Impact of Toeholds in Corporate Takeovers

Abstract
This study tests the significance of a toehold variable in predicting corporate takeovers. This study is the first to test the toehold variable in the Australian market and uses two previously designed toehold variables as well as two newly designed variations. The toehold variables are found to be statistically significant, and when applied to an out-of-sample data set correctly classify 82% of companies as either a target or non-target. When the model is used to form an investment portfolio it achieves significant positive abnormal returns and successfully beats the return of the ASX 300 index. The results of this study further support the importance of a toehold variable in takeover prediction models. It has also been found that the unique position of having a bid that acts as both a buying and selling price has incredible advantages. Essentially, gaining a toehold results in a win-win situation. If, you have a toehold you can profit through purchasing only the limited amount of shares left at a premium versus the full amount. While if you have a toehold and you lose an auction to a rival bidder you can profit through selling your shares at a higher than purchase price. Overall, it is clear that toeholds are an intelligent, advantages strategy. It is this conclusion that has resulted in the new era of investment strategy toehold research.

Keywords: Toehold, Takeover Prediction, Investment Strategy, Abnormal Retu**rns**

JEL Classification: G10, G11, G34

1. Introduction

An investment portfolio made up of companies subject to takeover offers achieves abnormal returns (Goldie, 2014). This study uses a takeover predication model with newly conceived 'toehold' variables to enhance the model's predictive power and subsequently lead to a more optimal investment portfolio that achieves abnormal returns.

In the modern day superior investment returns are desired by not only the famous Wall Street firms and investment professionals, but also by the ever increasing superannuation funds, family offices and everyday retail investors. With the global rise of index funds and their stable returns, the everyday investors now desire more and more to warrant a movement in capital to any alternative form of investing (Cremers *et al.*, 2016). As such, pressure on hedge funds, investment funds and all those engaged in investing, to 'beat the market' has increased substantially.

The concept of 'beating the market' or achieving abnormal returns was established in relation to the Efficient Market Hypothesis (EMH). EMH was first developed throughout the 1900's by a range of economists such as Milton Friedman, Eugene Fama and George Stigler (Markham, 2013). The underlying ideology is that asset prices in equilibrium, such as stock prices, have already incorporated all publicly available information and would change due to the release of new information (Shiller, 2003). The implication of this is that one cannot predict the return of a stock price before the release of new information and as such it is not possible to achieve superior returns above the market.

EMH has not boded well with investment professionals and academics alike, and since its introduction they have stuck at the task of disproving EMH through achievement of superior investment returns. One particular situation that can make this possible is the corporate takeover. Takeovers are result of perceived arbitrage opportunities that exist when management is inefficient (Cebenoyan *et al.*, 2015). Given this, the takeover scenario provides a somewhat loop hole to EMH. The announcement of a takeover offer often results in an increase in share price (Danbolt *et al.*, 2016). By investing in a stock prior to this announcement, the opportunity exists to gain from the price run-up, irrelevant of whether the actual takeover proves successful or not. A portfolio consisting of takeover targets that benefit from this price run-up have been proven to achieve abnormal returns (Goergen & Renneboog, 2004).

The problem of course is the development of a tool capable of predicting these events. Studies from the early 1980's up to the current day have had mixed results in their attempts to create such a tool (Brar *et al.*, 2009; Espahbodi & Espahbodi, 2003; Palepu, 1986; Powell, 1997). Currently, there remains no consensus method of predicting these takeover targets and in turn realising the financial gains. As such the takeover prediction puzzle is of key interest to not only academics but also private practitioners.

This study is an addition to the literature in the quest of solving the takeover prediction puzzle by using toeholds as a takeover indicator and investment strategy to the Australian market. The newly developed toehold variables are found to be statistically significant at the 1% level in the takeover model. When applied to an out-of-sample dataset, the estimated model correctly classifies 82% of companies as either a target or non-target. When a portfolio is created from this model, positive abnormal prediction returns would be achieved relative to the ASX300.

The rest of the paper is set out as follows; Section 2 introduces the reader to toeholds and takeovers. Existing studies on takeovers and toeholds are reviewed in Section 3. Section 4 addresses the conceptual considerations, data, and model specifications. In Section 5 the estimated model is applied to real world data. Finally, Section 6, concludes the paper.

2. Takeover and Toeholds

The corporate takeover is a complex transaction and there a range of strategies that acquirers engage in to improve their ability to complete it successfully. One such method is the gaining of a 'toehold'. Toeholds are a merger-and-acquisition (M&A) strategy, where a company buys a limited number of shares in a target firm prior to initiating M&A discussions with the target firm (Strickland *et al.*, 2010). According to s606 of the Australian *Corporations Act 2001* (Cth), it is prohibited to acquire voting right shares of a company if the new voting rights cause a total holding of above 20% of the company's shares, with the exception being an offer for a takeover.[1] It is this area from 0% to 20% of voting right shares that are known as a toehold.

The benefits of toeholds in takeovers are extensive. Major ones are as follows. (1) Toeholds increase the likelihood of shareholders accepting offers, and in turn help solve the free rider problem (Betton & Eckbo, 2000; Chowdhry & Jegadeesh, 1994; Hirshleifer & Titman, 1990; Shleifer & Vishny, 1986). (2) Toeholds are also effective in executing difficult takeovers - those defined as having a low expected return (Dai, 2016). (3) Holding of a toehold also raider to test full acquisitions and if used correctly can help protect themselves for uncertainty risk (Povel & Sertsios, 2014; Smit & Kil, 2017). This occurs as the toehold reduces the asymmetrical information between the target and acquirer (Aintablian *et al.*, 2017). (4) In a bidding competition, toeholds act as sufficient deterrents to rival bidders (Bessler *et al.*, 2015; Bulow *et al.*, 1999). In the case of a rival bidder still choosing to enter the bidding competition,

[1] Other exceptions include (1) No more than a 3% increase every 6 months (creep), (2) Acquisition resulting from a rights issue, (3) Downstream acquisition resulting from relevant interests in another listed entity and (4) Acquisitions resulting from a scheme arrangement.

the owner of a toehold required less of a bid jump to force the rival to exit the competition (Dodonova, 2012).

Generally, the owning a toehold will result in a more aggressive bid (Singh, 1998). This is due to the unique position of their bid being not only a buying price, but also a selling price. If a rival bidder was to enter the competition, the toehold owner then has the choice to either compete or sell his shares at the new higher price (due to the original offer causing a price run-up). Corporate raiders that are aware of this unique situation have utilised a toehold to attract rival bidders to the table only to drop out, profiting from the rivals increased bid (Carroll & Griffith, 2010).

There is a question: would any price rise (due to a toehold position) before a takeover announcement increase the premium a toehold owner would have to pay for the remainder of the shares? Generally, an acquirer is financially better off to purchase a toehold and then announce the takeover (Bris, 2002). This way the price rise will only occur to the shares not already owned by the acquirer.

3. Existing Studies on Takeovers and Toeholds

There is a wide array of theories explaining the motivations for corporate takeovers. Traditional concepts include synergies, agency and hubris (Hodgkinson & Partington, 2008; Porter & Singh, 2010; Roll & Richard, 1986; Seth *et al.*, 2000). Alongside these, newer theories such as the information asymmetry theory, the turnaround theory and the cream skinning theory have also been proposed (Chueh, 2013).

The market for corporate control theory refers to underperforming or undervalued firms becoming attractive takeover targets (Liang *et al.*, 2017). When firms suffer from underperformance it often indicates poor internal governance and provides motivation for an external management takeover. This theory suggests that takeovers can be predicted using published financial data. These includes factors which are hypothesised to increase the probability of a takeover announcement, such as inefficient management and growth resource imbalance (Rodrigues & Stevenson, 2013).

Through the comparison of investment performance versus earnings per shares growth, of active acquirers, Hogarty (1970) was able to show desire for profitability as a major motivation for takeovers. This is compared to Jensen (1988) found reasons such as political and economic conditions, management inefficiency and deregulation as valid causes of mergers and acquisitions. Given the wide array of motivations and the different factors associated with each, it is of no surprise that no single model has consistently been able to predict these events. This ‘takeover puzzle’ has only caused an increase in academics determined to solve it.

Palepu (1986) conducted a review of previous statistical practices in predicting takeovers, drawing attention to flaws, and setting a new standard for research in this area. Following this pioneer work, significant studies by (Powell, 1997, 2004, 2015), Barnes (1998) and Chueh (2013) have all added to takeover prediction literature.

In a recent Australian study, Rodrigues and Stevenson (2013) attempted to use a large combination of forecasting methods such as logistic and neural models to improve the overall accuracy of takeover predictions. They concluded that multiple models outperformed a single model. However, when applied to an out-of-sample, their models were only able to classify 40% of targets correctly. Khan and Myrholt (2018) were the first to apply a takeover prediction model on the Oslo Stock Exchange. Using a model built on 153 Norwegian public targets, the authors applied their model to an out-of-sample dataset attempting to correctly classify companies as either a takeover or non-takeover. The authors only achieved an average correct classification rate of 32%. Nonetheless, they did find evidence that financial proxies for underperforming management and liquidity increased chances of takeover.

Froese (2013) used a UK sample from 1996 to 2010 to create a conditional logit regression model for predicting takeovers. Similar to past studies, he focused on financial variables such as price earnings ratio and current ratios. Testing on a 2011 to 2012 out-of-sample dataset the authors achieved a 75% overall correct classification rate. Unfortunately however, this was predominately in the form of non-targets, with the correct classification rate of targets only being 54%. When the authors' model was used to create an investment portfolio it achieved a market adjusted return of 9.7% per annum.

Financial and market data are often the best indicators of factors such as underperformance and profitability. As such, takeover prediction models have predominately focused on these types of variables as they match established takeover motivations. However, given the unsuccessful nature of previous takeover studies it would be beneficial to adopt of qualitative or unobserved variables in takeover prediction modelling.

Toehold is one such variable. It is traditionally considered unobservable, and has been hardly incorporated into takeover prediction modelling, with Baixauli and Fernández (2009) being the only exception. The major reason for its exclusion from previous studies seems to lie in the difficulty of drawing data on the exact holdings of shareholders. Baixauli and Fernández (2009) made the first ever attempt to develop a takeover prediction model featuring a toehold variable. Based on the laws of the Spanish stock exchange[2], they used the notices of substantial holdings to quantify the toehold. The manual process to obtain this information was substantial. When the model was applied to an out-of-sample dataset it achieved a 72% correct classification rate.

[2] The Spanish stock exchange stipulates that any holdings that increases or decreases total share holdings by 5% or a multiple of 5% must be announced via a significant holdings notification.

A portfolio constructed from the model achieved abnormal returns. To date, it remains the only study to include toeholds in a takeover prediction model.

Given the ongoing takeover puzzle, the established benefits of toeholds in takeovers, and the significance of the work by Baixauli and Fernández (2009) further research is warranted. This current study adds to takeover research with due attention to the role of the toehold variable.

4. Empirical Modelling

4.1 Conceptual considerations

A company's share price generally increases when they are subject to a takeover offer. Therefore, an investment portfolio made up of companies subject to takeover offers, is likely to achieve abnormal returns. As such being able to predict which companies may be subject to these takeover offers becomes very important. Given the advantages of having a toehold to acquirers, they have frequently used this strategy to aid their takeovers (Smit & Kil, 2017). Hence, any information concerning toeholds can provide valuable clues as to whether a company may be subject to a takeover. This then provides strong support to include a variable representing the toeholds of a company in takeover prediction modelling.

In the pioneer work by Baixauli and Fernández (2009). They included toehold information in the econometric modelling and proved that in the Spanish Stock Market a variable representing the toeholds was significant in contributing to the likelihood of a company receiving a takeover offer. Both Spain and Australia are developed countries with a high standard of living, and are market orientated therefore, it is reasonable to postulate that a toehold would have similar impacts on the takeovers in the Australian context. Indeed, because of the shortage of studies in this area, Baixauli and Fernández (2009) concluded their study by calling for more research in other diverse markets. Elaborations lead to the first proposition of this study.

Proposition 1: Toehold shareholding contributes positively to takeovers in the Australian market.

This original method of quantifying toeholds, developed by Baixauli and Fernández (2009), featured no requirements on which shareholders should be included. As such, all shareholders who had a toehold in the given time period included in the formation of the variable. However, it is highly unlikely that any acquirer would reduce their holdings prior to announcing a takeover offer. Therefore, by including owners who had reduced their holdings, the accuracy of the toehold variable could be compromised. Significant noise could be reduced from the toehold variable if these shareholders were excluded from the formation. This would result in a variable that provides more accurate indication of shareholders likely to launch a takeover offer. This leads to the second proposition.

Proposition 2: Excluding shareholders who reduced their level of stock improves the accuracy of the toehold variable.

4.2 Data

To verify the propositions of this study, both in-sample and out-of-sample data are used. All datasets are in relation to companies listed on the Australian Stock Exchange (ASX). Historical takeover data, financial data and notices of substantial holdings have all been obtained via Morningstar DatAnalysis. All share price, index price and bond yields have been obtained via Yahoo Finance.

In-sample Dataset

The in-sample dataset covers a period from the 1st of January 2010 to the 31st of December 2015, and is the group of companies that are used to estimate the prediction model. This time period is post global financial crisis (GFC) implying that it should be a realistic indicator of standard market conditions, while it is recent enough to allow testing on the most current time periods (2016 & 2017). Matched sampling has been used for this dataset, an appropriate method if a maximum likelihood estimator is used (Owen, 1998). As such the in-sample dataset includes an equal number of takeovers and non-takeovers.

Restrictions on the selection of companies include: (1) financial-based companies were not included; (2) a company has to have been listed for at least 3 years prior to takeover and has the full financial data available for those three years; and (3) the company has been trading at above ten cents at the time of their annual or semi-annual reporting date (this requirement is usually not applied till the investment stage but has been incorporated earlier in an attempt to create a ready to use portfolio following predictions).

The toehold data was obtained via the notice of substantial holdings forms. According to s 671B of the *Corporations Act 2001* (Cth), a notice of substantial holding must be submitted to the ASX when the total value of the voting rights in a publicly listed company moves from below 5% to above 5%. Following this, a notice must be submitted for every movement of 1% or more, above the 5% threshold. Data on the substantial holdings notice goes back exactly two years.

Throughout the period there was a total of 33 takeovers that met the requirements. These were combined with another 33 companies that did not receive a takeover, forming an in-sample dataset of 66 companies. Similar to other studies (Baixauli & Fernández, 2009; Chueh, 2013; Powell, 2004), these 33 non-takeover companies were matched on a yearly, sector and approximate market capitalisation basis to each takeover company within the set. The descriptive statistics of the in-sample dataset can be found in *Appendix 1.*

Out-of-sample Dataset

The out-of-sample dataset is drawn from the ‘true’ population of firms for the year 2016, referring to all companies listed on the 1st of January 2016. The same requirements as the in-sample dataset have been applied. Identical to the in-sample dataset, both financial and market information of the companies from the most recent financial reports are used, as well as the notices of substantial holdings for the two years previous. In total, there are 368 companies in the out-of-sample dataset which meet the requirements, with 13 of them receiving a takeover between the beginning of 2016 and the end of 2017. The descriptive statistics of the out-of-sample dataset can be found in *Appendix 1*.

Investment Sample

The investment sample uses data drawn from the price movements of the selected stocks and indexes from 2013 to 2017. The period from 2013 to 2015 is used to form the beta/risk factor for each stock while the 2016 to 2017 period is used to test the portfolio performance. Alongside this, the Australian two-year bond yield was used as a representative of the risk-free rate of return. The All Ordinaries index and the Vanguard Index Exchange Traded Fund (VAS) (proxy for ASX300) have been used as representatives of the market's average return.

4.3 Model Specifications

A logistic regression is first applied to the in-sample dataset. It is then tested for its accuracy on the same dataset by assigning a percentage to each company as their likelihood of being taken over. Here a cut-off point is determined. The cut-off point is the percentage that determines whether a company is classified as a target or a non-target. If the percentage value is higher than the cut-off point, the company is classified as a target, while a lower values results in a non-target classification. The cut-off point is a topic of much debate and various values have been proposed, for example, Powell (2001), Palepu (1986) and Rodrigues and Stevenson (2013). Based on the intention to improve the work of Baixauli and Fernández (2009) the same method of determining the cut-off point as theirs, has been used in this study. That is, for the in-sample dataset, the cut-off point is determined as the percentage that maximises correct classifications (minimises the combination of Type I and Type II errors).

The estimated model is then applied to the out-of-sample dataset and tested for classification accuracy. This accuracy is tested on a six month, one year and two year bases. The ten companies with the highest takeover percentage in the two models that had the highest correct classification rates are chosen. These ten companies are then used to form a portfolio and tested for abnormal stock returns relative to indexes over a six-month, one-year and two-year period, respectively.

Prediction Model

The Binomial Logit model is used in this study and it is one of the most widely used in takeover prediction models (Barnes, 1998; Brar *et al.*, 2009; Dietrich & Sorensen, 1984; Doumpos *et al.*, 2004; Espahbodi & Espahbodi, 2003; Powell, 2004; Rodrigues & Stevenson, 2013). The output of the model has two options; 1 which equates to a takeover and 0 which equates to no takeover. The functional form of the model is shown in Equation (1).

$$Acquisiton\ of\ Company\ i = y = \begin{Bmatrix} 1\ if\ takeover\ occured \\ 0\ if\ takeover\ did\ not\ occur \end{Bmatrix}$$

$$Y = \alpha + BX \tag{1}$$

where *B* represents all of the unknown coefficient estimates and *X* represents all of the independent variables. A toehold variable is one of the independent variables, alongside seven other control financial variables. The seven control variables are shown in *Table 1*. Out of the seven control variables, five have established history as being significant in identifying targets from non-targets. They are market capitalisation, earnings per share, debt to equity ratio, current ratio, price to book ratio (Davis & Stout, 1992; Dietrich & Sorensen, 1984; Hasbrouck, 1985; Monroe, 1973; Palepu, 1986; Sorensen, 2000; Stevens, 1973; Yuh, 1999).

The remining two variables, Earnings before interest and tax (EBIT) growth and price earnings (PE) ratio, have either not been tested, or have been tested but found to be insignificant (Monroe

& Simkowitz, 1971; Stevens, 1973). It should be noted that as the sample has been matched on a size basis, the market capitalisation variable is not expected to be significant. EBIT growth's inclusion has been chosen due to it increasing relevance in the financial and investment banking industry. As such, it is theorised that it may be a new proxy for company performance and has an expected positive sign. PE ratio has been tested in multiple studies with no clear consensus towards its significance. It is now proposed that the PE ratio represents undervaluation and the opportunity to achieve 'quick' capital gains (Stevens, 1973). Therefore, a negative sign is expected with a low PE ratio increasing likelihood of takeover.

Table 1: *Financial control variables included in the logit regression model*

Variable	Abbreviation	Representative of	Expected Sign
Log Market Cap	Log_mc	Company Size	Neg
EBIT 1-Year Growth	GROWTH	Company Growth	Pos
Earnings per share	EPS	Profitability	Pos
Debt to Equity Ratio	DER	Financial Leverage	Neg
Current Ratio	CR	Liquidity	Pos
Price Earnings Ratio	PER	Undervaluation	Neg
Price/Book Value	PBV	Inefficient Management	Neg

The full logit model is shown in Equation (2).

$$\begin{aligned} y = \alpha + \beta_{1i}(\log\_mc) + \beta_{2i}(Growth) + \beta_{3i}(EPS) + \beta_{4i}(DER) + \beta_{5i}(CR) \\ + \beta_{6i}(PER) + \beta_{7i}(PBV) + \beta_{9i}(TOEHOLD) + \epsilon_i \end{aligned} \quad \mathbf{(2)}$$

Using a logit model and the maximum likelihood estimator Equation (3) is produced.

$$\hat{y} = \ln\left(\frac{P_{ij}}{(1 - P_{ij})}\right) \quad \mathbf{(3)}$$

Using algebra the above model can be rearranged to form Equation (4).

$$P_{ij} = \frac{1}{1 + e^{-\beta X}} \quad \textbf{(4)}$$

where P_{ij} is the probability that firm i is the target of a takeover bid and X is the vector of measured attributes for firm i, which include the toehold measures.

The model produces the likelihood of takeover for both the in-sample and out-of-sample datasets. The classification process is shown by Equation (5).

$$Classification\ of\ Company\ i = y = \begin{Bmatrix} Target\ \ if > Cutoff \\ Non - Target\ if < Cutoff \end{Bmatrix} \quad \textbf{(5)}$$

Toehold Variable

In Australia substantial shareholder notices are required for every 1% move above the 5% threshold. Australia has a takeover threshold of 20%, meaning an acquirer is able to purchase up to 20% (19.99%) of a company's shares before they are required to make a formal tender offer. Therefore, the toehold will be defined as a holding of between 5% and 20%. The toehold factor calculates the acquisition program of a potential bidder.

The acquisition program is defined by the shares held by bidder c, of a target firm i. This is described at each moment, by the pairs $\pi_j\ and\ t_j$ where $j = 1,2 \ldots, q$, with q being the number of purchase and sales operations made by the potential bidder c in the target firm i when the order to buy or sell, j, is given and, t_j, is the moment at which the order is given. In order to determine the values of π_j and t_j the notice of substantial holdings will be used as an approximate.

To calculate the size of the acquisition program, AP_{ci}, Equation (6) is used. This takes into account both the percentage of shares held, π_j, at each moment of time, t_j, and the time, $t_{j+1} - t_j$, during which that percentage is held.

$$AP_{ci} = \sum_{j=1}^{q} \pi_j * \left(t_{j+1} - t_j\right) \approx \sum_{j=1}^{q} P_{cj} * n_{cj} \tag{6}$$

The percentage held, π_j, and the length of time they are possessed for $t_{j+1} - t_j$, is approximated by P_{cj} and n_{cj} respectively. P_{cj} is the percentage of shares held by bidder c, when a notice of substantial holdings is made to the ASX and n_{cj} is the number of periods between notices. Let $\bar{\pi}$ equal the maximum percentage of shares able to be acquired in the period $[t_0, t_f]$. As 20% is the maximum in Australia that is allowed to be acquired before a takeover must be announced, then it holds that in any period, $[t_0, t_f]$, where there has been no takeover announcement that $0 < P_{cj} < \bar{\pi}\ \forall j, j = 1,2,3 \ldots q$. The bidder maximises their likelihood of takeover success when $AP_{ci} = \bar{\pi}$ and minimises his success when $AP_{ci} = 0$. This formula allows the quantifiability of a toehold position.

The next step is to make this toehold measure relative. This is conducted by dividing Equation (6) by the maximum toehold possible, multiplied by total periods of holding. This study will define periods semi-annually.

$$\omega_{ci} = \frac{AP_{ci}}{AP_{\max}} = \frac{\sum_{j=1}^{q} \pi_j * (t_{j+1} - t_j)}{(t_f - t_0) * \bar{\pi}} \approx \frac{\sum_{j=1}^{q} P_{cj} * n_{cj}}{(t_f - t_0) * \bar{\pi}} \tag{7}$$

Given equation (7) it is always fulfilled that $0 \leq \omega_{ci} \leq 1$. When $\omega_{ci} = 0$, the minimum acquisition program is occurring and in the case that $\omega_{ci} = 1$, then the maximum acquisition program is occurring. Equation (6) and (7) have accounted for a toehold and made it relevant over time. The final step is to incorporate this into a variable. Here it is important to account for multiple toehold owners. Multiple owners would increase the chance of a takeover occurring and as such need to be included in the variable. The way to account for this is to separate the toehold variable into two different variations. These include the TOEMAX, which is the maximum acquisition program present, and the TOEMEAN, which is the average acquisition program among toehold owners. The equations are shown below.

$$TOEMAX_i = \left\{ \frac{\sum_{j=1}^{q} P_{cj} * n_{cj}}{(t_f - t_0) * \bar{\pi}} \right\} \quad \textbf{(8)}$$

$$TOEMEAN_i = \frac{1}{n} \sum_{c}^{n} \left\{ \frac{\sum_{j=1}^{q} P_{cj} * n_{cj}}{(t_f - t_0) * \bar{\pi}} \right\} \quad \textbf{(9)}$$

As an extension to Baixauli and Fernández (2009), two new variations are proposed for the toehold variable. In the original work by Baixauli and Fernández (2009), toehold variables include all stock owners, even those within the two years that had reduced their holdings. It is argued that those who reduced their holdings are unlikely to be acquirers. This exclusion would improve the accuracy of the toehold variable. The two new variables are developed to accommodate such considerations. They are calculated in the exact same manner as Baixauli and Fernández (2009) and will be defined as TOEMAXINC and TOEMEANINC. Overall, a larger toehold variable indicates a more intense acquisitions program and in turn, a higher chance of takeover.

Four different logit models will be estimated, each featuring a different variation of the toehold indicator: TOEMAX, TOEMEAN, TOEMAXINC, and TOEMEANINC. An example of how the variables are derived is can be found in *Appendix 2*, remembering that periods are defined as semi-annual.

Abnormal Returns

To evaluate the abnormal returns the capital asset pricing model (CAPM). The CAPM formula is as follows.

$$ER = R_f + \beta\left(R_m - R_f\right). \quad \textbf{(10)}$$

where R_f represents the risk-free rate and is approximated by the two-year Australia Government Bond yield. R_m represents the return on the market and is approximated by the ASX 300 (Vanguard Exchange Traded Fund) return. According to efficient market theory, abnormal returns are any returns that are greater than the expected return of a security when taking into account the risk-free rate, market return and individual asset risk premium (Brailsford *et al.*, 2015). By comparing the return of the portfolio derived from the prediction model, to the expected return (ER) based off the CAPM model, the success of the investment strategy can be determined.

4.4 Regression Output

Regression results of the four individual logistic models from the in-sample dataset are given in *Table 3*. Each model features a variation of the toehold variable. In all four models the only independent variable that is statistically significant is this toehold variable. *TOEMEAN* and *TOEMAX* are significant at the 5% level, while *TOEMEANINC* and *TOEMAXINC* are both significant at the 1% level. These results show that the acquiring of a stake or toehold in a company is a strong indication of potential acquisition and provide strong support to Proposition 1. The results of *TOEMEANINC* and *TOEMAXINC* also suggest that the modification to the toehold variable has resulted in a more significant indictor, which strongly supports Proposition 2.

Table 3: *Logistic Regression Output*

	M1: TOEMEAN		M2: TOEMAX		M3: TOEMEANINC		M4: TOEMAXINC	
Variables	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Log_mc	-0.118	(0.171)	-0.116	(0.170)	-0.115	(0.174)	-0.140	(0.174)
Growth	0.195	(0.281)	0.188	(0.276)	0.182	(0.280)	0.191	(0.274)
EPS	0.016	(0.012)	0.014	(0.012)	0.016	(0.012)	0.015	(0.012)
DER	0.060	(0.245)	0.041	(0.241)	0.055	(0.246)	0.050	(0.244)
CR	0.004	(0.012)	0.005	(0.012)	0.004	(0.012)	0.005	(0.012)
PER	-0.009	(0.011)	-0.009	(0.011)	-0.009	(0.012)	-0.008	(0.012)
PBV	-0.025	(0.112)	-0.006	(0.111)	-0.027	(0.111)	-0.016	(0.110)
_Cons	0.777	(2.908)	0.905	(2.869)	0.713	(2.962)	1.130	(2.929)
TOEMEAN	2.757**	(1.085)						
TOEMAX			1.666**	(0.800)				
TOEMEANINC					2.880***	(1.016)		
TOEMAXINC							2.250***	(0.822)
No. Obs.	66		66		66		66	
Prob>Chi^2	0.138		0.237		0.094*		0.128	
Log Likelihood	-39.597		-40.541		-38.963		-39.473	
Pseudo R^2	0.134		0.114		0.148		0.137	

Note: *, **and ***: statistical significance at the 10%, 5% and 1% levels. M1-4 = Models 1 to 4.

According to *Table 3* all of the financial control variables do not seem to have significant impacts on takeovers in the Australian context. *Growth*, *EPS*, and *CR* all have positive signs as expected. *DER* also has a positive sign; however, this is in contrary of economic theory (Palepu, 1986; Stevens, 1973). A possible reason for this may be due to the expansionary monetary conditions of Australia during the time period under investigation and thus the ease at which debt was/is available throughout the sample period.

Log_mc, *PER* and *PBV* all have negative signs, consistent with economic theories (Davis & Stout, 1992; Palepu, 1986). A low market capitalisation inherently makes acquisition easier while a low *PER* and *PBV* value suggests that the company may be undervalued and in turn a prime target for acquisition.

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5. Application and Discussion

The estimated models are first applied to both the in-sample and out-of-sample dataset to test their ability of correctly classifying companies (targets or non-targets). The models are then used to form a portfolio of companies from the out-of-sample data set. A simulation investment is made in these companies and they are used to test for abnormal returns.

5.1 Predictive Ability

Table 4, shows the ability of the logistic regression models to classify companies as either a takeover or non-takeover within the in-sample dataset. The table displays how many targets were correctly classified as targets, how many non-targets were correctly classified as non-targets, and how many companies overall were correctly classified.

***Table 4**: Models accuracy In-sample (total number of companies = 66)*

	M1: TOEMEAN		M2: TOEMAX		M3: TOEMEANINC		M4: TOEMAXINC	
In-Sample: 2010 – 2015								
Cut-off	55%		55%		58%		61%	
No. Targets	33		33		33		33	
Targets Correctly Classified	22	(67%)	18	(55%)	20	(61%)	16	(48%)
No. Non-Targets	33		33		33		33	
Non-Targets Correctly Classified	26	(79%)	27	(82%)	27	(82%)	29	(88%)
Overall correct Classification	**48**	**(72%)**	**45**	**(68%)**	**47**	**(71%)**	**45**	**(68%)**

The mean models, Model 1 and Model 3, achieved better results with overall correct classifications of 72% and 71%, respectively. Model 1 had the highest correct target classification (67%). Model 4 had the highest correct non-target classification rate (88%). These in-sample results are considered standard for takeover prediction models and are comparable to the results of Baixauli and Fernández (2009) who achieved roughly 75% to 82% correct classification in-sample.

Table 5 shows the predictive power of the models on the out-of-sample datasets. Interestingly, there is an increase in predictive power of all four models. Model 4 achieved the highest overall correct classification score for the six-month, one-year and two-year time periods respectively. The same scores for all other models are one to four percentage points lower.

Table 5: *Models accuracy Out-of-sample (total number of companies = 368)*

	M1: TOEMEAN		M2: TOEMAX		M3: TOEMEANINC		M4: TOEMAXINC	
Out-of-Sample: 6 Months (First half of 2016)								
Cut-off	55%		55%		58%		61%	
No. Targets	2		2		2		2	
Targets Correctly Classified	1	(50%)	1	(50%)	1	(50%)	1	(50%)
No. Non-Targets	366		366		366		366	
Non-Targets Correctly Classified	284	(78%)	284	(78%)	291	(80%)	298	(81%)
Overall correct Classification	**285**	**(77%)**	**285**	**(77%)**	**292**	**(80%)**	**299**	**(81%)**
Out-of-Sample: 1 Years (Full 2016)								
Cut-off	55%		55%		58%		61%	
No. Targets	5		5		5		5	
Targets Correctly Classified	3	(60%)	3	(60%)	3	(60%)	3	(60%)
No. Non-Targets	363		363		363		363	
Non-Targets Correctly Classified	283	(78%)	283	(78%)	290	(80%)	297	(82%)
Overall correct Classification	**286**	**(78%)**	**286**	**(78%)**	**293**	**(80%)**	**300**	**(82%)**
Out-of-Sample: 2 Years (2016 to 2017)								
Cut-off	55%		55%		58%		61%	
No. Targets	13		13		13		13	
Targets Correctly Classified	9	(69%)	9	(69%)	9	(69%)	8	(62%)
No. Non-Targets	355		355		355		355	
Non-Targets Correctly Classified	281	(79%)	281	(79%)	288	(81%)	294	(81%)
Overall correct Classification	**290**	**(79%)**	**290**	**(79%)**	**297**	**(81%)**	**302**	**(82%)**

Overall, Model 3 and Model 4, the models featuring the newly developed toehold variables, achieved better results. The correct classifications of these models in the out-of-sample period was above average and significantly higher than Baixauli and Fernández (2009) who only achieved a maximum of 72% out-of-sample. This result is very promising: not only has the toehold variable been found to be statistically significant, but the inclusion of the newly created variables, *TOEMEANINC* and *TOEMAXINC*, has resulted in models with improved ability to successful classify companies as either a takeover or non-takeover.

It should be noted that overall the models' correct classifications of targets, were much lower than their correct classification of non-targets. The model with the highest overall correct classification rate, Model 4, only achieved a 50% correct target classification rate in the six month period and 60% and 62% in the one and two year periods, respectively. This is inherently due to the nature of the data and is often not commented on by other studies (Palepu, 1986; Rodrigues & Stevenson, 2013). The two year out-of-sample data featured 368 companies of which only 13 takeover targets, less than 4%. This imbalance substantially increased the difficulty of correctly classifying targets. This imbalance is further increased when the out-of-sample dataset is reduced to one year and six month periods.

5.2 Economic Consequences

Model 3 and Model 4 have been chosen for portfolio creation as they were the most successful models throughout the three out-of-sample time periods. *Table 6* displays the results of the investment portfolios. This is compared to both the All Ordinaries index and the ASX 300. The top 10 ranked companies from each model were identified and then evaluated as an equally weighted portfolio on a monthly basis. The abnormal returns were also calculated on a monthly basis.

Table 6: *Out-of-Sample returns and Abnormal Returns (AR) for portfolio of predicted targets based on Model 3 and Model 4 as well as the returns of Market Benchmarks.*

Date	M3: TOEMEANINC		M4: TOEMAXINC		Market Benchmark	
	Return	Abnormal Return	Return	Abnormal Return	All Ords	ASX300
31/01/2016	-1%	0%	-1%	0%	-2%	-2%
29/02/2016	4%	2%	1%	0%	2%	3%
31/03/2016	7%	4%	2%	0%	5%	5%
30/04/2016	14%	9%	9%	6%	8%	8%
31/05/2016	9%	6%	8%	5%	5%	5%
6 Month Return (30/06/2016)	**15%**	**7%**	**24%**	**18%**	**12%**	**12%**
31/07/2016	17%	11%	15%	10%	9%	10%
31/08/2016	14%	8%	12%	7%	9%	11%
30/09/2016	12%	8%	9%	6%	7%	7%
31/10/2016	16%	10%	7%	3%	9%	10%
30/11/2016	16%	7%	8%	2%	13%	14%
1 Year Return (31/12/2016)	**17%**	**9%**	**15%**	**9%**	**12%**	**12%**
31/01/2017	10%	1%	29%	23%	14%	14%
28/02/2017	10%	-2%	24%	15%	17%	18%
31/03/2017	11%	-1%	21%	12%	18%	18%
30/04/2017	11%	2%	21%	14%	14%	15%
31/05/2017	14%	4%	22%	15%	14%	15%
30/06/2017	15%	6%	22%	15%	14%	15%
31/07/2017	20%	10%	25%	18%	14%	15%
31/08/2017	25%	15%	37%	30%	14%	15%
30/09/2017	40%	29%	41%	32%	18%	19%
31/10/2017	49%	36%	41%	31%	19%	20%
30/11/2017	52%	37%	45%	34%	22%	23%
2 Year Return (31/12/2017)	**50%**	**36%**	**55%**	**45%**	**22%**	**21%**

Note: Portfolio featured the 10 top ranked companies per model. Companies that received a takeover offer were liquidated the month following announcement. All other companies followed a buy and hold strategy. Returns were calculated on a monthly basis. ASX300 is a proxy for the Vanguard Exchanged Traded fund (VAS) which mirrors the return of the ASX 300 before fees.

Table 6 shows both portfolios achieved positive results, beating the indexes. Model 3 achieved a 15% return after six months, 17% after one year and 50% after two years. This is significantly larger than the equivalent 12%, 12% and 21% return achieved by the index over the same time frames. Model 3 was also able to achieve an abnormal return of 7%, 9% and 36% through the three time periods. The results of Model 4 were superior, with returns of 24%, 15% and 55% over the same periods, abnormal returns of 18%, 9% and 45%, respectively.

What needs to be noted is the percentage of companies in each portfolio that were targets and non-targets. The portfolio based off Model 3 featured ten companies of which only one was subject to a takeover offer. The ten companies making up the portfolio from Model 4 featured only two companies subject to a takeover offer. This supports the results of a previous study by Fernández and Baixauli (2003) that found abnormal returns occur for not only companies that receive a takeover, but those viewed likely to receive one. The companies included in both portfolios can be found in *Appendix 3.* Overall, the portfolios have achieved positive results beating the index and achieving abnormal positive returns. These results provide further support to both propositions of this study.

6. Conclusion and Implications

Corporate raiders benefit from engaging in the use of a toehold when aiming to acquire a company. As such, the holding of toeholds is a highly insightful indicator for portfolio investors to predict takeovers. In using Australian data it was attempted to verify that a toehold would increase chances of takeover success and if only shareholders that increased or maintained their levels of stock are included that the accuracy of the toehold variable in a takeover prediction model would improve.

The results from the study strongly support the two propositions. The toehold variable is very important in predicting takeovers in the Australian context. Improvement on the work of Baixauli and Fernández (2009) was successfully made. By modifying the toehold variable to exclude stock holders that have reduced their holdings over the time period, significant noises have been reduced from the toehold variable. As a result of the improvement, the models have greater power for out-of-sample prediction. Importantly, the models can be used to construct portfolios that achieve significant abnormal returns.

The manual process of quantifying a toehold variable is extensive. Nonetheless, the added predictive value is substantial and satisfying. Future studies concerning predictive models are encouraged to look include this variable in their models. More research in this area will further contribute to the quest of developing a more practical, and widely accepted, takeover prediction model.

This paper provides significant implications for a diverse audience such as investment professionals, investment bankers, C-level executives, corporate raiders and fellow researchers. The incorporation of a toehold variable helps derive insights not realized in previous takeover models. The toehold variable provides a level of the acquisition strategy/stage of potential acquirers, therefore, any investment bank or private equity firm that held this model exclusively would have an advantage over competitors. An accurate takeover prediction model can also provide important information to C-level executives looking to 'manage' their company according to their desire for a successful or unsuccessful takeover. Alongside this, any model that can achieve abnormal returns would be of interest to the investment profession. It is hoped that these implications, combined with the potential of solving the takeover puzzle, will see this research to contribute both academically and practically.

7. Appendices

7.1 Appendix 1

Descriptive Statistics

In-sample Data Set

Variable	Obs.	Mean	Std. Dev.	Min	Max
Log_mc	66	17.3630	1.9246	12.5591	22.4157
Growth	66	0.3384	1.7279	-0.8332	11.9227
EPS	66	5.3789	28.4414	-71.07	150.1
DER	66	0.4194	1.2879	-0.8912	7.537
CR	66	12.1636	27.2639	0	146.39
PER	66	-5.4783	43.8253	-300	115
PBV	66	2.2006	4.8142	-1.03	36.78
TOEMEAN	66	0.3857	0.2714	0	0.9995
TOEMAX	66	0.5142	0.3573	0	0.9995
TOEMEANINC	66	0.3944	0.3101	0	0.9995
TOEMAXINC	66	0.4796	0.3669	0	0.9995

Out-of-sample Data Set

Variable	Obs.	Mean	Std. Dev.	Min	Max
Log_mc	368	19.3905	2.3332	9.8374	25.6930
Growth	368	0.6000	1.966	-1.71	14.2391
EPS	368	16.5525	48.7562	-342.3	308.6
DER	368	0.4685	0.8572	-3.2058	6.7735
CR	368	3.1361	14.6379	0.01	217.45
PER	368	19.9693	130.3427	-287.67	2191.67
PBV	368	2.2418	20.8558	-255.76	301.71
TOEMEAN	368	0.3476	0.1909	0	0.9995
TOEMAX	368	0.4685	0.2740	0	0.9995
TOEMEANINC	368	0.3347	0.2075	0	0.9995
TOEMAXINC	368	0.4242	0.2773	0	0.9995

7.2 Appendix 2

Company I

Shareholder A

Years	Periods	Holding
1.5 Years ago	3	15%
2 Years ago	1	5%

Using equation (6)

$$AP_{Ai} = (5 * 1) + (15 * 3) = 50$$

These values are now made relative using equation (7)

$$\omega_{Ai} = \frac{50}{4 * 20} = 0.625$$

Toehold of Shareholder A = 0.625

Shareholder B

Years	Periods	Holding
0.5 Year ago	1	10%
1.5 Years ago	2	18%

Using equation (6)

$$AP_{Bi} = (18 * 2) + (10 * 1) = 46$$

These values are now made relative using equation (7)

$$\omega_{Bi} = \frac{46}{3 * 20} = 0.767$$

Toehold of Shareholder B = 0.767

The next step is to calculate the TOEMEAN, TOEMAX, TOEMEANINC and TOEMAXINC. Using equation (8) and (9).

TOEMEAN = $\frac{\mathbf{0.625+0.767}}{\mathbf{2}} = \mathbf{0.696}$	Mean value of shareholder A and B's toehold.
TOEMAX = 0.767	Max value of shareholder A and B's toehold.
TOEMEANINC = 0.625	As shareholder B decreased their holding they are not included.
TOEMAXINC = 0.625	As shareholder B decreased their holding they are not included.

As can be seen the newly designed toehold variables, TOEMAXINC and TOEMEANINC resulted in lesser values than the original variations. This is a result of Shareholder B reducing their holding throughout the period. A reduction in holding reduces chance of takeover, as such, the lower values are a more accurate indication of takeover probability. This example highlights the advantages of the new toehold variables.

7.3 Appendix 3

Investment Portfolios

Toemeaninc

Code	Takeover
CSL	No
SST	No
BKL	No
FLT	No
COH	No
CTX	No
ESV	No
PGR	Yes
JHX	No
ORE	No
CSL	No

Toemaxinc

Code	Takeover
CTX	No
CSL	No
COH	No
PGR	Yes
BKL	No
SST	No
FLT	No
SFM	Yes
SDA	No
AMI	No
CZZ	No

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