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Predicting mergers and acquisitions

John D'Angelo
University of Central Florida

PREDICTING MERGERS AND ACQUISITIONS

By

JOHN ANTHONY D'ANGELO

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ABSTRACT

Being able to predict a merger or acquisition before it takes place could lead to an investor earning a premium, if they owned shares of the targeted firm before the merger or acquisition attempt is announced. On average acquiring firms pay a premium when acquiring or merging with a targeted firm. This study uses publicly available financial information for 7,267 attempted takeover targets and 52,343 non-targeted firms for the period January 3, 2000 through December 31, 2007 to estimate (using logit) predictive models. Financial ratios are constructed based on six hypotheses found in the literature. Although statistical evidence supports a few of the hypotheses, the low predictive power of the models does not indicate the ability to accurately predict targeted firms ahead of time, let alone with any economic significance.

DEDICATION

For my mentor and close friend, Dr. James H. Gilkeson, for pushing me to strive for higher learning continuously and showing me that hard work doesn't come easily,

For my late father, Pat T. D'Angelo, and mother, Diane L. D'Angelo, who sacrificed their livelihood for the sake of making mine better and whose love and support can never be matched,

You have all made me the person I am today.

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1. INTRODUCTION

The Mergers and Acquisitions (M&A) process is one researchers have spent the past four decades examining. M&A deals exist for both publicly held and privately held companies. An advantage of examining publicly held and traded companies versus privately held companies is the access to their (publicly available) company-specific financial information; most importantly filings with the U.S. SEC and common stock price data. For this reason, most research examines public company data. One reason one might want to predict mergers and acquisitions is that a researcher can use financial characteristics and other public data in building a model to forecast potential targets. A target is a firm that is being sought by another firm (the acquiror), which is then either absorbed into, or merged with the acquiror. Being able to predict which firms are likely targets would be beneficial for a firm who is looking to remain independent because they "may alter their financial characteristics and hence forestall acquisition…Furthermore, there is potential for individual investors to profit from knowing in advance which firms are likely to be taken over" (Adelaja, Nayga, and Farooq 1999, p. 3). The difference between a merger and an acquisition is minimal and thus all deals discussed in this paper will not seek to differentiate between the two. The minimal difference between mergers and acquisitions is that both types of deals appear to possibly reward common stockholders because acquirors typically pay a premium for the target company.

M&A deals generally begin with internal (private) meetings between the acquiror and the potential target. If these meetings are satisfactory for both the potential acquiror's and target's boards of directors, a Letter of Intent is sent to the target by the acquiror. The Letter of Intent is a document which contains contingencies based on firm characteristics such as financial statements, annual reports, a general breakdown of the customer base, and a review of capitalization and ownership structure (Paulson 2000). This information can be extremely private, therefore target firms need reasonable assurance that the potential acquiror won't steal their proprietary information. This is accomplished through legal forms which protect their sensitive information, such as a Non-Disclosure Agreement.

If these contingencies are agreed upon, then the two parties will proceed to the next step, the Due Diligence stage. During the Due Diligence stage the target allows the potential acquiror to see specific inner workings of the target's day-to-day operations. This can lead to a potential conflict of interest if the acquiror walks away from (abandons) the deal knowing the inner workings of the target. For that reason the contingencies listed in the Letter of Intent will contain certain non-disclosure clauses regarding proprietary information being passed along from the target to the acquiror.

If the Due Diligence stage proves satisfactory to both parties, they will seek an appropriate financing arrangement. When determining appropriate financing, it is not uncommon for deals to take months or years to be agreed upon (Paulson 2000). After financing has been agreed upon (assuming a publicly held entity), shareholders must vote to approve the deal. If the shareholders do not approve the deal, the acquiror may restructure the terms and again attempt to gain shareholder approval. If shareholders approve and the board of directors of the target firm remains interested in the deal, a friendly takeover may take place. The parties then enter the stage of the agreement where the target's employees (or acquiror's new employees) guide the acquiror's management by "making sure the acquired company perform[s] up to its purchased expectations" (Paulson 2000).

During the early internal meetings between the target and potential acquiror, the attempt to acquire the target may be viewed by the target's board of directors either positively or negatively. As stated earlier, if an offer is viewed in a positive way by the board of directors, a friendly transaction may take place; however, if the target's board of directors opposes the offer and the acquiror continues to pursue the deal, it becomes a hostile takeover attempt.

Hostile takeovers can assume many forms. One of these is a tender offer (cash tender offers are illegal in the U.S. under the Williams Act). In a tender offer, the acquiring company makes a public offer to the target shareholders at a fixed price above the current market price. If 50% plus one shares are tendered, the deal is successful. The acquiror may also work to attain the support or agreement of a simple majority of the target's shareholders, whereby those shareholders vote out current management and replace it with one that will approve the deal. This is known as a proxy fight. Alternatively, the potential acquiror may purchase shares of the target on the open market so they can appoint a representative to the target's board of directors—this is called a creeping tender offer.

Gaining management's initial approval of a proposed acquisition is not the only concern for a potential acquiror; financing is another. M&A transactions are rather large, with an average deal size of $356M during the first five months of 2011 (Bloomberg 2011 M&A Outlook), and financing may take more than one form. The acquiror may offer cash for shares of the target, an exchange of their common shares for shares of the target, or some combination of cash and stock. In an all-cash deal, the acquiror pays a fixed amount per share of the target's common stock. In all-stock offers, the acquiror agrees to exchange its shares for the stock of the target. According to Van Wyk (2010), the acquiror's stock sees "negative drift in the year following a takeover announcement" (p.15). Negative drift means that share prices of acquiring firms has been found to decrease on average after M&A deals have been announced.

The next step of the M&A process is for the acquiring firm to seek majority shareholder approval. Target firms may already have in place different safeguards designed to protect themselves in the event of a hostile takeover attempt. One such measure is simply increasing the proportion of shareholders needed to approve a takeover to a supermajority. Supermajority shareholder approval is a requirement for shareholder approval which is above 50% plus one shares. The purpose is to decrease the likelihood of shareholder approval of a takeover. Another measure the target firm may enact is a poison pill. A poison pill allows all but majority shareholders to buy new shares at a discount—this can greatly increase the purchase price of a target firm, if the target is being sought by an outside acquiror.

In the event the acquiring firm achieves a shareholder majority, a transaction may occur. As discussed earlier, these deals may have rather large stock price movements, which means investors may be able to profit. Investors looking to profit from M&A transactions are usually looking to receive the typical premium, paid by the acquiror, over the target's share price as of the announcement date. To do this, the investor must be holding the target firm in their portfolio when the potential takeover is announced. The majority (45%) of premiums paid by acquirors during 2010 were under 10%, 15% of premiums were in the 10%-25% range, and 30% of deals resulted in a premium between 25% and 50% (Bloomberg 2011 M&A Outlook). If investors hold just a small number of these target stocks in their portfolio, they may earn returns greater than their benchmark (termed abnormal returns).

This research project attempts to develop a model to predict potential targets. Only a few researchers have built models which produce the desired results. Therefore, the goal of this paper is to design and estimate a model of M&A target identifications which is superior to those found in the existing literature.

2. LITERATURE REVIEW

Predicting potential targets of an M&A deal using financial characteristics began with the work of Simkowitz and Monroe (1971). Simkowitz and Monroe (1971) find evidence of a difference in financial characteristics between target firms and acquiring firms. Using a multiple discriminant model, they find that targets have smaller market capitalization, lower price-to-earnings (P/E) ratios, lower dividend payout ratios, and lower equity growth than that of their acquiring firm counterparts. A potential flaw of multiple discriminant analysis is the underlying assumptions of the model which tend to inflate its predictive ability (Palepu 1986). Multiple discriminant analysis assumes normality of data, uses equal-size (referred to as equal-share) samples of both targets and non-targets (any firm that is not a target), and assumes equality of dispersion matrices. Nevertheless, their study provides a framework for predicting mergers and acquisitions from differences in the target and acquiring firms' financial characteristics.

Stevens (1973) finds evidence contrary to the findings of Simkowitz and Monroe (1971). He finds that liquidity is an important factor differentiating between targets and acquiring firms, but not the dividend payout ratio or P/E ratios. Stevens (1973) uses a model similar to that of Simkowitz and Monroe (1971) which may therefore indicate an inflated predictive ability. The conflicting view of these researchers and others—for example, Castagna and Matolcsy (1976), Belkoui (1978), and Dietrich and Sorenson (1984)—led to the formulation of six hypotheses about mergers and acquisitions. They are: the Inefficient Management Hypothesis, the Growth-Resource Mismatch Hypothesis, the Industry Disturbance Hypothesis, the Firm Size Hypothesis, the Asset Undervaluation Hypothesis, and the Price-to-Earnings (P/E) Hypothesis.

The Inefficient Management Hypothesis "is based on the finance theory premise that acquisitions are a mechanism by which managers of a firm who fail to maximize its market value are replaced" (Palepu 1986). Inefficient management has been proxied by a number of variables that are expected to be inversely related to the likelihood of a takeover. These variables relate to profitability, dividends and dividend growth, or average excess stock return. Palepu (1986), Barnes (1999), Adelaja, Nayga, and Farooq (1999), and Cudd and Duggal (2000) find evidence supporting this hypothesis.

The Growth-resource Mismatch Hypothesis is based on the notion that a mismatch between a firm's growth and its financial resources make the firm a likely target. This "implies that two types of firms are likely targets: low-growth, resource-rich firms and high-growth, resource-poor firms" (Palepu 17). The variables used to proxy this hypothesis are sales growth, liquidity, leverage, and slight variations thereof and are expected to be directly (positively) related to the probability of a takeover. These variables are "commonly put forward in the popular financial press as well as in corporate finance textbooks" (Palepu 17). Palepu (1986), Barnes (1999), Adelaja, Nayga, and Farooq (1999), Cudd and Duggal (2000), Powell (2004), Camerlynck, Ooghe, and Langhe (2005), Baixauli (2009), and Pervan (2010) find evidence supporting this hypothesis.

The Industry Disturbance Hypothesis is based on "economic disturbance theory [which] suggests that acquisitions cluster by industry. A factor that signals the acquisition likelihood of a firm is, therefore, the recent history of acquisitions in its industry" (Palepu 18). This direct influence is proxied by a dummy variable signifying whether or not there has been any M&A

activity in the appropriate sector during the previous fiscal year (prior to observation). Palepu (1986) and Cudd and Duggal (2000) find evidence supporting this hypothesis.

The Firm Size Hypothesis proposes that smaller firms are likely to be takeover targets, similar to the findings of Simkowitz and Monroe (1971). This idea is based on the premise that smaller firms have less "transaction cost" associated with being takeovers than larger firms. If a hostile takeover attempt occurs, smaller firms are unlikely to be able to "defend" themselves against a larger acquiror. Palepu (1986), Cudd and Duggal (2000), Alcalde and Espitia (2003), and Pervan (2010) find an inverse relationship between firm size and takeover probability.

The Asset Undervaluation Hypothesis claims that firms with lower market-to-book ratios are more likely to be targets because they are "cheap" relative to their higher market-to-book counterparts. Since market-to-book value is based on accounting principles and not underlying asset prices, this hypothesis seems arbitrary. Baixauli (2009) finds evidence supporting this hypothesis.

The Price-to-Earnings Hypothesis suggests firms with lower P/E ratios are more likely to be acquired than those with higher P/E multiples. Palepu 1986 claims:

> "According to the proponents of this hypothesis, bidders with high P/E ratios seek to acquire low P/E firms to realize an 'instantaneous capital gain' because of the belief that the stock market values the earnings of the combination at the higher P/E ratio of the acquiror" (p. 18).

This variable, like the Asset Undervaluation Hypothesis, also suggests that firms with lower P/E ratios are "undervalued" compared to their higher P/E ratio counterparts, possibly fueling a "bargain" takeover process.

These six hypotheses were examined jointly by Palepu (1986). Palepu (1986) corrects the methodology of past researchers, such as Stevens (1973), by using modeling techniques which incorporate more robust assumptions allowing the model to be less biased in its predictive ability. He uses a logit model, which can handle more robust (non-normal) data, rather than a binary model (such as multiple discriminant analysis). He also uses non-equal share samples, which further reduces bias in his modeling technique. The use of a logit model requires an optimal cut-off probability be assumed, developed, and chosen (because a logit model estimates a potential target's probability of being acquired, not a yes/no (0, 1) decision.) The determination of an optimal cut-off probability is critical in decision-making because a lower cut-off can potentially misclassify too many non-target firms as potential targets, and could possibly erase any potential abnormal returns (assuming equal weightings of potential targets in the portfolio). In contrast, too high a cut-off probability will potentially misclassify target firms as non-targets, producing a portfolio with too few securities to be well-diversified. The performance of a poorly diversified portfolio is too dependent on the performance of each security in it.

Palepu's (1986) model has a target predictive ability of 80% and a non-target predictive ability of 45%. According to him, "the strategy of investing in the 625 [out of the possible 1,117] firms identified by the model to be potential targets is found to result in statistically insignificant excess returns” (p. 32). He did, however, find support for four of the six academic hypotheses—Inefficient Management Hypothesis, Growth-resource Mismatch Hypothesis, Industry Disturbance Hypothesis, and Size Hypothesis.

Barnes (1999) develops a new way to determine the optimal cut-off probability—sorting financial characteristics data by sector. He suggests that Palepu’s (1986) “criterion of error minimization is inappropriate if out-performance of the market is the objective.” (p. 297) In its place, he uses a “profit-maximization criteria” which, alas, does not yield positive abnormal returns nor increase his model’s predictive power relative to Palepu’s (1986). Barnes (1999) also uses what he calls industry-adjusted data. These are financial data which are normalized by sector or industry. Normalizing the data accounts for industry-specific dispersions. One takes the observed value for a firm, subtracts the industry mean and divides by the industry standard deviation (this is also referred to as an industry-relative ratio). While not producing positive abnormal investment returns, Barnes’ models “perform better than chance” (p. 283). Cudd and Duggal (2000) verify the ability of industry-relative ratios to “convey significant additional information” (p. 117).

Adelaja, Nayga, and Farooq (1999) create a prediction model based on non-financial as well as financial characteristics. They find evidence supporting five of their non-financial characteristic hypotheses: the Control Hypothesis, the Attitude Hypothesis, the Previous Bids Hypothesis, the Litigation Hypothesis, and the Other Hypothesis. They explain their hypotheses as follows:

> The Control Hypothesis suggests that there is a relationship between the degree of control officers have over the board and the probability of actual takeover occurring.

> The Attitude Hypothesis suggests a positive relationship between a friendly takeover attempt and the likelihood of firm being merged or acquired.
>
> The Previous Bids Hypothesis suggests that the number of previous bids is positively related to the likelihood of being taken over.
>
> The Litigation Hypothesis brings in the dimension of legal issues arising in a takeover. It is hypothesized that an inverse relationship exists between the presence of litigation and the likelihood of a targeted firm being taken over.
>
> The Other Hypothesis suggests an inverse relationship between the existence of other ongoing acquisition plans by the target or bidder (Other) and the likelihood of a targeted firm being taken over. (Adelaja, Nayga, and Farooq (1999), pgs. 9-11)

With proxies for these hypotheses, their model has a predictive accuracy of 62.9%, which is less than their financial characteristic model, which has 74.5% accuracy. This suggests the need for a model inclusive of both financial and non-financial characteristics.

Powell (2004) attempts to determine the appropriate method for estimating an optimal cut-off probability. He adds another non-financial variable: whether the proposed takeover is hostile or friendly. He claims that "multinomial (multiple variables) models generate significant and positive buy-and-hold abnormal returns when a strategy of predicting hostile targets only is adopted" (p.63). While admitting that his model misclassifies large numbers of non-targets as hostile targets, he argues "hostile multinomial portfolio reveals that while hostile targets correctly predicted by the model generate large positive abnormal returns, firms misclassified as hostile targets also earn positive abnormal returns" (p.63). He explains further that "hostile targets…are larger in size, so the multinomial model, by design, 'filters out' firms that are more likely to be in financial distress, giving rise to a portfolio with positive abnormal returns" (p.63).

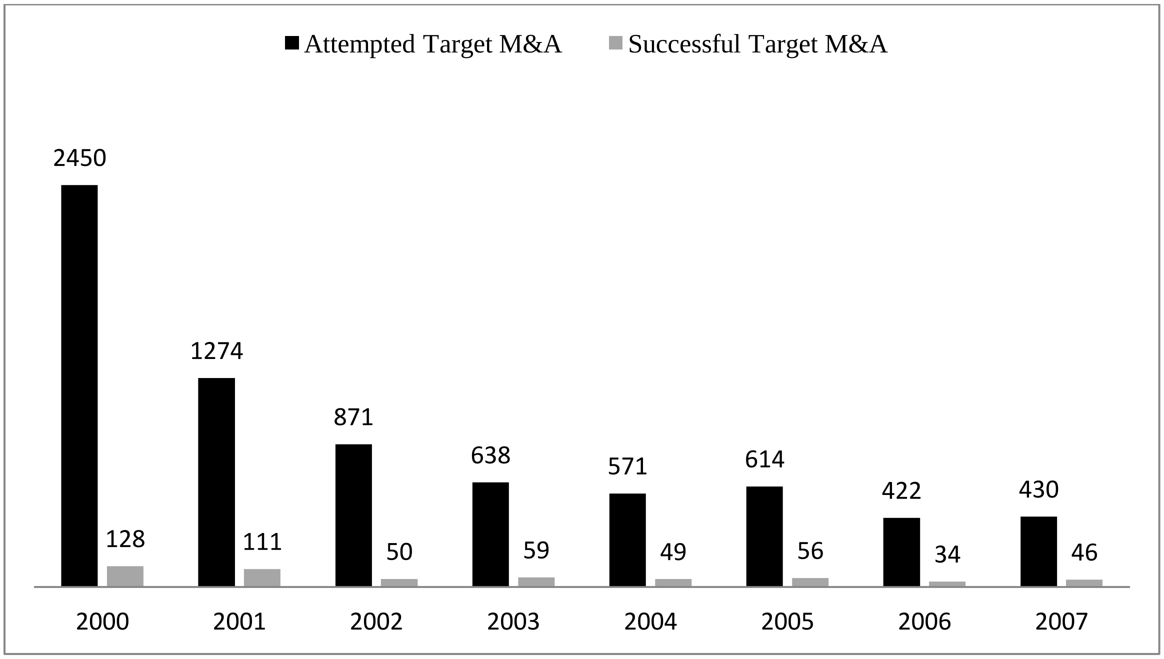
The insight provided by Palepu (1986), Barnes (1999), Adelaja, Nayga, and Farooq (1999), and Powell (2004) have shaped the prediction literature to be more accurate, less biased, and inclusive of non-financial data. The goal of this paper is to develop a model that incorporates parts from each of these prior studies and to estimate that model using the logit specifications and more recent available data.

3. DATA AND METHODS

3.1 Target Firm Data

Target firm data was collected from the SDC database for the time period January 3, 2000 through December 31, 2007. There were 82,617 target firms found during that time period. Of those target firms found, 7,267 had all of the available data needed to create the variables used in this study. A target is defined as a firm that was merged into or acquired by another firm or attempted to be merged or acquired within a particular year. It is very common for a target firm to have multiple observations as a non-target in prior years, but only be considered a target in the year it was acquired or attempted to be acquired. Figure 1 shows the number of targets in each year of the period studied. The smaller bars in Figure 1 indicate the number of firms for which the merger or acquisition attempt was successful. Figure 1 shows that there was very heavy M&A activity during the initial years of the period studied. A decline in M&A activity took place after 2000-2002 and M&A activity became more stable. Figure 1 indicates that a very low percentage of target firms are successfully acquired.

Figure 1: Total Targets for Time Frame (1/3/00 – 12/31/07)



3.2 Non-Target Firm Data and Variable Specifications

The non-target data was collected from the WRDS database. 91,763 non-target firm observations were collected and of those there were 52,343 which had all of the necessary information available for the variables used in this study. The variables used in this study are described below in Table 1.

Table 1: Description of Variables

Variables	*Description*
Return on Equity	Net Income / Common Equity
Growth-Resource Dummy	1 if firm has low growth-high liquidity-low leverage, or high growth-low liquidity-high leverage, 0 if otherwise
Leverage	Net Debt / Common Equity
Liquidity	Current Assets / Current Liabilities
Industry Dummy	1 if takeover attempt occurred in prior year sector, 0 if otherwise
Size	Total Assets
Market-To-Book	Market Value (4 weeks prior to announcement) / Book Value
Price-To-Earnings	Share price (4 weeks) prior to announcement / Earnings per Share

*Note: all balance sheet and income statement items cover the last twelve months

Following Palepu (1986), the Growth-Resource Dummy is 1 for "low-growth, resource-rich firms and high-growth, resource-poor firms" and 0 otherwise. Palepu (1986) defines high growth as five-year average revenue growth rate greater than the industry mean. The Growth-Resource Dummy in this study defines high growth as return on equity greater than the industry mean. This is an upward biased measure due to the ability of a company to payout some of its net income. Two companies with the same return on equity may be growing differently due to the company's retention ratio (percent of net income retained). The Liquidity, Size, Industry Dummy, Market-to-Book Ratio, and Price-to-Earnings variables follow Palepu (1986) as noted in Table 1. The Leverage variable used in this study is defined slightly differently from Palepu's (1986) total debt-to-equity ratio. The Industry Dummy variable "…suggests that acquisitions cluster by industry" (Palepu 18). This variable takes a value of 1 when a particular industry had M&A activity during the previous year.

3.3 Target and Acquiror Fims

The data in Table 2 display the respective means of target and acquiror firms for the explanatory variables. Data for the 7,267 target and 7,267 acquiror firms was gathered from the SDC Database.

Table 2: Target's Versus Acquirors

	Target	*Acquiror*
Return on Equity	-0.494	0.099
Liquidity (Current Ratio)	3.138	3.087
Leverage (Net Debt/Common Equity	1.358	0.124
Size (Total Assets)	4160.127	5625.237
Market-to-Book Ratio	5.510	3050.88
Price-to-Earnings Ratio	16.313	40.566

The differences between the target return on equity and acquiror return on equity mean values for the independent variables suggest target firms performed worse (lower ROE) than acquirers. This is in agreement with the Inefficient Management Hypothesis which states "managers of a firm who fail to maximize its market value are replaced" (Palepu p. 16). This finding confirms the work of Palepu (1986), Barnes (1999), Adelaja, Nayga, and Farooq (1999), and Cudd and Duggal (2000).

The minimal difference between target liquidity and acquiror liquidity suggests that targets have a current ratio similar to those of their non-target counterparts. The liquidity proxy is a component of the GRDummy variable which "implies that two types of firms are likely targets: low-growth, resource-rich firms and high-growth, resource-poor firms" (Palepu p. 17). The targets found in this study appear to be resource-rich firms.

The difference between mean target leverage (LEV) and mean acquiror leverage shows that acquirors had on average only twelve cents of debt per dollar of equity compared to targets which was more than ten times that amount. The leverage difference shown in Table 2 may have been a function of what took place during the turn of the 21st century—the credit crisis. The relaxed federal regulation of commercial banks paired with artificially low interest rates created a loose credit environment. This in turn could explain the higher return on equity for targets which were able to lever up returns. Since this study ends in fiscal year 2007, the whole picture cannot be seen as the Great Recession began in the early parts of 2008.

The mean size differential between targets and acquirors confirms the Firm Size Hypothesis, which claims that smaller firms are more likely to be takeover targets. This is similar to the findings of Simkowitz and Monroe (1971) and in-line with the findings of Palepu (1986), Cudd and Duggal (2000), Alcalde and Espitia (2003), and Pervan (2010).

The differences between the target and acquiror market-to-book ratios (MTB) offers support for the Asset Undervaluation Hypothesis which claims firms with lower market-to-book ratios are considered cheap compared to their high market-to-book counterparts. This supports the findings of Baixauli (2009). The reason the average acquiror market-to-book ratio is significantly higher than the target average is from eight acquirors having MTB ratios over one million.

Finally, the lower target mean price-to-earnings ratio compared to acquiror price-to-earnings ratio is in-line with the Price-to-Earnings Hypothesis which posits firms with lower P/E multiples are more likely to be acquired than those with higher P/E multiples.

3.4 Model Specifications and Observation Normalization

The logistic regression tests are conducted for three different samples of the available data. The first test is the Control Model, analogous to Palepu's (1986) model in explanatory variables used and analogous to Barnes (1999) in terms of the method used to transform the data. The data was transformed by a process called normalization. For the estimated models, all data were normalized by industry. To normalize a variable means the following:

$$\frac{X - \mu}{\sigma}$$

Where X is the observed value found in the population, μ is the industry mean for that particular variable, and σ is the industry standard deviation for a particular variable. The minimum and maximum values for normalized data can be construed as how many standard deviations that value was above or below the industry mean.

The first test excludes observations in which any variables have a negative value (before normalization). The Semi-Relaxed (second) Model replaces the Price-to-Earnings variable with Net Income and includes observations in which Net Income is either positive or negative (before normalization). The Relaxed (third) Model replaces the Net Income variable in place of the Price-to-Earnings variable and includes all observations. Since the Semi-Relaxed and Relaxed

Models include the Net Income variable with negative observations, the Return on Equity (Net Income / Common Equity) variable will also have negative observations.

3.5 Expectations of Estimated Models

The expectations for parameter estimates based on the six hypotheses (described earlier) are listed in Table 3. These are identical to Palepu's (1986) expectations.

Table 3: Expectations of Test Results

Hypothesis	**Variable**	**Parameter Expected Sign**
Inefficient Management	Return on Equity (ROE)	-
Growth-Resource Mismatch	GRDUMMY LIQ LEV	+
Industry Disturbance	IDUMMY	+
Firm Size	SIZE	-
Asset Undervaluation	MTB	-
Price-to-Earnings	PE	-

4. RESULTS AND DISCUSSION

4.1 Control Model Summary

Summary statistics for the target data (normalized) used in the Control Model are found below in Table 4. Summary statistics for the non-target data (normalized) used in the Control Model are found in Table 5.

Table 4: Target Summary Statistics for the Control Model

Variables	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Return on Equity	.079	3.357	-2.048	152.906
Liquidity	.280	2.318	-9.841	99.195
Leverage	-.083	.877	-2.721	24.073
Size	.520	4.184	-1.126	139.160
Market-To-Book	.024	1.026	-1.639	24.198
Price-To-Earnings	.035	1.855	-2.350	107.702
Industry Dummy	.775	.418	0	1
Growth-Resource Dummy	.335	.472	0	1
		Observations = 4,896		

Table 5: Non-target Summary Statistics for the Control Model

Variables	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Return on Equity	.001	1.013	-1.641	40.365
Liquidity	.158	2.001	-2.974	178.356
Leverage	-.046	1.091	-5.841	54.719
Size	.464	5.659	-1.584	307.310
Market-To-Book	.020	1.394	-1.885	97.592
Price-To-Earnings	.007	1.304	-38.636	104.729
Industry Dummy	.759	.427	0	1
Growth-Resource Dummy	.323	.468	0	1
		Observations = 19,328		

For every data sample (observations in Control Model, Semi-Relaxed Model, and Relaxed Model), there is information across 70 industries—an industry being defined by the first two numbers of a firm's SIC code. The logistic regression (logit) for the Control Model uses the normalized data summarized in Exhibits 5 and 6. The estimated model is shown in Table 6. Statistical significance is derived from the p-value having a value less than .05.

4.1.1 Control Model Estimation

P_i = Prob ($TAKEOVER_i$ = | ROE_i, $GRDUMMY_i$, LIQ_i, LEV_i, $IDUMMY_i$, $SIZE_i$, MTB_i, PE_i)
where $TARGET_i = 1$ if firm *I* was targeted and $TARGET_i = 0$ if firm *I* was not targeted.
$P(TARGET_i) = \alpha + \beta_1 ROE_i + \beta_2 GRDUMMY_i + \beta_3 LIQ_i + \beta_4 LEV_i + \beta_5 IDUMMY_i + \beta_6 SIZE_i + \beta_7 MTB_i + \beta_8 PE_i$

Table 6: Estimated Control Model

Logistic Regression				Number of Observations	24,224	
				LR chi-squared(8)	37.850	
				Prob > Chi-squared	0.0000	
Log Likelihood = -12173.466				Pseudo R-squared	0.0016	
Ind. Variables	*Coefficient*	*Standard Error*	*Z-score*	*Prob > l z l*	*95% Confidence Interval*	
Return on Equity	.034	.0138	2.50	0.013	.007	.062
Liquidity	.024	.008	2.99	0.003	.008	.040
Leverage	-.059	.022	-2.70	0.007	-.101	-.016
Size	.002	.003	0.61	0.539	-.003	.007
Market-to-Book	.006	.006	0.31	0.756	-.029	.040
Price-to-Earnings	.012	.010	1.20	0.232	-.008	.031
Industry Dummy	.082	.038	2.13	0.033	.007	.156
Growth Resource Dummy	.055	.034	1.61	0.108	-.012	.121
Constant	-1.464	.035	-41.67	0.000	-1.533	-1.395

The Control Model predicts only .16% of the variation of being a target or non-target using the independent variables. The variables that are statistically significant (using a 5% cut off p-value) in explaining whether a firm is a target are Return on Equity, Liquidity, Leverage, and the Industry Dummy. The positive coefficient for the IDummy variable supports the Industry Disturbance Hypothesis which suggests acquisitions cluster by industry (a positive correlation). The positive coefficient for the Liquidity variable supports the Growth-Resource Mismatch Hypothesis which "implies that two types of firms are likely targets: low-growth, resource-rich firms and high-growth, resource-poor firms" (Palepu 1986). Lastly, the negative coefficient on the Leverage variable conflicts with the Growth-Resource Mismatch Hypothesis. Overall, the Control Model cannot predict with enough reliability to be economically or statistically significant.

4.2 Semi-Relaxed Model Summary

The Semi-Relaxed Model is similar to the Control Model. The Price-to-Earnings variable is replaced with the Net Income variable in this model. This model includes observations where the Return on Equity and Net Income variables have negative values compared to the Control Model which omitted all negative observations. Net Income could be a substitute for the P/E ratio, because we expect less profitable firms to be more likely to be taken over. Also, when a firm reports negative net income, the P/E ratio does not exist (in any meaningful way). Using the Net Income variable in place of the P/E ratio captures this effect. The liquidity variable has also been squared in this model so the logit can complete the estimation.

There are 45,288 non-target and 7,267 target observations used in the Semi-Relaxed Model estimation. Summary statistics for the target and non-target normalized data used in the Semi-Relaxed Model are shown in Table 7 and Table 8, respectively. The Semi-Relaxed Model has more than twice the number of observations as the Control Model possibly allowing for more economically significant results. The estimated Semi-Relaxed Model is shown in Table 9.

Table 7: Target Normalized Data Used in the Semi-Relaxed Model

Variables	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Return on Equity	.032	.734	-32.692	10.851
Liquidity	-.423	1.218	-22.826	38.551
Leverage	.268	.863	-.984	24.459
Size	.237	1.658	-1.046	34.753
Market-To-Book	-.024	.648	-1.392	31.897
Net Income	.195	1.527	-12.784	27.195
Industry Dummy	.646	.478	0	1
Growth-Resource Dummy	.066	.249	0	1
		Observations = 7,267		

Table 8: Non-target Normalized Data Used in the Semi-Relaxed Model

Variables	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Return on Equity	-.005	1.036	-63.158	18.397
Liquidity	.068	.942	-1.819	47.586
Leverage	-.043	1.012	-26.104	53.562
Size	-.038	.841	-1.308	24.583
Market-To-Book	.004	1.045	-1.676	79.518
Net Income	-.031	.882	-45.590	22.665
Industry Dummy	.814	.389	0	1
Growth-Resource Dummy	.012	.108	0	1
		Observations = 45,288		

4.2.1 Semi-Relaxed Model Estimation

P_i = Prob ($TAKEOVER_i$ = | ROE_i, $GRDUMMY_i$, LIQ_i, LEV_i, $IDUMMY_i$, $SIZE_i$, MTB_i, NI_i)
where $TARGET_i = 1$ if firm *i* was targeted and $TARGET_i = 0$ if firm *i* was not targeted.
$P(TARGET_i) = \alpha + \beta_1 ROE_i + \beta_2 GRDUMMY_i + \beta_3 LIQ_i + \beta_4 LEV_i + \beta_5 IDUMMY_i + \beta_6 SIZE_i + \beta_7 MTB_i + \beta_8 NI_i$

The Semi-Relaxed Model explains less than 5.57% in the variation of whether a firm is a target or non-target using the independent variables listed above. This provides somewhat stronger results compared to the Control Model in terms of predicting target firms. In contrast with the Control Model, every independent variable is statistically significant. The Semi-Relaxed Model supports the Growth-Resource Mismatch Hypothesis and the Asset Undervaluation Hypothesis, but provides results contrary to the Inefficient Management Hypothesis, Size Hypothesis, and the Industry Disturbance Hypothesis.

Table 9: Estimated Semi-Relaxed Model

Logistic Regression				Number of Observations	52,555	
				LR chi-squared(8)	2351.05	
				Prob > Chi-squared	0.0000	
Log Likelihood = -19947.965				Pseudo R-squared	0.0557	
Ind. Variables	*Coefficient*	*Standard Error*	*Z-score*	*Prob > l z l*	*95% Confidence Interval*	
Return on Equity	.139	.021	6.59	0.000	.097	.180
Liquidity	.002	.001	3.05	0.002	.001	.003
Leverage	.272	.019	14.62	0.000	.236	.309
Size	.154	.015	9.98	0.000	.124	.184
Market-to-Book	-.313	.031	-10.10	0.000	-.374	-.252
Net Income	.075	.016	4.71	0.000	.044	.106
Industry Dummy	-.883	.028	-31.64	0.000	-.937	-.828
Growth Resource Dummy	1.277	.078	16.49	0.000	1.125	1.429
Constant	-1.261	.023	-54.41	0.000	-1.306	-1.215

4.3 Relaxed Model Summary

The Relaxed (third) Model is similar to the Semi-Relaxed Model except it eases the criterion for inclusion allowing observations in which any variables have negative values. Approximately 7,267 target firms and 52,343 non-targets are used in estimating the Relaxed Model. The target observations used in estimating the Relaxed Model are the same as in the Semi-Relaxed Model. The loose criteria for the Relaxed Model are meant to capture more non-targets and potentially a more realistic and economically robust model. The summary statistics for the target and non-target normalized data used in the third model are shown in Table 7 and Table 10, respectively.

Table 10: Non-target Summary Statistics Used in the Relaxed Model

Variables	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Return on Equity	.001	1.002	-45.524	58.233
Liquidity	.05	1.300	-2.340	144.220
Leverage	-.000	1.002	-36.243	73.567
Size	.004	1.042	-1.734	27.070
Market-To-Book	.000	1.003	-57.150	49.005
Net Income	.004	1.064	-53.382	39.015
Industry Dummy	.813	.390	0	1
Growth-Resource Dummy	.053	.225	0	1
		Observations = 52,343		

The logistic regression results for the Relaxed Model are shown in Table 11.

4.3.1 Relaxed Model Estimation

P_i = Prob ($TAKEOVER_i$ = | ROE_i, $GRDUMMY_i$, LIQ_i, LEV_i, $IDUMMY_i$, $SIZE_i$, MTB_i, NI_i)
where $TARGET_i = 1$ if firm *i* was targeted and $TARGET_i = 0$ if firm *i* was not targeted.
$P(TARGET_i) = \alpha + \beta_1 ROE_i + \beta_2 GRDUMMY_i + \beta_3 LIQ_i + \beta_4 LEV_i + \beta_5 IDUMMY_i + \beta_6 SIZE_i + \beta_7 MTB_i + \beta_8 NI_i$

The Relaxed Model predicts about 5% of the variation in firm target likelihood being explained by the independent variables. This five percent explanatory power is more predictive than the Control Model, but, overall provides no meaningful reliability in predicting targets. All but two of the variables are statistically significant in the Relaxed Model. Although this model tests significant (due to a Chi-squared value below .05) and 6 of the 8 independent variables are statistically significant, this model does not support any of the hypotheses discussed in Table 3 except for Liquidity. Overall, the third model cannot predict, with any economic significance, the likelihood of a firm being a target.

Table 11: Estimated Relaxed Model

Logistic Regression				Number of Observations	59,610	
				LR chi-squared(8)	2173.78	
				Prob > Chi-squared	0.0000	
Log Likelihood = -21011.22				Pseudo R-squared	0.0492	
Ind. Variables	*Coefficient*	*Standard Error*	*Z-score*	*Prob > l z l*	*95% Confidence Interval*	
Return on Equity	-.015	.016	-0.97	0.334	-.045	.015
Liquidity	.059	.011	5.42	0.000	.038	.080
Leverage	.011	.015	0.73	0.465	-.018	.040
Size	.259	.010	24.96	0.000	.239	.279
Market-to-Book	.047	.011	4.12	0.000	.025	.070
Net Income	-.208	.015	-14.16	0.000	-.237	-.179
Industry Dummy	-.870	.027	-31.73	0.000	-.923	-.816
Growth Resource Dummy	-1.628	.114	-14.30	0.000	-1.851	-1.405
Constant	-1.334	.023	-58.91	0.000	-1.378	-1.290

5. CONCLUSION

A summary of the findings for this study are provided in Table 12. This study has found minimal evidence supporting the six hypotheses (Inefficient Management, Growth-Resource Mismatch, Industry Disturbance, Firm Size, Asset Undervaluation, and Price-to-Earnings) being tested. The idea that "past performance does not indicate future results" certainly appears to apply in this area. The target likelihood predictors (independent variables) during the time period January 3, 2000 through December 31, 2007 may have been affected by the Financial Crisis of 2008. Although the crisis did not fully develop until 2008, the lax credit lending standards, which were in place for years prior, may have played a role in much of the performance of these firms.

Future researchers should be cautious during time periods during any sort of bubble or possible systemic failure in the US financial system. Perhaps the implementation of some sort of barometer of overall credit lending or commercial lending health metric should be used for future model estimations. Upon further examination of the prior researchers' studies, they do not comment on their goodness of fit measures, but rather its "predictive ability". Since large institutions do this type of research regularly, the chance to exploit any market irregularities should be slim to none (which might be why prior researchers don't include a goodness of fit measure in their findings). If a model exists which predicts with economic significance whether or not a firm is a future target, the metrics used and defined appear to be more complex than those used in the existing literature and in this study. After all, in an efficient, fair market everyone has the same information and opportunities for easy profits are wiped out almost instantly.

Table 12: Summary of Results

Explanatory Variables	Hypotheses Expectations	Control Model	Semi-Relaxed Model	Relaxed Model
Return on Equity	-	+	+	
GRDummy	+		+	-
Liquidity	+	+	+	+
Leverage	+	-	+	
IDummy	+	+	-	-
Size	-		+	+
Market-to-Book	-		-	+
Price-to-Earnings	-		*	*
Pseudo-R-squared		0.0016	0.0557	0.0492

Note: * means the variable was not used in that model, "+" means the coefficient was positive and statistically significant at the 5% level, and "-" means the coefficient was negative and statistically significant at the 5% level.

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