy (concentration) and reduce the portfolio of predicted targets to a reasonable level for investment purposes. A portfolio of 13 commonly predicted targets across our four model specifications contains 5 actual takeover targets, an accuracy which exceeds the chance benchmark by some 274 percent. This portfolio is also significantly more accurate than the implementation of any single model for prediction. Although our paper combined predictions across different binomial logit methodologies, future research could examine the viability of combining predictions across binomial and discriminant analysis methodologies, or using multiple layer neural networks to filter the predicted targets of one of these methodologies.

Fourthly, evidence is provided concerning the ability of multinomial logit models to outperform the predictive accuracies of binomial models for the prediction of successful takeover targets and hostile takeover targets individually. Although our evidence confirms the contention of Powell (1997, 2004) that the binomial model is indeed misspecified, our results indicate that the binomial model is the most appropriate for the purposes of ex-ante prediction (when investment is the purpose of prediction). Multinomial models are unable to predict a higher concentration of targets in the portfolio of predicted targets, and also unable to predict a higher concentration of either successful or hostile targets. These results suggest that returns would be significantly reduced from an investment in the multinomial model predictions. Future research should reconsider the applicability of the multinomial model to prediction for investment purposes, as larger samples should improve their ability to select the targets of interest.

Finally, this paper provides evidence that significant positive abnormal returns may be made from an investment in the commonly predicted targets of binomial logit models. Over a two year holding period, our portfolio of predicted targets reports a significantly positive CAAR of 23.37 percent after robustness adjustments (68.67 percent prior to robustness adjustments). No published binomial logit study employing the correct sampling methodology has reported such a result. We believe this accuracy stems from the strict application of all methodological improvements suggested by the literature, and the use of a number of different methodologies to discern only commonly predicted targets. Researchers such as Rege (1984) have proposed that such ability contradicts the Efficient Markets Hypothesis for reasons explained in Section 1.2 of this thesis. We resist drawing such conclusions. Fama (1998) argues that we must provide significant and consistent evidence of an anomaly, as one result such as ours may be the result of chance rather than an empirical fact. And until our model predicts with 100 percent accuracy, there is still the chance that non-targets predicted to be targets may perform so poorly that any abnormal returns made by actual non targets are eroded by the non-targets predicted to be targets. Even so, our conclusion is that significantly positive abnormal returns may be made from an investment in the commonly predicted targets of binomial logit models.

BIBLIOGRAPHY

Agrawal, Anup, and Jeffrey F Jaffe, 2003, Do Takeover Targets Underperform? Evidence from Operating and Stock Returns, *Journal of Financial and Quantitative Analysis* 38, 721-746.

Allison, Paul D, 2006, *Logistic Regression Using the SAS System*. Cary, NC: SAS Institute.

Altman, Edward I, 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance* 23, 589-609.

Barber, Brad M, and John D Lyon, 1997, Detecting long-run abnormal stock returns: The empirical power and specification of test statistics, *Journal of Financial Economics* 43, 341-372.

Barnes, Paul, 1990, The Prediction of Takeover Targets in the UK by means of Multiple Discriminant Analysis, *Journal of Business Finance and Accounting* 17, 73-84.

Barnes, Paul, 1999, Predicting UK Takeover Targets: Some Methodological Issues and Empirical Study, *Review of Quantitative Finance and Accounting* 12, 283-301.

Bartley, Jon W, and Calvin M Boardman, 1986, Replacement-cost-adjusted Valuation Ratio as a Discriminator among Target and Non-target Firms, *Journal of Economics and Business* 38, 41-55.

Bartley, Jon W, and Calvin M Boardman, 1990, The Relevance of Inflation Adjusted Accounting Data to the Prediction of Corporate Takeovers, *Journal of Business Finance and Accounting* 17, 53-72.

Bansz, R, 1981, The relationship between return and market value of common stock, *Journal of Financial Economics* 9, 3-18.

Belkaoui, Ahmed, 1978, Financial Ratios as Predictors of Canadian Takeovers, *Journal of Business Finance and Accounting* 5, 93-108.

Bradley, M, A Desai, and E Kim, 1983, The Rationale Behind Interfirm Tender Offers: Information or Synergy? *Journal of Financial Economics* 11, 183-206.

Brown, Stephen J, and Jerold B Warner, 1985, Using Daily Stock Returns, *Journal of Financial Economics* 14, 3-31.

Bugeja, M, and T Walter, 1995, An empirical analysis of some determinants of the shareholder premium in takeover bids, *Accounting and Finance* 35, 33-60.

Dietrich, Kimball J, and Eric Sorensen, 1984, An Application of Logit Analysis to Prediction of Merger Targets, *Journal of Business Research* 12, 393-402.

Eddey, P, 1991, Corporate Raiders and Takeover Targets, *Journal of Business Finance and Accounting* 18, 151-171.

Fama, Eugene F, 1980, Agency Problems and the Theory of the Firm, *Journal of Political Economy* 88, 288-307.

Fama, Eugene F, 1998, Market Efficiency, long-term returns, and behavioural finance, *Journal of Financial Economics* 49, 283-306.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fogelberg, G, CR Laurent, and D McCorkindale, 1975, The Usefulness of Published Financial Data for Predicting Takeover Vulnerability, University of Western Ontario, School of Business Administration (*Working Paper 150*).

Franks, J, and R Harris, 1989, Shareholder wealth effects of corporate takeovers: The UK experience, *Journal of Financial Economics* 23, 225-49.

Golbe, Devra, and Lawrence White, 1988, Mergers and Acquisitions in the United States Economy: An aggregate and historical overview; in A Auerbach *Mergers and Acquisitions*, Chicago: University of Chicago Press.

Gort, Michael C, 1969, An Economic Disturbance Theory of Mergers, *Quarterly Journal of Economics* 83, 624-642.

Gugler, Klaus, Dennis C Mueller, and B Burcin Yurtoglu, 2005, The determinants of Merger Waves, Utrecht School of Economics (*Working Paper 05-15*).

Gujarati, Damodar N, 2003, *Basic Econometrics*, Fourth Edition. New York: McGraw Hill.

Harris, Robert S, John F Stewart, David K Guilkey, and Willard T Carleton, 1984, Characteristics of Acquired Firms: Fixed and Random Coefficient Probit Analyses, *Southern Economic Journal* 49, 164-184.

Hasbrouck, Joel, 1985, The characteristics of takeover targets and other measures, *Journal of Banking and Finance* 9, 351-362.

Hosmer, DW, and S Lemeshow, 1989, *Applied Logistic Regression*. New York: John Wiley and Sons.

Jaffe, Jeffrey F, 1974, Special Information and Insider Trading, *Journal of Business* 47, 410-428.

Jennings, DE, 1986, Judging Inference Adequacy in Logistic Regression, *Journal of the American Statistical Association* 81, 471-476.

Jensen, Michael C, 1986, Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers, *American Economic Review* 76, 323-329.

Jensen, Michael C, and William H Meckling, 1976, Theory of the Firm: Managerial behaviour, agency costs, and ownership structure, *Journal of Financial Economics* 3, 305-360.

Jensen, Michael C, and Richard S Ruback, 1983, The Market for Corporate Control: The Scientific Evidence, *Journal of Financial Economics* 11, 5-50.

Jovanovic, Boyan, and Peter Rousseau, 2002, The Q-theory of mergers, *American Economic Review* 92, 198-204.

Kennedy, V, and R Limmack, 1996, Takeover Activity, CEO Turnover, and the Market for Corporate Control, *Journal of Business Finance and Accounting* 23, 267-293.

Kothari, S, and J Warner, 1997, Measuring Long Horizon Security Performance, *Journal of Financial Economics* 43, 301-339.

Lewellen, Wilbur G, 1971, A Pure Financial Rationale for the Conglomerate Merger, *Journal of Finance* 26, 521-537.

Lo, Andrew W, 1986, Logit versus Discriminant Analysis: A Specification Test and Application to Corporate Bankruptcies, *Journal of Econometrics* 31, 151-178.

Lyon, John D, and Brad M Barber, 1997, Detecting long-run abnormal stock returns: The empirical power and specification of test statistics, *Journal of Financial Economics* 43, 341-372.

Mandelker, Gershon, 1974, Risk and Return: The Case of Merging Firms, *Journal of Financial Economics* 1, 303-335.

Manne, Henry G, 1965, Mergers and the Market for Corporate Control, *Journal of Political Economy* 73, 110-120.

Marris, Robin, 1963, A Model of the "Managerial" Enterprise, *Quarterly Journal of Economics* 77, 185-209.

Martin, Kenneth J, and John J McConnell, 1991, Corporate Performance, Corporate Takeovers, and Management Turnover, *Journal of Finance* 46, 671-687.

McDougall, F, and D Round, 1986, The determinants and effects of corporate takeovers in Australia: 1970-1981, Australian Institute of Management – Victoria, and the National Companies and Securities Commission, Victoria, 3-207.

Miller, Merton H, and Franco Modigliani, 1964, Dividend Policy, Growth, and the Valuation of Shares, *Journal of Business* 34, 411-433.

Mitchell, Mark L, and J Harold Mulherin, 1996, The impact of industry shocks on takeover and restructuring activity, *Journal of Financial Economics* 41, 193-229.

Mitchell, Mark L, and Erik Stafford, 2000, Managerial Decisions and Long-Term Stock Price Performance, *Journal of Business* 73, 287-329.

Morck, R, A Shleifer, and R Vishny, 1988, Characteristics of Targets of Hostile and Friendly Takeovers, in AJ Auerbach, *Corporate Takeovers: Causes and Consequences* (University of Chicago Press, Chicago), 101-129.

Morrison, Donald G, 1969, On the Interpretation of Discriminant Analysis, *Journal of Marketing Research* 11, 156-163.

Myers, Stewart C, and Nicholas S Majluf, 1984, Corporate Financing and Investment Decisions when Firms have Information that Investors do not, *Journal of Financial Economics* 13, 187-221.

Ohlson, J, 1980, Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research* 18, 109-131.

Palepu, Krishna G, 1986, Predicting Takeover Targets: A Methodological and Empirical Analysis, *Journal of Accounting and Economics* 8, 3-35.

Platt, Harlan D, and Marjorie D Platt, 1990, Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction, *Journal of Business Finance and Accounting* 17, 31-51.

Powell, Ronan G, 1997, Modelling Takeover Likelihood, *Journal of Business Finance and Accounting* 24, 1009-1030.

Powell, Ronan G., 2001, Takeover prediction and portfolio performance: A note, *Journal of Business Finance and Accounting* 28, 993-1011.

Powell, Ronan G., 2004, Takeover Prediction Models and Portfolio Strategies: A Multinomial Approach, *Multinational Finance Journal* 8, 35-72.

Ravenscraft, David J, and Frederic M Scherer, 1987, Mergers, Sell-Offs, and Economic Efficiency. Washington: Brookings Institute Press.

Rege, Udayan P, 1984, Accounting Ratios to Locate Takeover Targets, *Journal of Business Finance and Accounting* 11, 301-311.

Rhodes-Kropf, Matthew, and S Viswanathan, 2004, Market Valuation and Merger Waves, *Journal of Finance* 59, 2685-2718.

Simkowitz, Michael A, and Robert J Monroe, 1971, A Discriminant Function for Conglomerate Targets, *Southern Journal of Business* 38, 1-16.

Singh, A, 1971, *Takeovers: Their Relevance to the Stock Market and the Theory of the Firm*. Cambridge: Cambridge University Press.

Smith, Richard L, and Joo-Hyun Kim, 1994, The Combined Effect of Free Cash Flow and Financial Slack on Bidder and Target Stock Returns, *Journal of Business* 67, 281-310.

Stevens, David L, 1973, Financial Characteristics of Merged Firms: A Multivariate Analysis, *Journal of Financial and Quantitative Analysis* 8, 149-158.

Stock, James H, and Mark W Watson, 2007, *Introduction to Econometrics*, Second Edition. Boston: Pearson Addison Wesley.

Trautwein, Friedrich, 1990, Merger Motives and Merger Prescriptions, *Strategic Management Journal* 11, 283-295.

Walter, Richard M, 1994, The Usefulness of Current Cost Information for Identifying Takeover Targets and Earning Above-Average Stock Returns, *Journal of Accounting, Auditing, and Finance* 9, 349-377.

Wansley, J, R Roenfeldt, P Cooley, 1983, Abnormal Returns from Merger Profiles, *Journal of Financial and Quantitative Analysis* 18, 149-162.

Zanakis, SH, and C Zopounidis, 1997, Prediction of Greek Company Takeovers via Multivariate Analysis of Financial Ratios, *Journal of the Operational Research Society* 48, 678-687.

APPENDIX A – MULTICOLLINEARITY ANALYSIS

Table A.1 – Correlogram for the Combined Adjusted Model

VAR	1	2	4	5	6	7	8	9	10	12	13	14	15	16	17	19	20	21	22	23
1	1.00																			
2	0.44	1.00																		
4	0.49	***0.84***	1.00																	
5	-0.67	-0.67	-0.16	1.00																
6	0.47	0.47	0.67	-0.21	1.00															
7	0.06	0.06	0.11	-0.03	0.08	1.00														
8	-0.04	-0.05	0.00	-0.09	0.06	-0.18	1.00													
9	-0.17	-0.37	-0.51	0.14	-0.60	0.02	0.06	1.00												
10	0.04	0.08	0.06	-0.03	-0.01	0.03	0.14	-0.10	1.00											
12	-0.27	0.03	0.14	0.28	0.12	0.07	0.02	-0.06	-0.03	1.00										
13	0.03	0.04	0.00	-0.01	-0.08	-0.07	-0.10	0.01	-0.09	-0.16	1.00									
14	0.38	0.01	0.03	-0.76	0.02	-0.02	-0.06	-0.12	0.00	-0.07	0.16	1.00								
15	-0.01	0.06	0.00	-0.01	-0.06	-0.03	-0.11	0.01	-0.08	-0.12	***0.96***	0.14	1.00							
16	0.18	0.08	0.08	-0.09	0.20	0.03	0.37	-0.03	0.05	-0.11	-0.07	0.03	-0.08	1.00						
17	0.26	0.20	0.22	-0.11	0.31	0.08	-0.08	-0.13	-0.08	0.00	-0.12	0.03	-0.11	-0.07	1.00					
19	-0.42	0.02	0.00	0.84	0.01	0.01	0.07	0.07	0.00	0.20	-0.16	***-0.97***	-0.15	-0.02	0.00	1.00				
20	-0.13	0.21	0.19	0.31	0.09	0.08	-0.06	-0.10	0.01	0.66	-0.16	-0.02	-0.15	-0.05	0.18	0.22	1.00			
21	0.24	0.04	0.29	0.00	0.10	0.09	0.05	-0.18	0.02	0.03	0.00	-0.02	-0.05	-0.09	0.09	0.04	0.07	1.00		
22	0.53	0.24	0.28	-0.44	0.19	0.12	-0.07	-0.01	0.05	-0.15	-0.13	0.20	-0.14	0.13	0.19	-0.19	0.10	0.10	1.00	
23	0.19	0.13	0.09	-0.11	0.12	0.01	-0.20	0.00	0.01	-0.11	-0.11	0.03	-0.09	-0.05	0.06	-0.02	0.09	-0.01	0.64	1.00

Table A.2 – Variance Inflation Factors for the Combined Adjusted Model

VARIANCE INFLATION FACTORS	
1 – ROA	4.70
2 – ROE	5.14
4 – EBIT/SE	6.20
5 – FCF/TA	**13.77**
6 – DIV/SE	3.79
7 – EBIT GWTH	1.18
8 – ACTIVITY	1.95
9 – M/B	2.42
10 – P/E	1.11
12 – CAPEX/TA	2.74
13 – CURRENT	**17.79**
14 – (CA-CL)/TA	**51.93**
15 – QCK ASSETS	**16.82**
16 – PAYOUT	1.52
17 – NET GEAR	1.32
19 – TL/TA	**71.58**
20 – LT DEBT/TA	4.71
21 – INDUSTRY	1.60
22 – Ln (TA)	3.61
23 – NET ASSETS	2.17

APPENDIX B – BACKWARD STEPWISE LOGISTIC REGRESSIONS

Table B.1 – Backward Stepwise Results for Single Raw Model

Variable	Parameter Estimate	Prob > Chi Sq
Intercept	-13.14	(<0.01)
8 – ACTIVITY	-0.64	(0.07)
16 – PAYOUT	-3.01	(<0.01)
22 – LN (TA)	0.78	(<0.01)
23 – NET ASSETS	0.00	(<0.01)

* Variables 2, 5, 10, and 13 were eliminated due to their potential to cause problems of multicollinearity.

Table B.2 – Backward Stepwise Results for Single Adjusted Model

Variable	Parameter Estimate	Prob > Chi Sq
Intercept	-0.58	(0.02)
8 – ACTIVITY	-0.59	(0.03)
12 – CAPEX/TA	0.34	(0.07)
16 – PAYOUT	-0.22	(0.07)
20 – LT DEBT/TA	-0.21	(0.11)
22 – LN (TA)	12.07	(<0.01)
23 – NET ASSETS	-0.19	(0.09)

* Variables 2, 13, and 19 were eliminated due to their potential to cause problems of multicollinearity.

Table B.3 – Backward Stepwise Results for Combined Raw Model

Variable	Parameter Estimate	Prob > Chi Sq
Intercept	-12.36	(<0.01)
6 – DIV/SE	7.90	(0.02)
8 – ACTIVITY	-0.65	(0.08)
16 – PAYOUT	-2.61	(<0.01)
17 – NET GEAR	-0.54	(0.01)
22 – LN (TA)	0.74	(<0.01)
23 – NET ASSETS	0.00	(0.01)

* Variables 4, 5, 13, 15, and 19 were eliminated due to their potential to cause problems of multicollinearity.

APPENDIX C – PALEPU CUTOFF ESTIMATION CLASSIFICATIONS

Table C.1

Single Raw Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	812	186	998
Target	18	44	62
Total	830	230	1060
Concentration Ratio		19.13%	
Relative to Chance		227.07%*	

Single Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	787	207	994
Target	20	42	62
Total	807	249	1056
Concentration Ratio		16.87%	
Relative to Chance		187.29%*	

Combined Raw Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	840	156	996
Target	24	38	62
Total	864	194	1058
Concentration Ratio		19.59%	
Relative to Chance		234.25%*	

Combined Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	749	245	994
Target	19	43	62
Total	768	288	1056
Concentration Ratio		14.93%	
Relative to Chance		154.30%*	

^ Indicates that the overall predictions of the model are significantly better than chance at the 1 percent level of significance according to the Proportional Chance Criterion.
’ Indicates that the overall predictions of the model are significantly better than chance at the 5 percent level of significance according to the Proportional Chance Criterion.
* Indicates that the prediction of targets individually is significantly greater than a chance selection at the 1 percent level of significance according to the Maximum Chance Criterion.
~ Indicates that the prediction of targets individually is significantly greater than a chance selection at the 5 percent level of significance according to the Maximum Chance Criterion.

APPENDIX D – PALEPU CUTOFF PREDICTION CLASSIFICATIONS

Table D.1

Single Raw Model’	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	773	173	946
Target	73	35	108
Total	846	208	1054
Concentration Ratio		16.83%	
Relative to Chance		64.22%~	

Single Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	699	245	944
Target	55	53	108
Total	754	298	1052
Concentration Ratio		17.79%	
Relative to Chance		73.24%*	

Combined Raw Model’	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	800	146	946
Target	77	31	108
Total	877	177	1054
Concentration Ratio		17.51%	
Relative to Chance		70.92%*	

Combined Adjusted Model^	Predicted Outcome		
Actual Outcome	Non-Target	Target	Total
Non-Target	668	273	941
Target	53	55	108
Total	721	328	1049
Concentration Ratio		16.77%	
Relative to Chance		62.87%~	

^ Indicates that the overall predictions of the model are significantly better than chance at the 1 percent level of significance according to the Proportional Chance Criterion.

’ Indicates that the overall predictions of the model are significantly better than chance at the 5 percent level of significance according to the Proportional Chance Criterion.

* Indicates that the prediction of targets individually is significantly greater than a chance selection at the 1 percent level of significance according to the Maximum Chance Criterion.

~ Indicates that the prediction of targets individually is significantly greater than a chance selection at the 5 percent level of significance according to the Maximum Chance Criterion.

APPENDIX E – PORTFOLIO OF COMMONLY PREDICTED TARGETS

Table E.1 – Portfolio of Commonly Predicted Targets

ASX Code	**Full Name**	**Bid Date**
ATM	Aneka Tambang Tbk	N/A
LIM	Lionore Mining International Ltd	N/A
ALN	Alinta Limited	13/03/2006
APA	APA Group	N/A
GAS	GasNet Australia Group	19/06/2006
PHY	Pacific Hydro Ltd	29/03/2005
SAX	Stadium Australia Group	15/11/2006
BPC	Burns, Philp, and Company	N/A
MCG	Macquarie Communications Infrastructure Group	N/A
VBA	Virgin Blue Holdings Ltd	28/01/2005
AUN	Austar United Communications Ltd	N/A
FXJ	Fairfax Media Ltd	N/A
REG	RG Capital Radio Ltd	**Delisted**
SIG	Sigma Company Ltd	N/A

APPENDIX F – UNIVARIATE COMPARISON OF MEANS FOR SUCCESSFUL AND UNSUCCESSFUL TARGETS VERSUS NON-TARGETS

TABLE F.1	Successful Target Mean vs. Non-Target Mean	Unsuccessful Target Mean vs. Non-Target Mean
Variable	t-statistic	t-statistic
1 – ROA	**3.40 (+)**	**2.60 (+)**
4 – EBIT/SE	1.89	1.59
6 – DIV/SE	1.41	1.00
7 – EBIT GWTH	0.23	0.18
8 – ACTIVITY	**-3.44 (-)**	-2.42
9 – M/B	-0.19	-0.11
10 – P/E	1.01	0.68
12 – CAPEX/TA	**2.79 (+)**	1.96
15 – QCK ASSETS	-1.05	-0.97
16 – PAYOUT	-2.48	-1.81
17 – NET GEAR	0.90	0.63
20 – LT DEBT/TA	1.55	1.15
21 – INDUSTRY	0.25	0.16
22 – Ln (TA)	**3.30 (+)**	2.57
23 – NET ASSETS	-0.60	-0.56

Note: Reported t-statistics in bold type indicate that the mean values are significantly different between target and non-target firms at the 1 percent level of significance. Significantly positive (negative) values indicate that the mean financial ratio of the type of target under consideration is significantly larger (smaller) than the mean financial ratio for non-targets.

APPENDIX G – UNIVARIATE COMPARISON OF MEANS FOR HOSTILE AND FRIENDLY TARGETS VERSUS NON-TARGETS

TABLE G.1	Hostile Target Mean vs. Non-Target Mean	Friendly Target Mean vs. Non-Target Mean
Variable	t-statistic	t-statistic
1 – ROA	**3.53 (+)**	**2.74 (+)**
4 – EBIT/SE	1.92	1.64
6 – DIV/SE	1.51	1.02
7 – E IT GWTH	0.25	0.18
8 – A TIVITY	**-3.00 (-)**	**-2.99 (-)**
9 – M/B	-0.10	-0.16
10 – P/E	0.99	0.73
12 – CAPEX/TA	**2.88 (+)**	2.06
15 – QCK ASSETS	-1.11	-0.97
16 – PAYOUT	-2.08	-2.33
17 – NET GEAR	0.85	0.70
20 – LT DEBT/TA	1.47	1.27
21 – INDUSTRY	0.25	0.18
22 – Ln (TA)	**3.28 (+)**	**2.76 (+)**
23 – NET ASSETS	-0.60	-0.54

Note: Reported t-statistics in bold type indicate that the mean values are significantly different between target and non-target firms at the 1 percent level of significance. Significantly positive (negative) values indicate that the mean financial ratio of the type of target under consideration is significantly larger (smaller) than the mean financial ratio for non-targets.