PREDICTING ACQUIRING FIRMS: A NEW DISCOVERY FROM THE GROWTH-RESOURCE IMBALANCE HYPOTHESIS

Jean-Mathieu Gareau

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By: Jean-Mathieu Gareau

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Signed by the final examining committee:

Dr. Alexandra Dawson, Chair

Dr. Nilanjan Basu, Examiner

Dr. Saif Ullah, Examiner

Dr. Sandra Betton, Supervisor

Approved by Dr. Sandra Betton, Chair of Department

December 7th 2010 Dr. Graham Carr, Dean of Faculty

ABSTRACT

PREDICTING ACQUIRING FIRMS: A NEW DISCOVERY FROM THE GROWTH-RESOURCE IMBALANCE HYPOTHESIS

Jean-Mathieu Gareau

The growth-resources hypothesis has been widely used empirically to develop models to predict takeover targets. This hypothesis states that firms with low (high) growth and high (low) resources make good potential targets. In this thesis I test this hypothesis in the context of predicting future acquirers. Using binary, multinomial and two-step logit models, I document that a firm's growth is actually the main factor leading to acquisitions, contrary to the generally accepted view that a firm's cash position is one of the primary factors associated with future acquisition activity. As such, the growth-resources imbalance hypothesis is partly validated: high growth-low resources firms are the most likely to make a bid while low growth-high resource firms which were expected to be the most likely to acquire, are, in fact, the least likely to take over other firms. These results are robust to different measures of the imbalance variables and are consistent with the market timing theory. In a hold out sample, I find that the binary logit models show higher prediction accuracy than the multinomial logit models.

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I. Introduction

Mergers and acquisitions are the events with the most impact in corporate finance and often represents the largest, and in some ways the riskiest, investment that a firm makes. One simply have to look at the scope some of the largest historical deals, such as the merger of AOL and Time Warner ($164 billions) or the purchase of Mannesman by Vodafone ($183 billions) to appreciate the scope of these events and the immense stakes of the related parties. Very high market attention is generated and investors can lock in spectacular profits if they are on the right side of the transaction before and at the announcement of a deal. Bearing that in mind, it is now well documented in the literature that the shareholders of the target firms reap the majority of the mergers and acquisitions' rewards as the bidding firms usually end up holding the bag, gaining very little or losing in the long term.

Given this information, it is quickly understandable that the real money in M&A is made with target firms and explains the extended empirical research on the subject: a significant number of researchers have developed models to forecast future takeover targets and then invest in a portfolio of companies that would generate the highly coveted abnormal returns (Palepu; 1982, 1986, Barnes; 1999, Powell; 2004, Hyde; 2009). These studies rely on several generally accepted hypotheses about the characteristics of target firms that are incorporated in the models. Among these is the growth-resources imbalance hypothesis[1] which states that a firm with low growth opportunities and high liquidity or low liquidity and high growth is most likely a good target: high liquidity firms are attractive due to their high cash position while high growth firms represent an opportunity for mature acquiring firms to expand.

Acquirers have, in general, not received as much attention in empirical research as targets for the obvious reason that they do not create the significant short-term profit opportunities as targets do, which is still considered a puzzle. That being said, there is an increasing number of papers that consider firm and deal characteristics as well as

[1] It is sometimes also referred to as the growth-resources mismatch hypothesis.

corporate governance to try to pinpoint the underlying reasons why bidding firms to engage in what usually develops into a value destructing deal. This study builds on this stream of research.

In this paper, I take the growth-resources imbalance hypothesis and apply it in the exact opposite way as it is used in the empirical literature: I use this hypothesis to build a model useful in predicting future acquirers. I argue that, even though firms with an imbalance make good acquisition targets, they are also likely to become acquirers. Consider a firm that has high liquidity and low growth: if it wants to maximize shareholder wealth, it can either pay out the cash to shareholders or it can acquire a company with a high level of growth. Conversely, a firm with high growth but no resources to fuel it will seek to either raise funds or acquire a cash-rich firm to reach a balance and emerge from the transaction in a better condition. In this thesis I focus on the acquiring decision rather than the financing/dividend decision. The acquisition decision hypothesis is tested with binary, multinomial and 2-step binary logit models using different definitions of growth and resources for robustness checks.

The results in this study provide evidence that the growth-resources hypothesis holds partially for bidders. I find that the growth of the firm, calculated as the past 2 and 3 years average sales growth is the main driver for a firm to make an acquisition. In my sample of 6976 bids from 1995 to 2008, firms which have high growth and low resources are the most likely to become acquirers, followed by those with high growth and high resources. The firms with low growth and high resources, which given the framework of this paper were expected to make an acquisition are actually found to be the least likely to become acquirers. I also find that the binary logit models have a higher prediction accuracy than the multinomial logit models. However, the 2-step binary logit model outperforms all other models.

The work reported here is interesting for various reasons. For scholars, the results reported open the door to further studies and a deeper understanding of the motives for acquisitions. These results also challenge some commonly held view on the motivations of acquirers: contrary to popular beliefs, the main motivation for a firm to make a bid is not excess cash or liquidity (Harford;1999), but rather it is growth. For practitioners in the M&A industry, like investment bankers, the models built here perform significantly better than chance and could provide additional support in their decisions regarding acquirers: these firms represent the main clients for investment bank, and a positive outcome generated by the models here would add significantly to the impact of the sales pitch of a consultant thrown at the prospected firm. If the models are proven useful and accurate enough to add even one signature from a customer for an investment bank, then it has its reasons to be used.

The remainder of this paper is organized as follow: section II reviews the vast literature of mergers and acquisitions, section III explains the hypothesis and section IV, the data and sample used. The methodology and models are reviewed in section V and VI, respectively and the results are presented in section VII. The prediction accuracy of the models is reported in section VIII. Section IX relates the estimated probability to make an acquisition to the deals' abnormal returns and section X concludes.

II. Literature Review

a. On Targets

When examining the empirical results of mergers and acquisitions, one can easily understand the interest in this aspect of corporate finance. The stock market reacts rapidly and significantly to merger announcements and creates many opportunities for investors, especially those with inside information, to emerge wealthier from these events. This is especially true for the targets of takeovers. During all merger waves, shareholders of target firms see their net worth increase significantly. For example, Dodd and Ruback (1977) find cumulative average abnormal returns of 20.89% from the announcement date to 20 days after takeovers between 1958 and 1978. Around the announcement date, all studies report very high abnormal gains: 6.2% during the 1963-

1978 period (Eckbo;1983), 22.51% from 1980 to 1995 (Graham et al.;2002) and 21.2% in the 1990's (Mulherin and Boone;2000). The same trend is observed using a longer event window around the announcement date. Eckbo(1983) finds a CAAR of 14.08% for the period (-20;+ 10) and Lang et al.(1989) find a CAAR for targets of 40.3% during the (-5;+5) window for their respective periods.

Although the majority of the gains occur very close to the announcement date, increased stock price movements are apparent well before the event is publically announced. This run-up in price, as shown by Schwert(1996) starts as early as 42 trading days before the deal is announced. This run-up implies that the market partially anticipates such a deal as the event date approaches, whether it is from rumors, information leaks or, more importantly, increased insider trading. The post-announcement returns are influenced by the deal's attitude: hostile bids led to a CAAR of just under 32% while friendly bids triggered a CAAR of "only" 22% (Servaes; 1991) in the US for the 1972 to 1987 period.

Given the size of the wealth effect documented in the empirical evidence, it is logical that investors would attempt to predict which firms are going to become targets and create a portfolio of such firms in order to capture these abnormal returns. The first probabilistic model of acquisition was developed by Palepu (1982) for this purpose and he used a logit model to predict takeover targets using accounting ratios. While performing better than chance, the Palepu model suffered from a lack of prediction ability in a random sample. Using a similar logit model approach, Hasbrouck(1985) finds that target firms characteristics are weighted towards a low Tobin's Q ratio and, to a lesser extent, by financial liquidity.

Several shortcomings in this matched sample logit methodology were identified and corrected by Palepu (1986). Common issues with the simple logit prediction model include: error rate estimates that inaccurately represent the performance of the model in the population, arising from the use of a non-random sample; and the use of arbitrary cutoff probability for the prediction tests that lead to hard-to-interpret error margins.

Examining the same hypothesis as in Palepu (1982) and the methodologically-enhanced binary logit model, Palepu (1986) shows that a portfolio of firms selected by the model fails to outperform the market.

Barnes(1999) builds on Palepu's work to predict takeover targets in the United Kingdom and make significant improvements: incorporating industry-adjusted ratios to correct for the usage of a holdout sample drawn from the estimation sample and choosing a cutoff point that minimizes the costs of misclassification of target firms. However, no significant improvement in performance is observed and he concludes that the use of financial ratios only is unlikely to outperform the market: given the diversity of merger motives and their relative importance over time, using a single cross-sectional model is unlikely be highly successful in predicting targets.

Despite the above conclusions, researchers have continued to examine the predictability of takeover targets – either by examining different samples or by improving the methodology. Arbel and Kim (1998) use a binary logit model to predict target firms in the hospitality industry, but with low predictive accuracy. Adelaja et al.(1999) propose a two stage M&A model in the food industry: the probability of being targeted and the probability of being taken over. They build two logit models, one for each stage, to test their hypothesis. They find that financial ratios are good proxies for a firm to be **targeted** while governance (degree of officer control, attitude towards the transaction, number of prior bids, presence of litigations during negotiations and the involvement of both parties in the negotiation of a simultaneous bid) has a high impact on the probability of being **taken over.** The authors report that their models have 74.5% and 62.9% classification accuracy respectively.

Powell (2004) estimates a multinomial model using four logit equations to predict takeover targets of friendly and hostile deals using firms' financial ratios. He shows that multinomial models have better predictive powers than binary models: when tested for abnormal returns, a portfolio of hostile deal targets identified by that model generates positive abnormal buy-and-hold returns. Hyde (2009) focuses on all deals since they generate returns even if they are unsuccessful and used a sample of Australian firms. He argues that previous studies are biased since they exclude unsuccessful deals from their sample. He also argues that both type 1 and type 2 errors[2] must be low: previous literature attributes low abnormal performance to the probability cutoff chosen for their portfolio due to the choice of a high type 2 errors (incorrectly classifying a firm as a target) in order to minimize type 1 errors (incorrectly classifying a target as a non-target). His model is very successful at identifying takeover targets in the holdout sample and generates significant abnormal returns with robust results.

While Palepu (1982, 1986) claims that that target-predicting models have very limited use, others have reported that their models could well outperform the market in identifying future targets with prediction accuracies 47% (Powell;2001) and north of 60% (Espahbodi and Espabohdi; 2003)[3]. Such claims can't be easily dismissed because of the dynamic relationship between financial ratios and the likelihood of a firm being acquired. In comparison, forecasting bankruptcy, another important corporate event, is easier because firms going under are much more likely to exhibit the same patterns over time than likely target firms. While it is still unclear if a robust and efficient model can be built in order to consistently beat the market by predicting targets, many researchers have also worked on the other side of the M&A equation, the acquirers.

b. On Acquirers

Empirical evidence shows a puzzling disparity between bidder and target gains from takeovers: targets' shareholders witness a significant wealth increase while acquirers'-shareholders make insignificant gains. Asquith (1983) reports abnormal returns of 0.2% for the window (-2;0) from 1962 to 1976 while Eckbo (1983) reports an abnormal 0.7% increase in shareholder wealth over the (-1,1) event window for the same study period (1963-1978). Using a sample from the 1980's, Byrd and Hickman (1992) report a -1.23%

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[2] Type 1 error refers to the model not identifying a takeover target in the portfolio while type 2 error is incorrectly identifying a non takeover target.
[3] The prediction accuracy is calculated as (correctly predicted targets + correctly predicted non-targets) / total sample size.

abnormal return for the (-1;0) window and, more recently, Lehn and Zhao (2006) find that, between 1990 and 1998, CEOs that made bad bids (average of -7.03% abnormal returns in the (-5; 40) window) are highly likely to be fired, while CEOs who are better bidders (0.28% CAAR) for the same window usually stay in the firm. Loderer and Martin (1992) find that on average, bidders in the 1966 to 1986 period did not underperform a portfolio of control firms over the five years following acquisition rather earning the required rate of return. Agrawal et al. (1992) find that bidders on the NYSE from 1955 to 1987 lost 10% of stockholder values in the 5-years post-merger when acquiring NYSE or AMEX targets. In contrast, Gregory (1997) documents significant long term returns after completion of a merger or a tender offer from 1984 to 1992 in the United Kingdom. It is thus clear that, unlike targets, the evidence regarding acquirers' performance is mixed.

Firm Characteristics

It has, however, been found that firms that become acquirers tend to outperform the market before the deal announcement. More specifically, Bradley and Sundaram (2004) found that in the 1990s, public acquirers outperformed the market by 50% and that acquisitions ''are the results of good performance''. Bradley and Sundaram (2006) further confirm these preliminary results that good performance leads to acquisitions and not the opposite, and add that firms that make several acquisitions tend to perform better than infrequent bidders. Harford (1999) also documents that there is an increased probability of a firm becoming an acquirer if they show higher abnormal (pre-bid) returns or higher sales growth. These results, suggesting that good performance leads to acquisition, are consistent with those of Asquith, Bruner and Mullins (1983) and Roll (1986).

Several studies try to explain the relatively poor returns that acquirers exhibit after acquisition. For example, Travlos (1987) finds that stock acquisitions lead to significant losses for bidding shareholders while cash bidders earned normal returns from 1972 to 1981 in the US. He also notes that firms with poor returns tend to pay with equity. These results are independent of the type of takeovers. Pre-acquisition run-up is significantly better if stocks are used as a method of payment (Bradley et al. 2004). This result is consistent with the market timing hypothesis which states that managers willingly use overvalued stocks to purchase real assets: the acquisition announcement sends a signal to shareholders that stocks are overvalued and thus the price reacts accordingly and drifts downwards. Lang et al. (1991) tested the relationship between a firm's net present value (NPV) projects using Tobin's Q as a proxy and the post-acquisition returns of bidders. They found a negative relationship between cash flows and post-bid performance for firms with low Q ratio (bad NPV projects) but not for high Q firms.

Intuitively, one should expect a significant relationship between a firm's cash on hand and the performance of the acquisition. Hyde (2009) suggests that cash rich firms engage in value decreasing transactions and finds that they destroy seven cents of value per dollar of cash and short term investments held when engaging in mergers and acquisitions. He also documents that these firms are more likely to make diversifying acquisitions and their targets are less likely to attract other bidders. His results are consistent with Jensen and Meckling's (1976) agency theory where managers are willing to engage in value-destroying behaviors rather than paying the extra cash-flows to their shareholders. Smith and Kim (1994) show that bidders with high free cash flow tend to pay too much for their targets and that such firms show lower returns when they acquire targets with low financial slack , while slack-poor acquirers buying high cash flow targets tend to show higher returns. Oler (2008) also finds that a high level of cash in acquiring firms is strongly and negatively influencing post acquisition returns.

Moeller et al. (2004) focus on firm size to predict post-acquisition returns and find a strong size effect in their sample: while the equally-weighted returns at the announcement date is positive (1.1%), the acquirers showed an average loss 25.2M$ after controlling for the M&A activities in their respective industries. These results show that, although acquirers show a positive return on average over the period 1980 to 2001, some deals involving very large firms destroy enough value to affect the results of the whole sample. This effect may have started in this specific sample period as, before the 1980s, firms were less likely to be taken over: during those pre-80s years, the most powerful anti-takeover measure was firm size because of the relative difficulty of financing very large acquisitions. The decade of the 80s saw financial innovations such as “junk bonds in the US and mezzanine debt in the UK” that helped companies “overcome the traditional obstacles in the financial markets and acquire very large targets”[4]. Chatterjee (2004) tested the effect of this past “immunity” but failed to find improved performance in acquirers buying such targets compared to both other acquirers and to the market. Thus, in order to acquire targets of this magnitude, it is easily arguable that the size of the acquirers must strongly influence the probability of becoming an acquirer.

Another characteristic that has been shown to affect firms’ bidding decisions is their level of research and development. The market tends to incorrectly evaluate future synergies for merging firms when the acquisitions involve high technology firms than in other type of deals (Luo; 2005). To address this issue, Kallunki and Pykkö (2008) test a sample consisting exclusively of technology deals between 1992 and 2004 where the acquirer was in the United States, and found that the level of bidder R&D is positively related to long term abnormal returns, more precisely to abnormal returns in the 3rd year following acquisition. It is also argued that this misevaluation is an undervaluation of future cash flows by investors due to information asymmetry at the time of the transaction.

In addition to trying to link quantitative measures to merger performance, research has also examined the influence of qualitative variables, such as those measuring corporate governance, on acquirer performance. Even though upper management is theoretically working for the shareholders, they are the ones involved in the negotiations on the terms of the deals, and should have a direct effect on the performance of the firm post-announcement. Datta et al. (2001) examine the relationship between executive

[4] Chatterjee (2004)

compensation and stock performance around acquisitions and find that the managers' equity-based compensation is strongly and positively related to the acquiring firm's stock performance around and after acquisition announcement. In contrast, Reis (2008) finds no evidence of a relationship between managerial incentives and shareholders' wealth increase: both target and bidder CEOs' incentives show no correlation with their respective shareholders' wealth. However, he does find that managerial incentives strongly influence the **success** of a takeover. Furfine & Rosen (2009) find a relationship between CEO option-based compensation and an increase in acquirer's default risk following a diversifying merger, and the effect is greater when the firm exhibits poor stock performance prior to the bid. Malmendier and Tate (2002) examine CEO behavior for signs of "overconfidence", notably, if they regularly buy shares and if they refrain from exercising in-the-money options of their own firm. They found that overconfident CEOs have a higher tendency to invest in a project the higher the firm's cash flows and the more funds they have at their disposal. This finding is consistent with the view that managers prefer to invest in bad projects rather than distributing the funds to their shareholders and that cash rich firm engage in value-destroying transactions.

Jaffe et al. (2009) show that the CEO, as an individual, is related to the performance of bidding firms: good performance persists when the same CEO makes multiple bids and the second deal of a firm shows an earnings increase of 1.02% compared to firms with a previously unsuccessful bid that kept its CEO. This translates into a mean increase of $175M in value creation "for the shareholders of an average sized bidder"[5]. While economically significant, these results do not account for another important determinant of firm performance: the board of directors. The CEO of a firm doesn't act on his own and is helped by the firm's directors. Thus, in the same way that a competent CEO can make better acquisitions, it is expected that a better board of directors helps in the decisions made by the CEO and should, therefore, influence performance. Schonlau and Vir Singh (2009) document this relation between the whole board of directors and the performance of a merger and find that more central boards

[5] Jaffe et al. (2009)

(boards with better connections with other boards) earn significantly better post-acquisition returns on average than for less central boards. They also report a positive relationship between board centrality and the probability of engaging in mergers and acquisitions, both as a target or as an acquirer, and of using cash as a means of payment. The richer the board's external connections with other firm's top management the better the information surrounding the transaction thereby resulting in better performance.

Deal Characteristics

Rather than focusing on the mode of payment and pre-bid acquirers' variables, a growing body of research looks at the type of firms that are sought. The results of these studies show some consistency: Conn et al. (2003) find that UK public acquirers of domestic and cross-border public targets generated negative abnormal post announcement returns while deals involving private targets saw positive announcement returns and no abnormal post-transaction returns. Fuller et al. (2001) found that, in a sample of frequent acquirers (5 or more bids in a 3 years span), shareholders of firms that acquire a public target earn significantly negative returns where these returns are significantly positive for private targets and subsidiaries of public firms. This suggests that bidders pay a relatively lower price in a less liquid market. Bradley and Sundaram (2006) further confirm these results and find that the size of the firm isn't the most important variable in determining how the market reacts at announcement, but rather the public status of the target firm. Faccio et al.(2006), in their study on Western European countries from 1996 to 2001, find that buyers lose an average of 0.38% when buying listed targets and gain 1.48% when acquiring unlisted targets. These findings were confirmed by Ekkayokkaya et al. (2009) but they also show that acquirers that buy unlisted targets suffer from a substantial loss in the long run. They hypothesize that these results may be because of the investors' optimism towards the limited and biased information available at the transaction announcement for the unlisted target firms.

Bradley and Sundaram (2004) find similar results for US acquirers in the 1990s, where the market reacted positively to the acquisition of non-public targets while reacting negatively to the acquisition of public targets **with stocks.** The notion that acquisition follows performance is consistent with Rhodes-Kropf et al. (2003) who show that mergers are cyclical and tend to occur in waves.

When making an acquisition, firms can choose between diversifying their activities and consolidating their position in their respective industry. Berger and Ofek (1995) argue that two benefits to diversification exist: a greater tax shield derived from the higher debt capacity and tax savings resulting from the losses of unprofitable segments that offset profits of other segments. They examine the diversification effect on firm value and document an average of 13% to 15% value loss from diversifying during the period from 1986 to 1991. They also point out that the tax savings are far too small in comparison in the average loss of value to be an incentive to diversify.

Applying the notion of diversification in M&As, Matrynova and Renneboog (2006) test the difference between diversifying deals and industry-related acquisitions in Europe during the 1990s, and find a bidding firm's CAAR of 0.45% for the former type of deals and 0.98% for the latter. Kaplan and Weisbach (1992) find that diversifying acquisitions, despite being as successful as their non-diversifying counterparts, are more likely to be divested following large takeovers. They also document that announcement returns predict the following divestitures: they are significantly lower for firms that later make unsuccessful divestitures than for those who later make successful ones or none at all. They also support the view that a divestiture doesn't mean a failed merger since 56% of the transactions that end in divestitures don't report a loss on the subsequent sale.

Betton et al. (2008) summarize the performance of acquirers: bidders gain the most when they are small and acquire private targets (average CAAR of 6.46%) while they lose the most when they are big and acquire public targets with stocks (average CAAR of -2.21%). While stock payment was once thought to be the most important factor to predict (negative) performance, firm size and target public status appear to have the greatest impact on acquiring firm stockholder returns.

c. On Mergers' Long-Run Performance.

In general, around the announcement day, targets' shareholder wealth increases and acquirers' make insignificant returns resulting in generally positive total gains. Thus, we would expect that mergers are value creating in the long-run, given the predictions of the market when the deal is announced. However when examining at the long-term post-merger performance, this conclusion is far from accurate. Acquirers' stock prices generally drift downwards and tend to underperform the market. This implies that synergy gains are generally overvalued by the market and the managers at announcement. If such is the case, then the (bad) acquirers risk becoming targets and being acquired because of poor performance. Mitchell and Lehn (1990) show that acquirers that make such value reducing deals tend to become target themselves, consistent with the Jensen and Ruback (1983) view on the disciplinary role of the takeover market. However, Offenberg et al. (2009) find evidence that buying these bad bidders in an attempt to recuperate the destroyed value is generally unsuccessful and acquirers lose more the worse the bidder is. Accurately assessing the long-run performance of merger is tricky but important and can help shed light on the causes of the generally poor performance.

Measuring long-term post-merger returns is ambiguous and highly dependent on the estimation model provided to predict the benchmark. Barber and Lyon (1997), argue that the most adequate benchmark measure is to compute the returns on a portfolio of similar firms matched by the size and book-to-market ratio for bidding and target firms before the takeover. Using this method, several studies looked at the long term merger performance. For example: Loughran & Vijh (1997) report underperformance when stocks are used as a means of payment as opposed to cash, and Mitchell & Stafford (2000) report generally negative long run performance. More recently, Moeller et al.

(2005) did not find evidence of significant abnormal long run performance after mergers.

Several hypotheses for long run underperformance have been proposed. The first view, supported by Shleifer & Vishny (2003) and Baker et al. (2007), is that the share price drift is a slow and simple correction of the market's overvaluation of the combined entity. This view emanates from behavioral finance and contradicts any form of market efficiency but the weak form, suggesting that the market adapts slowly as new information becomes available.

A second view on the long run performance topic arises from the theory that mergers and acquisitions are a response to industry shocks such as an increase in foreign competition and financial innovations (Mitchell and Mulherin; 1996). Andrade and Stafford (2004) add that these shocks are split between industry-specific and firm-specific events that both affect the likelihood of a merger while Andrade et al. (2001) suggest that these shocks explain why mergers and acquisitions tend to be "industry-clustering", especially during the last 30 years. Because the acquisition is a consequence of the firm's changing environment, Harford (2004) argues that once the firms are merged, they perform better than they would have if they had both remained independent, and that this "improved" performance can still be worse than the observed pre-merger performance.

The third hypothesis is that the underperformance of mergers and acquisition is an illusion created by the methodology used to compute the returns. Betton et al. (2008) investigate this issue and find that, using the buy-and-hold matched firm methodology, merged firms underperform, on average, their matched firms in value-weighted and equal-weighted estimates. However, when using the rolling portfolio technique in the same sample, they can't reject the null hypothesis of zero abnormal returns. They also find evidence that seriously weakens the results reported by the buy-and-hold methodology as being significantly negative abnormal returns. Thus, it seems that the results are highly dependent upon the methodology used.

III. Hypothesis

a. Takeover Motivations

Based on the empirical evidence reviewed thus far, acquiring firms' managers appear to overestimate the benefits of mergers or acquisitions and thus the events generally result in a wealth loss for acquirers' shareholders. Bearing this in mind, why would managers engage in value-reducing deals? There are three general motives suggested in the literature: synergy, agency and hubris.

Synergies imply that the combined firms should benefit from the transaction because they will perform better together rather than independently. Synergies can arise from increased buying power and thus lower costs, better use of resources and technology in the combined firm as well as increased distribution networks, among others. When the motive to merge is synergies, management is expected to act in the interests of the shareholders by trying to maximize their wealth.

Agency theory implies that managers would use excess liquidity to invest in a negative NPV project (in this case, an acquisition) rather than distributing the extra cash flows to the shareholders, or to repay a portion of the outstanding debt. Several motives for such a behavior exist: managers of a firm can acquire a target to diversify their personal portfolio; they can also do it to increase the firm's dependence on their own set of skills through the acquisition of a target specifically located in the CEO's managing specialty that may or may not be related to the acquirer's core business. Another motive is referred to as empire-building, where the sole goal is to increase the firm's size and the personal power of the CEO. Such actions are value-destroying for the firms in which these behaviors are witnessed and generally lead to a transfer of wealth from acquiring shareholders to acquiring managers and target shareholders. If agency is the motivation for takeovers, then management acts for its own interest and not the shareholders'.

The third motive, Hubris, suggest that managers engage in M&A due to overconfidence in their estimations and their overoptimistic outlook on the deals specifics and errors of judgment. However, measuring hubris is very ambiguous: forecasting errors are common for management and especially in M&As, since even the manager with the most evil intentions can make a misjudgment when appropriating his shareholder's wealth to himself. In this study, forecasting errors are expected to arise for all firms meaning that hubris should be present in the whole sample.

b. Framework & Hypothesis

This paper focus on a well-documented hypothesis in mergers and acquisitions: the growth-resource imbalance. While it has been used in the literature to predict future takeover targets (for examples see: Palepu, 1986; Ambrose & Megginson; 1992, Barnes; 1999, Powell; 2004), the underlying concept of the mismatch between the available resources in a firm and growth potential is also relevant for acquirers: for a firm to be efficient and prosper, it needs to maintain a balance between available growth opportunities and liquidity to materialize them. Their liquidity can be measured as the cash and liquid investments on hand, and the ability to borrow through leverage. Thus, very liquid firms will have relatively low leverage and high cash on hand. Another option to obtain liquidity is to issue more stock, provided the dilution from the issue is perceived as reasonable by the market.

If a firm doesn't have the necessary resources or access to resources to fuel its high growth and positive NPV projects, it can either renounce to them or enter the takeover market to acquire a target firm with high liquidity or debt capacity to compensate for their lack of funds. The opposite is also applicable: a firm with very high cash reserves and/or availability but no growth opportunity can correct for this imbalance by acquiring a low-cash, high-growth firm and correct the mismatch.

The motivations of managers to engage in mergers and acquisitions are directly linked to this concept. Managers of cash-rich firms have more freedom to use the funds for the good (or bad) of their shareholders than managers of low-liquidity firms: they may choose to acquire a target for reasons other than to correct the imbalance by which they benefit themselves at the expense of their shareholders. In contrast, managers of high-growth, cash-dry firms acquiring high resource firms are less likely to make a "bad" deal because of the increased control mechanisms created by issuing either stock or debt to finance the bid.

Hypothesis: The importance of the growth-resource imbalance is directly linked to the probability of a firm becoming an acquirer. Managers of firms with low growth and high resources are expected to exhibit agency behaviors and thus be the most prone to acquisition. Firms in the high growth-low resource tiers, where managers are expected to be motivated by synergy in acquisitions, are also expected to be the most likely candidates to acquire another firm.

In order to test the hypothesis, binary, multinomial and 2-step binary logit models are used. Regressions are built by quantifying the growth-resource imbalance as a ratio, as well as dummy variables. Tests are run on the whole sample and on the four subsamples of firms classified by their respective growth and resource level. Figure 1 shows the characteristics of the firms included in each subsamples as well as the expected probability that these firms will become acquirers P(A) or targets P(T). It is expected that firms that don't exhibit an imbalance have a low probability of taking over other firms while those who do are more likely to become active in the takeover market.

Figure 1. Growth-Resources Matrix and Expected Merger Activity Probabilities

		Growth	
		High	Low
Resources	High	Low P(A)	High P(A)
		Low P(T)	High P(T)
	Low	Moderate P(A)	Low P(A)
		High P(T)	Low P(T)

IV. Sample and Data Collection

a. Collection

The sample in this study was drawn from three different databases: Compustat for the accounting variables, SDC for the Mergers and Acquisitions dataset and CRSP for stock returns. The sample period is from January 1, 1995 to December 31, 2008. The 1995-2005 period is used as the estimation sample while the 2006-2008 period is used as the holdout sample to test the predictive abilities of the models developed in the paper.

All North-American firms were retrieved from the Compustat database, even if they became inactive during the studied period, for a total of 23 355 companies. From SDC, I extracted all US acquirers seeking to **do a merger** or **gain a majority interest** in a target – in other words, deals where the acquirer was seeking control of the target. Transactions where the bidder was in the financial or utility industry were excluded. The total number of bids extracted from the SDC database is 22 784.

b. Merging

i.Sdc and CRSP

I first matched the SDC database with the CRSP to get the companies' IPERM numbers. The matching was done by an acquiring company's CUSIP number. Because SDC and CRSP use 6-digit and 8-digit CUSIPs respectively, I matched using both the 6 digit CUSIP and appending the digits "10", "11","20" and "30" to obtain as many matches as possible. Then I matched again using the SDC 6 digit CUSIP by removing the last two numbers of the CRSP 8 digits CUSIPs.

I then manually checked if the IPERMS matched were identical. For the 150 that weren't, I manually checked them and only kept the bids on common equity, defined by the share codes 10 or 11. All other observations were removed. After these steps, there were 14679 deals in the combined SDC/CRSP database.

<u>ii. SDC and Compustat</u>

Compustat reports annual financial data according to fiscal year rather than calendar year. Sometimes, the year end reported by Compustat can extend as late as May of the next calendar year. To correct this problem and facilitate the matching of financial data with transactions and returns, I created another variable, “Year”, which is given a numerical value of the company’s fiscal year. For example, in 2008, a company with a fiscal year ending in May 2009 is given the value 2008 for the “Year” variable. For a company with a fiscal year ending between June and December, the Variable “Year” takes the value of the current year.

I matched the SDC/CRSP database using the 8 digit CUSIPs, cutting one digit from the Compustat 9 digit numbers. This matching process eliminated 3546 deals, further narrowing the sample to 11 133 transactions.

c. Final Sample

With the complete sample combining all three databases, I removed all financial and utilities firms from the Compustat report since utility firms act under regulations not present elsewhere in the corporate world while the financial institutions use different ratios to measure economic performance than typical firms. These firms are also under different regulations that affect their managerial decisions which could alter the results of the study if kept in the sample. All SIC codes starting with either 4 or 6 are classified as financial and utilities respectively and were accordingly removed. To make sure none of them were spared I also used the GICS codes, starting with 40 for financial and 55 for utilities and removing them from the database.

Because this study deals with acquisition of common shares, the limited partnerships (LP) and Exchange-Traded Funds (ETFs) were also dropped. The final sample consists of 6976 acquisitions[6], 13 860 firms, both acquirer and non-acquirer, and is spread across a 14 year period.

d. Comparison

Table 1 summarizes the characteristics of the population of acquirers taken from SDC database and Table 2 summarizes the same characteristics for the sub-sample of acquirers that matched with the Compustat database. The ''matched'' sample is very similar to the aggregate pool in terms of deal attitude, the target firm's public status and the lack of tender offers and mergers. The mean values of transactions are \$477.31M for the matched sample and \$475.14M for the aggregate sample while the medians are \$53.72M and \$33.75M respectively. The matched sample has a higher proportion of high value deals while the population mean is driven by some extremely big deals. Transaction values range from \$0.007M to \$89167.72M for the matched sample and from \$0.002M to \$164746.9M for the population.

[6] My filtering criterion for the bidding firm was that they have to be public firms for the accounting information to be available. However, in the final sample, there are still 105 firms that SDC classified as private firms but their accounting information is available from Compustat. They were thus kept in the sample.

TABLE 1. Descriptive Statistics of the Population of SDC Acquirers

# of Deals=22784				*# of Firms=13660*	
	Completed		**Withdrawn**		**Other**
Status	17710		1428		3646
	77.730%		6.268%		16.002%
	Friendly		**Hostile**		**Other**
Attitude	22151		144		489
	97.222%		0.632%		2.146%
	Public		**Private**		**Other**
Target Public Status	5131		13919		3734
	22.520%		61.091%		16.389%
Value Of Transaction ($M) (*N = 12458)*	**Mean**	**Median**	**Min ; Max**	**Skewness**	**Kurtosis**
	475.1367	33.753	{0.002; 164746.9}	23.1425	776.2631
		Yes		**No**	
Tender/Merger		944		21840	
		4.143%		95.857%	
		Yes		**No**	
Firm Attempted Multiple Acquisitions		3924		9736	
		28.726%		71.274%	

TABLE 2. Descriptive Statistics of the Acquirers in the Matched Sample

# of Deals = 6976 *# of Firms=2835*

Status	**Completed**		**Withdrawn**	**Other**	
	5914		470	592	
	84.776%		6.737%	8.486%	
Attitude	**Friendly**		**Hostile**	**Other**	
	6711		70	195	
	96.201%		1.003%	2.795%	
Target Public Status	**Public**		**Private**	**Subsidiary**	**Other**
	2171		3775	897	133
	31.121%		54.114%	12.858%	1.907%
Value Of Transaction ($M) (*N =5224)*	**Mean**	**Median**	**Min ; Max**	**Skewness**	**Kurtosis**
	477.3161	53.7175	{.007; 89167.72}	18.8962	500.6238
Tender/Merger		**Yes**		**No**	
		501		6475	
		7.182%		92.818%	
Firm Attempted Multiple Acquisitions		**Yes**		**No**	
		1408		1427	
		49.665%		50.335%	

The main difference between the samples concerns the frequency of firms attempting multiple acquisitions. In the matched sample, 49.67% of the firms attempted more than one acquisition while only 28.73% of firms in the aggregate sample made a bid twice or more. This suggest that there is a size effect that arises from the fact that the firms matched with Compustat are firms that have to report their financial information and, in general, are the larger firms.

To verify the size effect, I calculated the average and median firm size, using the firm's market capitalization as a proxy, for the companies that matched with Compustat and those that did not (the unmatched sample). The computation was done using values extracted from CRSP 41 days before the first bid of a firm in the sample period.

The average and median firm size for the matched sample are \$1754.825M and \$344.418M, respectively, while these values are \$1388.072M and \$145.368M for the unmatched sample. While the average size isn't overwhelmingly different for both samples, the median is more than twice as big in the matched sample: a substantial difference in firm size between both groups thus exists.

The ratio of the transaction value over firm size gives a better idea of the relative importance of a bid for a firm in both samples. The average transaction in the unmatched sample is twice as important as in the matched sample when compared to the acquirer's market capitalization (70.84% and 35.28% respectively). The same pattern is seen in the median values: 23.77% and 11.71% for the unmatched and the matched samples, respectively. This means that the deals in the sample that wasn't matched with Compustat are twice as important relative to firm size as in the matched sample. This could explain why there are more firms making multiple acquisition attempts in the sample used for this study, since the deals are relatively less important for the firms. These results are summarized in table 3.

Table 3. Comparison of Deal Value Relative to Firm Size in the Compustat Matched and the Non Matched Samples

Panel. A MATCHED SAMPLE (G=Billion, M=Million)

N= 1834

	Mean	Median	Min ; Max
Market CAP	$1.75G	$344.418M	{$420320 ; $144,291G}
Transaction Value/Market CAP	0.3528	0.1171	-

Panel B. UNMATCHED SAMPLE (G=Billion, M=Million)

N=1180

	Mean	Median	Min ; Max
Market CAP	$1.39G	$145.368.92M	{$402500 ; $184.25G}
Transaction Value/Market CAP	0.7084	0.2377	-

e. Event Study

This is a study about mergers and acquisitions that focus on acquirers based on certain characteristics of bidding firms. Because the firms were filtered in the aforementioned way, certain differences may appear in my sample of deals compared to the aggregate sample obtained from SDC. For this reason, I ran an event study on my matched sample and on the unmatched sample to measure the extent to which the estimation sample suffers from selection bias.

The estimation period of the study ranges from 41 trading days before announcement to 126 trading days after announcement. Six different event windows are used to measure the impact of the acquisition announcement. For each window, the Cumulative Abnormal Returns is calculated for both the matched and the unmatched samples by adjusting the firms' return with the market return and using the equally weighted index. Results for the firms' first bids only are also reported. Panel A. and Panel B of table 4 summarize the results for the matched and unmatched samples, as well the significance of the returns.

TABLE 4. CARs From the Samples by Event Window

Panel A. Matched Sample

	All Bids N=6264				Only 1st Bid N=2522			
Window	**Min %**	**Max %**	**Mean %**	**Median %**	**Min %**	**Max %**	**Mean %**	**Median %**
(-41,-32)	-3.239	5.174	-0.002	-0.004	-3.239	5.174	0.007	-0.001
(-31,-22)	-1.055	1.181	-0.001	-0.003	-1.055	1.181	0.001	-0.003
(-21,-12)	-0.934	1.87	-0.001	-0.004	-0.917	1.87	0.001	-0.002
(-11,-2)	-1.007	1.936	0.001	-0.002	-0.789	1.245	0.003	0
(-1,1)	-0.757	5.215	0.008	0.002	-0.653	5.215	0.016	0.004
(2,126)	-9.87	5.448	-0.111	-0.058	-9.87	5.448	-0.117	-0.059

Window	N	Mean Compound Abnormal Return	Precision Weighted CAAR	Positive: Negative	Patell Z	Portfolio Time-Series (CDA) t	Generalized Sign Z
(-41,-32)	6251	0.26%	0.06%	2926:3325	0.469	1.649**	-0.798
(-31,-22)	6251	0.33%	0.46%	2958:3293	3.345***	2.099**	0.0013
(-21,-12)	6251	0.46%	0.39%	2978:3273	3.284***	2.238**	0.0081
(-11,-2)	6250	0.79%	0.42%	3032:3218**	2.910***	4.746***	1.9**
(-1,1)	6250	0.95%	0.70%	3219:3031***	9.282***	10.851***	6.637***
(2,126)	6249	-8.04%	-5.61%	2263:3986***	-11.473***	-14.297***	-17.572***

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Panel B. Unmatched Sample

	All Bids N=3373				Only 1st Bid N=1765			
Window	Min %	Max %	Mean %	Median %	Min %	Max %	Mean %	Median %
(-41,-32)	-6.831	3.66	0.018	0	-6.831	3.66	0.039	0.013
(-31,-22)	-1.45	2.041	0.004	-0.004	-1.45	2.041	0.008	-0.004
(-21,-12)	-5.729	1.656	0.002	-0.005	-5.729	1.656	0.011	-0.004
(-11,-2)	-3.713	1.784	0.015	0.003	-3.713	1.784	0.019	0.004
(-1,1)	-1.112	1.936	0.024	0.004	-1.112	1.936	0.037	0.007
(2,126)	-12.787	8.709	-0.149	-0.098	-12.787	8.709	-0.112	-0.073

Window	N	Mean Compound Abnormal Return	Precision Weighted CAAR	Positive: Negative	Patell Z	Portfolio Time-Series (CDA) t	Generalized Sign Z
(-41,-32)	3358	-0.29%	-0.06%	1494:1864**	-0.225	-0.949	-1.858**
(-31,-22)	3359	0.78%	0.84%	1580:1779	3.285***	2.551***	1.103
(-21,-12)	3360	1.44%	1.58%	1612:1747***	6.47***	3.66***	1.944**
(-11,-2)	3360	2.92%	2.22%	1675:1685***	8.308***	9.118***	4.375**
(-1,1)	3359	2.75%	1.86%	1747:1612***	13.284***	16.440***	6.883***
(2,126)	3359	-11.31%	-9.28%	1047:2312***	-10.3***	-10.489***	-17.347***

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Prior to the bid announcement, the unmatched sample's mean CAR outperforms the matched sample, especially in the (41,-32), the (-21,-12) and the (-11,-2) windows. Around the day of the announcement, the unmatched sample still outperforms the matched sample with a mean CAR three times as high. In the (-41,-32) window, and around the announcement date, the range of CARs in the matched sample is much narrower than the unmatched one, while the mean is significantly lower.

When we isolate the firms' first bids, the mean CAR becomes higher for each window except after the bid in the matched sample. The same pattern exists for the median CAR, suggesting that first bids are generally more successful than subsequent bids. When both samples of 1st bids are compared, the range of CARs for the unmatched sample is wider, while the mean CAR is higher for each window. The firms in the unmatched sample, whether they are first bidders or including all bids, perform better, on average, than the sample used in this study, the exception being for the window after the bid (2,126), where it performs slightly worse.

To further expand on the event study, results of the daily event study were extracted. Figure 2 shows the CARs from both samples while Figure 3 plots the difference in abnormal returns from both samples on a daily basis. From the first graph we clearly see that stock price performance peaks on the day following the announcement for both samples, and then dives into negative territory as time goes on. Both samples follow the same trend, although the unmatched sample shows higher volatility and steeper movements in stock prices.

The second graph compares the difference in performance between both samples. Prior to the deal announcement, the companies in the unmatched sample clearly outperform the matched sample. However, once the bid is announced, the unmatched companies show CAARs declining at a faster rate than the matched sample. A possible explanation to this is the size effect identified in the samples: firms from the non-matched sample are smaller on average and necessarily receive less coverage from analysts. Without extensive coverage, the acquisition comes as a bigger surprise than for bigger firms, hence the sharp spike at the announcement day. This lack of coverage brings less interest in the firms' stocks, making it drift lower once the transaction is closed.

Even though the results of the event study on both samples are not identical, they are similar enough to conclude that no major bias exists, except from the more negative long term CARs of the unmatched sample and the size effect. One should bear in mind these differences in the interpretation of the results.

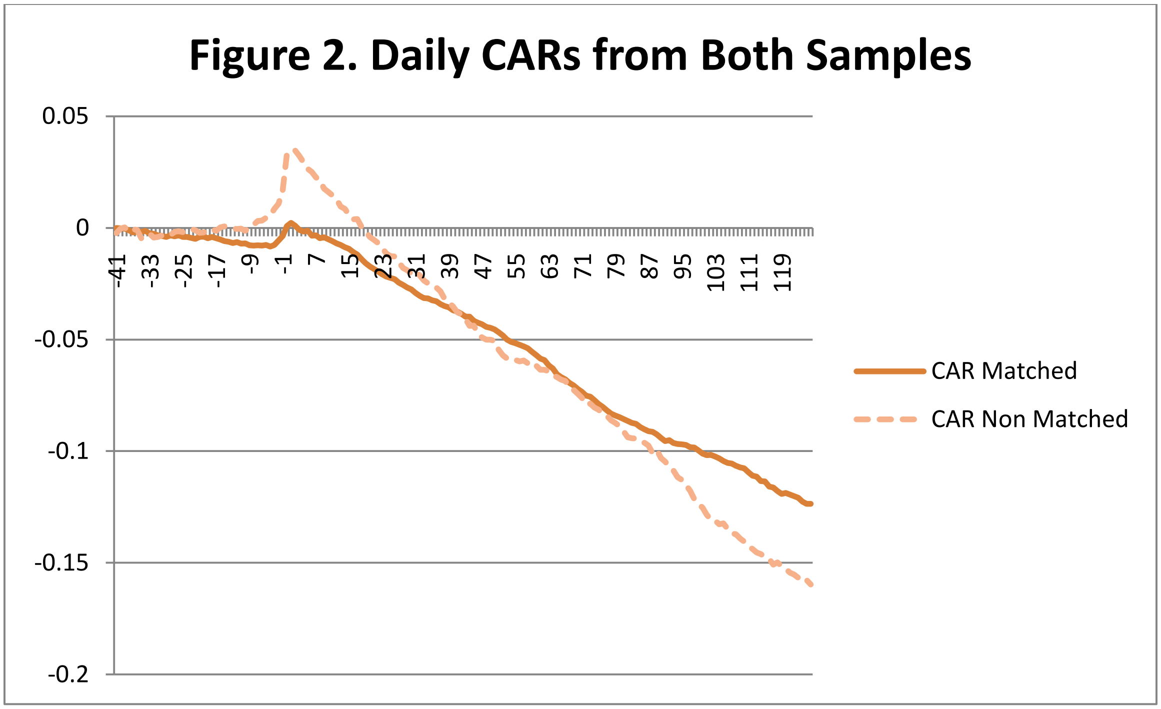


Figure 2. Daily CARs from Both Samples
0.05
0
-0.05
-0.1
-0.15
-0.2
-41
-33
-25
-17
-9
-1
7
15
23
31
39
47
55
63
71
79
87
95
103
111
119
CAR Matched
CAR Non Matched

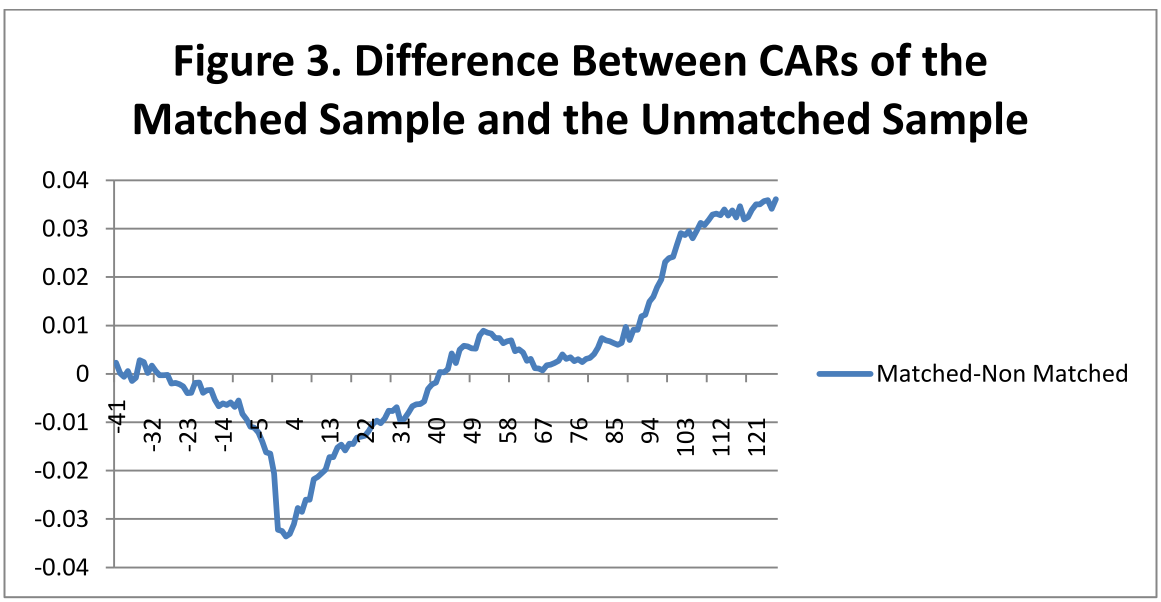
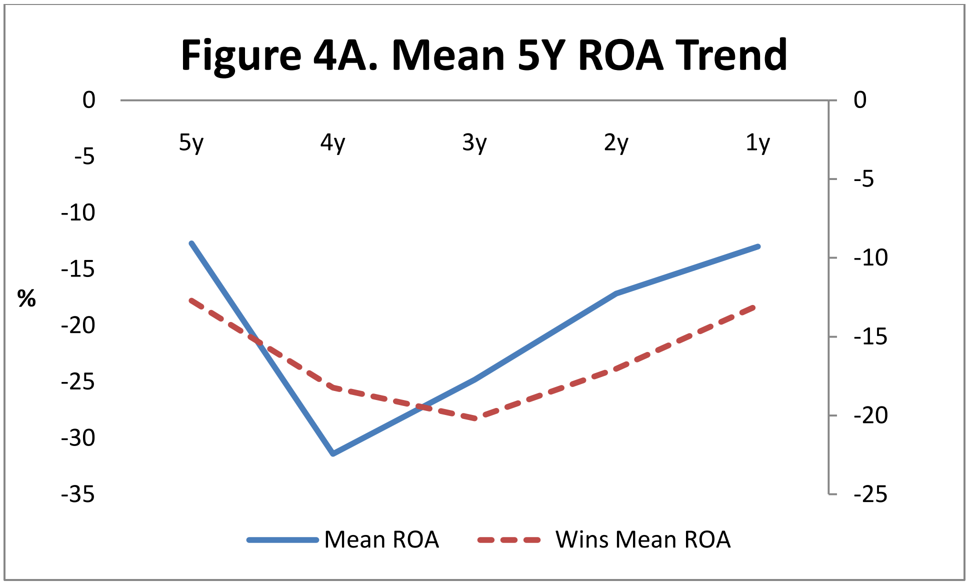
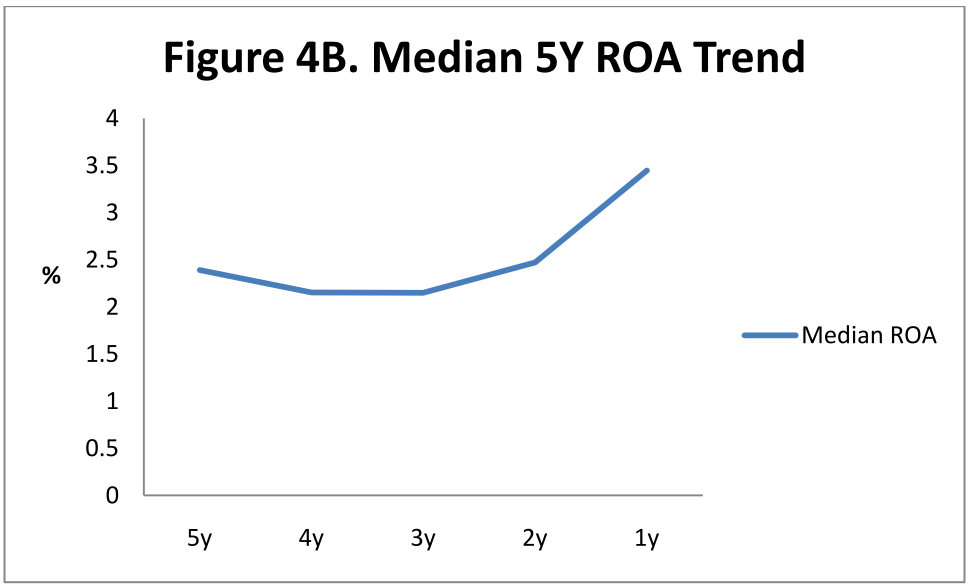


Figure 3. Difference Between CARs of the Matched Sample and the Unmatched Sample
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-41
-32
-23
-14
-5
4
13
22
31
40
49
58
67
76
85
94
103
112
121
Matched-Non Matched

F. ROA Trend

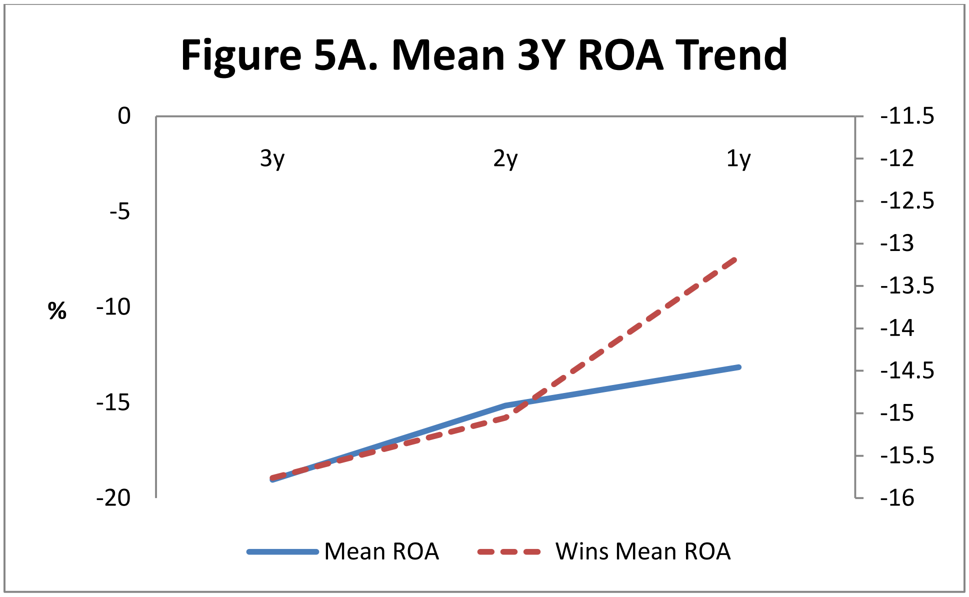
This section investigates the trend of firms' return on assets (ROA) prior to their first bid to see if future bidders outperform their non-acquiring peers. Results were computed for both 3 and 5 years prior to a firm's first bid. In order to be included in the results, the firms' ROA had to be available for each year prior to the deal. For example, for the 5 year trend, because the sample ranges from 1995 to 2008, only firms that did a first deal in the year 2000 or later were used to compute the results, since 5 years of data was available. The same logic was used for the 3 year trend. The following graphs show the results for both 3 years and 5 years trend. Figure 4A. reports the mean ROA and Figure 4B., the median ROA. Since the values' range was extreme, I winsorized the mean at the 0.5% level in both tails of the distribution to reduce the outliers' influence and to get more representative ROA values.

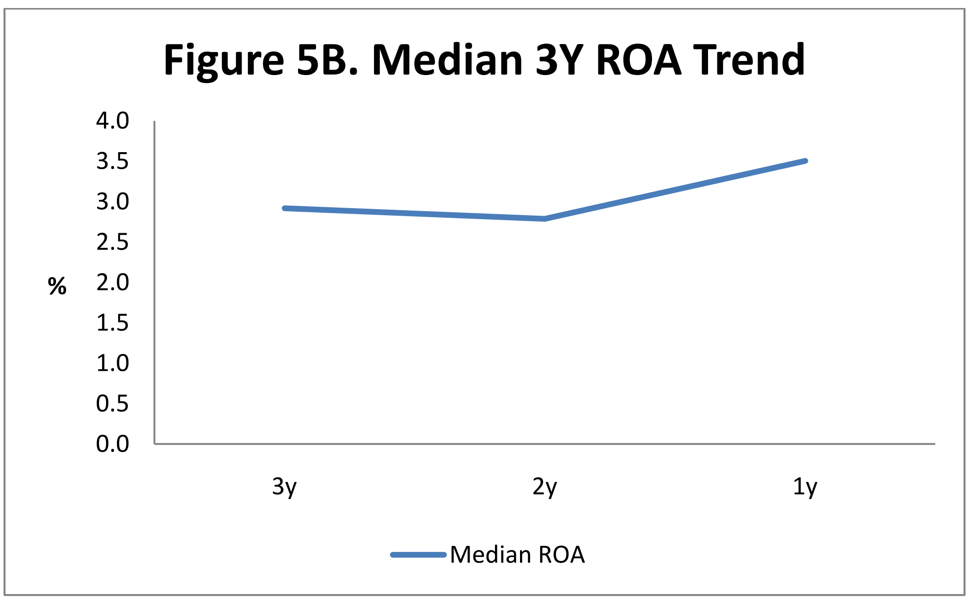




As Figures 4A and 4B illustrate, the 5 year trend is two-fold: from year -5 to year -3 the performance of the firm declines while from years -3 to -1 it gradually increases for both the mean and the median ROA. The huge disparity between the mean and median values suggests that some firms perform really poorly prior to the bid while the majority of them have positive return on assets.

For the 3 year trend from figure 5A and 5B, the results are consistent with the 5 year trend: performance gradually increases until the year prior to the bid, while the mean and median ROA are really different. The presence of some firms that perform very poorly in the sample is still evident.

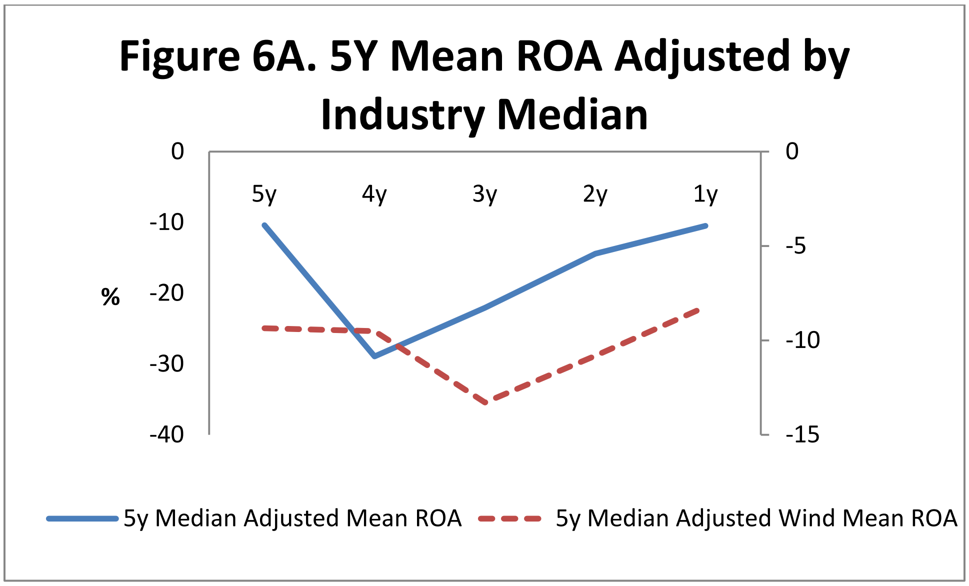


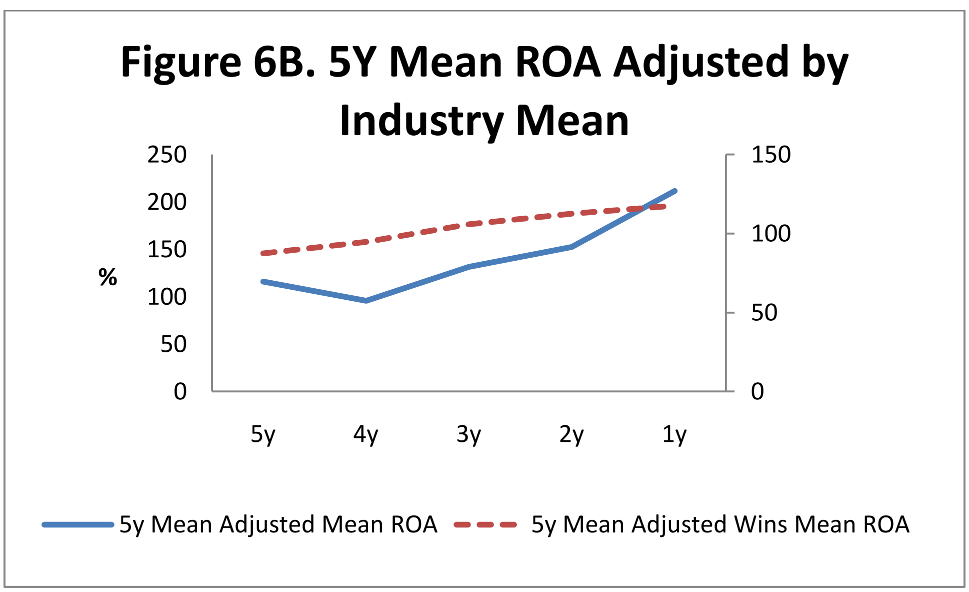


To put these numbers in perspective, the firms' returns were adjusted with their respective industry. I first extracted the mean ROA for each year, for each SIC code[7], using all the firms in my database. I then adjusted the ROA of my sample firms by their

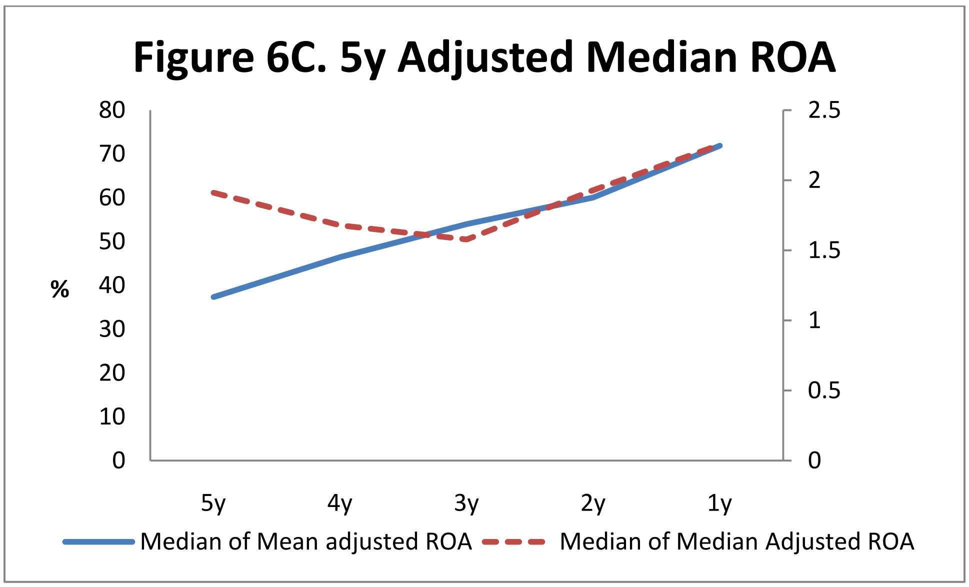
[7] I used the first 2 digits of the firm's SIC code to differentiate the industries.

respective industry (and therefore, SIC code). I finally computed the average and median for each year, both in my 3 year and 5 year trend samples. I also repeated the process using the industry median instead of the industry mean which gave me the ROA adjusted by industry median. Again, since some values were extreme, I winsorized 0.5% of the values in both tails of the distributions. All the results are reported in the following graphs for both the 3 year and 5 year periods.



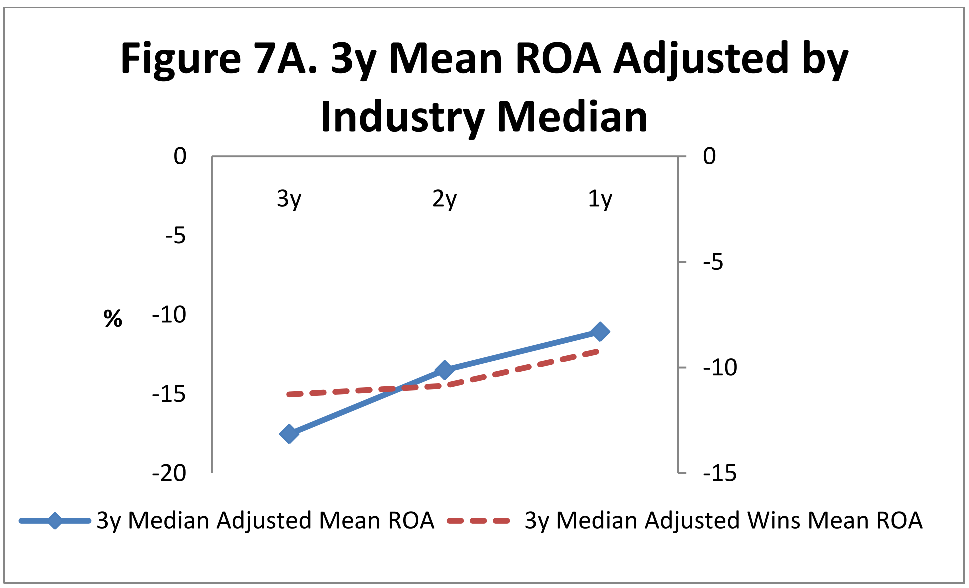


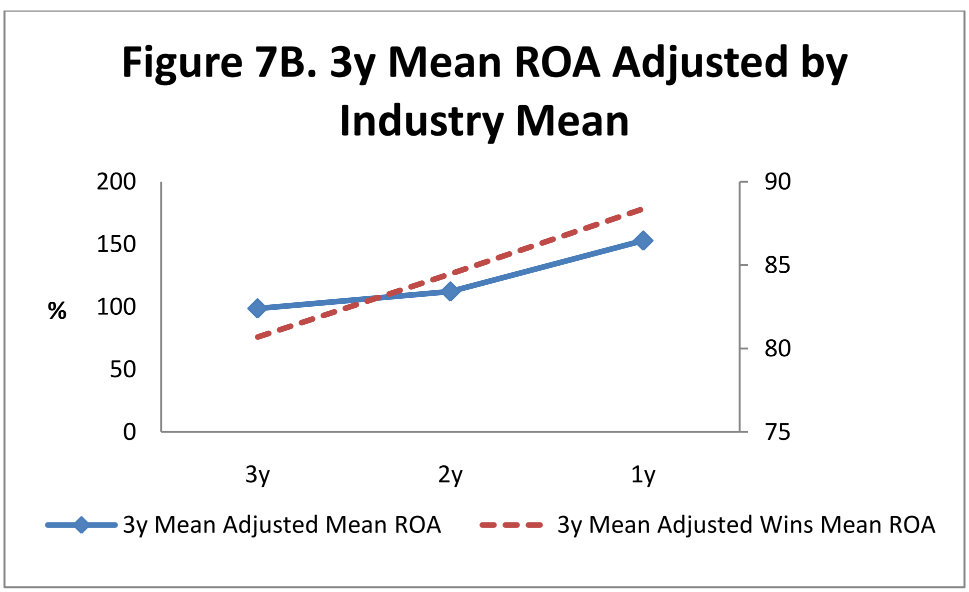
The values plotted in Figures 6A and 6B are average ROA adjusted by the industry mean. One can conclude that firms who will become acquirers underperform, on average, the industry median ROA on a given year. However, when performance is adjusted by the industry mean, future acquirer outperform their peers by a huge margin. Two explanations are possible. First, the firms that outperformed their respective industry did it in a most extreme way, pulling the mean ROA up. Second, it may be due to the fact that some industries had a really low number of observations which may have led to an extremely low average performance for a given SIC code: 25 industry-years have a total number of observations of one and 262 have less than thirty over a total of 722 industry-years.

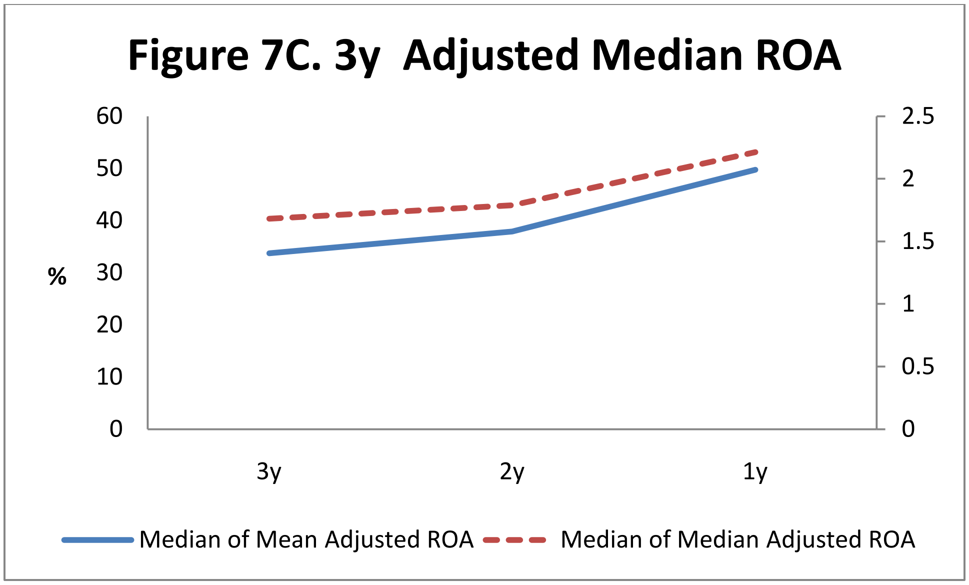


These graphs do not completely reflect the sample firms since the sample mean tells only part of the story. Figure 6C gives a better understanding of firm performance prior to acquisition: the effect of firms with extreme performance is neutralized and the plot gives a better idea of the performance in the sample. When we consider the median of both the industry mean and median adjusted ROA, it becomes clear that the majority of acquirers-to-be outperform their industry prior to making a bid. All the above graphs show the same trend: increasing performance from year -3 to year 0.

When plotting the same values over the three year period, (figure 7A through 7C), the results are essentially the same, except that the sample size is much larger due to the extended availability of the data. Once again, firms underperform their industry when their ROA is adjusted with the industry median, while they outperform when adjusted by the industry mean. As was the case with the 5 years median graph, the majority of firms outperform their industry in 3 years leading to the first bid, with the same upward trend that was exhibited in the 5 year graph.







From the results of this section, one can conclude that the majority of firms that are going to make a first bid show an increasing performance in the three years prior to the deal, and outperform other firms in their respective industry during that period. This is contrary to the view that firms make acquisitions to improve their performance. The underlying motivation for acquisition may be to maintain the high level of performance that the acquiring firm has pre-bid. The results shown here are consistent with Asquith et al. (1983), Roll (1986), Harford (2004) and Bradley & Sundaram (2004;2006) who also find that acquirers-to-be perform better than their competitors, and that firm performance may very well drive acquisitions.

V.Methodology

a. Sample Matrix

The first step to testing the hypothesis is to organize the matched sample into a matrix of acquirers based on their growth and resources. Using the definition of growth and resources of Palepu (1982), growth is defined as the average sales growth of the past 2 and 3 years, depending on data availability, since it is a good proxy for the company's past growth before acquisition.

For the resource component of the firm, two things have to be considered: current liquidity and the potential to raise capital. Since a firm's cash on hand and liquid investments are expected to have a direct impact on the firms' acquisition decisions, it needs to be included in the resource component of a company. However, cash is an absolute value and doesn't have the same relative importance depending on the size of the firm: a multi-billion firm with $10M on hand does poorly in terms of liquidity against a firm with a $100M market capitalization with the same cash position. For this reason, the ratio "Cash and Short-term Investments / Total Assets" is used to define liquidity. The leverage ratio (Debt / Equity) is used to measure the firms' potential to raise capital. As leverage increases, the firm's risk of default also increases, dragging the cost to raise debt with it. With a higher cost of debt, it becomes less appealing for a firm to raise capital using this method. Thus, a low value of leverage means a high potential to issue debt, while a higher value of leverage reduces that potential.

For a firm's growth and cash to be considered as "high", it has to be above the median value of its respective industry for the current year while those under the median are classified as "low". When leverage is higher than the industry median, the firm has a lower debt issuing potential and thus has lower resources. The opposite is true if leverage is smaller than the median. Thus, for a firm to be in the low-growth and high resource sample, it has to have lower sales growth, leverage, and higher liquidity than the respective industry median. Panel A. of Table 5 summarizes the 4 subsamples using these definitions of growth and resource. For firms making more than one acquisition in a year, only their first annual bid was kept. Firms that didn't qualify in one of the 4 above categories or lacked data availability for the computation of *Growth* or Resource are summarized in Panel B. of the table.

The industry median was chosen arbitrarily as an objective measure of comparison between the firm and the industry. It has the drawback of clustering the firms with extreme values with those who are just a little better than the industry, but still acts as a good benchmark to assess the firm's usage of its growth and resources.

Table 5. Growth-Resources Matrix

The matrix in Panel A. classifies the firms according to their respective growth and resources. To be classified as high growth, a firm must have its average last 2 years sales variation greater than the industry median. To be in the high resource category, the firm must have higher cash and short term investment over total asset **and** lower leverage than the industry median. Panel B. reports the results for firms that were not classified in a growth-resources tier. *Cash* and *stock deals* consist of deals where the mode of payment was 100% cash or stocks and *Mixed Deals* are deals where both cash and stocks were used.

Panel A. Matrix of Classified Firms

Resource		**Growth** High		**Growth** Low	
High	# Firm-Years	7087	# Firm-Years	6492
High	# Bids Next Year	480 (**6.77%**)	# Bids Next Year	289 (**4.45%**)
High	Cash Deals	71 (14.79%)	Cash Deals	66 (22.84%)
High	Stock Deals	198 (**41.25**%)	Stock Deals	62 (21.45%)
High	Mixed Deals	60 (12.5%)	Mixed Deals	37 (12.8%)
Low	# Firm-Years	8147	# Firm-Years	8217
Low	# Bids Next Year	659 (8.89%)	# Bids Next Year	512 (**6.23%**)
Low	Cash Deals	176 (26.71%)	Cash Deals	143 (27.93%)
Low	Stock Deals	147 (22.31%)	Stock Deals	84 (16.4%)
Low	Mixed Deals	97 (14.72%)	Mixed Deals	63 (12.3%)

Panel B. Unclassified Firms

# Firm-Years	77749
# Bids Next Year	2446 (3.15%)
Cash Deals	447 (18.27%)
Stock Deals	717 (29.31%)
Mixed Deals	273 (11.16%)

Firstly, when comparing the unclassified firms with those classified in the growth-resources tiers, one can quickly see that firms in all four combinations of growth and resources have higher occurrences of making a bid. Cash deals are more prevalent in all but the high growth- high resources sample than for the unclassified firms while the opposite is true for stock deals.

Three observations stand out from the table: high-growth high-resource firms are the most frequent users of stock for acquisitions (over 41% of their acquisitions). These firms are using their highly valued stocks to make an acquisition despite having a lot of cash. This is further confirmed when compared to the sample of firms that were not classified in any growth-resources tier.

Second, firms in the “low-low” sample are almost as likely to make an acquisition as those in the high-high (6.23% vs 6.77%) and 28% of their deals are paid cash even though their resources are low. Last and most importantly, firms with low growth, high resources, which we expected to have the greatest incentives to make an acquisition to correct this imbalance, are less likely to make a bid in the next year. This finding is surprising, and a possible explanation is that these firms are acquired before they even have a chance to make a bid. This view is consistent with Jensen & Meckling’ (1983) argument that the market for corporate control acts as a disciplinary force: managers who accumulate a lot of idle cash would be taken over by a more efficient management team.

To investigate this possibility, all deals where a firm was the target of a majority interest purchase or a merger were extracted from SDC, for the period of 1995 to 2005, and matched with the estimation sample of acquirers using the 8-digit CUSIP. From the initial sample of 7031 targets, 3038 deals were successfully matched. These successful matches were then divided in 4 subsamples using the same criterions as the acquirers.

In Table 6 are shown the comparative matrixes for bidders and targets where the hypothesized and observed acquiring/acquired frequencies are reported. The probability to make an acquisition P(A) and become a target P(T) are reported for each quadrant. The definition of resources has been relaxed to increase the sample size[8]: only the variable cash and short term investments over total assets is considered as the use

[8] The matrixes using both leverage and short term liquidity as well as exclusively leverage for the definition of resource are available in the appendix.

of the combination of both low leverage and high cash reduced the targets sample greatly.

TABLE 6. Growth-Resources Matrixes Comparing Expected and Actual Probability of M&A Activity

The left matrix shows the hypothesized likelihood that a firm will make a bid or become a target in the next year based on its level of growth and resources. The right matrix displays the actual frequency for both targets and acquirers. To be classified as high growth, a firm must have its average last 2 year sales growth greater than the industry median and to be in the high resource category, it must have higher cash and short term investments over total assets than the industry median **only.**

Hypothesized Likelihood of M&A Activity

		Growth	
		High	Low
Resource	High	Low p(A) Low p(T)	High p(A) High p(T)
	Low	Moderate p(A) High p(T)	Low p(A) Low p(T)

Actual Frequency of M&A Activity

		Growth	
		High	Low
Resource	High	P(A):7.14% P(T):4.39%	P(A):4.88% P(T):3.82%
	Low	P(A):7.16% P(T):3.89%	P(A):4.45% P(T):3.77%

Several interesting insights are evident from the above matrices: counter to what was expected, the growth-resource mismatch had little impact on the observed frequency of targets. The likelihood of becoming a target is qualitatively higher in the High/High quadrant and qualitatively lower in the Low/Low quadrant. In contrast, the frequency of acquisitions is much higher in the quadrants reflecting high growth. For the quadrant with high resources and low growth, the likelihood for a firm to become a target isn't high as expected given their high resources, which still doesn't explain why these firms aren't making acquisitions. This suggests that managers of high resource / low growth firms either aren't actively seeking to acquire for the sake of acquiring or that these managers are entrenched and consequently are protected from the disciple of the market.

According to these matrixes, growth appears to be strongly associated with the frequency of acquisitions. More than 7% of firms in both high growth sub-samples became acquirers while less than 5% became acquirers in the low growth subsamples. This suggests that the growth-resource imbalance potentially holds: firms may try to make an acquisition of a resource-rich firm to fuel their own high growth, but are not necessarily willing to spend their resources on acquisitions for the purpose of increasing their low growth. There is little distinction made across the samples for potential targets as the proportion of firms being taken over doesn't vary significantly. A test on two proportions confirmed the robustness of the differences between the four tiers with significance of 1%.

VI.The Models

The Growth-Resources Ratio

In this section I test the relationship between the probability of acquisition and the growth-resources imbalance hypothesis in a multivariate setting. The growth-resource ratio is the primary variable of interest in explaining the probability of a firm becoming an acquirer. The variables used to proxy for growth are the average sales growth over the past two years (reflecting past firm growth), and cash and short term investments divided by total assets[9]. As a robustness check, the average growth period was also extended to 3 years. Two alternate definitions of growth using the market-to-book ratio rather than past sales are also used and reported in the appendix. The use of this ratio differs from the sales growth since the market value reflects the investors' evaluation of future growth opportunities. The first alternative is to use the average last two years

[9] (Avg 2yrs Δ Sales) / (cash & short term Inv. / Total Assets)

change in the ratio to represent the average *change* in expected growth of the firm by investors. The average market-to-book ratio over the last two years is used as the second alternative definition to reflect the average *expected* growth of the firm. These variables are also computed for the three year period when data is available and can prove useful to determine if the market can anticipate the occurrence of an event long before it actually happens.

The resources of a firm can also be proxied by many alternative definitions. Cash and short term investment relative to the book value of the firm is used to reflect the true value of cash relative to the firm[10] to complement the cash over total assets resources proxy. Then, the free cash flows over total assets to measure the effect of an increase in cash reserves of a firm on the probability of making an acquisition is used. The results of these alternative definitions are also reported in the appendix.

The squared growth-resource ratio is also included in the analysis to give us the expected parabolic shape of the probability to make an acquisition. It also ignores the effect of a firm's negative growth on the dependant variable and influences the probability to make a bid based on the "absolute" value of the growth, and the ratio.

The Control Variables

The model also contains several control variables. *Leverage* acts as a proxy for a firm's capital structure and ability to raise debt and is used as a control variable since it is not included in the growth-resource ratio. *Merger* is a dummy variable that equals to 1 if the acquisition occurred during a merger wave (1995-2000) and *recession* is a dummy variable having a value of one if the year of the deal was declared a recession according to the National Bureau of Economic Research (NBER). *Past growth* is a variable that takes different definitions depending on the growth component of the growth-resource ratio. If, in the ratio, past sales growth is used, then the control variable *Past Growth* is

[10] Cash is an important component included of a firm's total assets and using the book value of a firm avoids having the variable in both the numerator and the denominator of the resource component. Therefore, it reflects the "real" value of money compared to the firm's used assets.

defined as the average past **anticipated growth** of a firm by the market proxied by the average past market-to-book ratio. If, on the other hand, the growth component of the ratio is proxied by either alternate definition using the market-to-book ratio, then the control variable *Past Growth* is proxied by the average past sales growth. These control variables are used to capture both the past expected growth and the actual past growth of a firm in the model. *Firm size* is estimated using a firm's total assets. Unlike most studies using OLS, this analysis uses the absolute value of a firm's asset and not its natural logarithm. The reason is simple: the nature of the logit model equation uses the $e^{\beta x}$ component which differs with the regular OLS regression. The purpose behind logging the total asset values is to assess the impact of a **percentage change** in the control variable on the dependant variable. Thus, if we log total assets, then the component becomes $e^{\beta \ln(x)}$ which is the equivalent of $x * e^{\beta}$, which reverts back to the absolute value of the variable. One can quickly see that logging the variable results in an automatic reverting to the original ''absolute'' value which would create the same issues as using the un-logged values in an OLS regression.

All the variables used in the models are summarized in Table 7. The correlation matrix in Table 8 shows that the sample doesn't suffer from multicollinearity issues.

Table 7. Variables Used in the Logit Models

Variables	Description	Compustat Item Id Used to Compute Variables
Growth Variables		
2 Years Sales	The average sales growth of a firm 2 years before y=0.	SALECHG1
3 Years Sales	The average sales growth of a firm 3 years before y=0.	SALECHG1
2 Years ΔMTB	The average *change* in market-to-book ratio for the past 2 years.	(BKVLPS*CSHO)/MKVAL
3 Years ΔMTB	The average *change* in market-to-book ratio for the past 3 years.	(BKVLPS*CSHO)/MKVAL
2 Years MTB	The average value of the market-to-book ratio for the past 2years.	(BKVLPS*CSHO)/MKVAL
3 Years MTB	The average value of the market-to-book ratio for the past 3 years.	(BKVLPS*CSHO)/MKVAL
Resources Variables		
Cash/TotAss	A firm's cash and short term investment over total assets.	CHE / AT
Cash/Bvfirm	A firm's cash and short term investment over the book value of the firm.	CHE / (BKVLPS*CSHO)
FCF/TotAss	A firm's total free cash flow over total assets.	FREECFL / AT
Control Variables		
Firm Size	A firm's total assets	AT
Leverage	A firm's total debts over total equity	DT / CEQ
Merger Wave	Dummy variable with a value of 1 if the current year is included in a merger wave.	-
Recession	Dummy variable with a value of 1 if the year is considered as a recession year.	-

Table 8. Correlation Matrix

The growth-resources ratio (G/R) is computed as (average last 2 year sales change/ (Cash & short term investment / Total assets)). G/R^2 is the value of the growth resources ratio squared. Firm size is proxied by a firm's total asset, leverage by total debt / total equity and past growth represent the average last 2 years market-to-book ratio.

Varivable	*G/R*	*(G/R)^2*	*Firm Size*	*Leverage*	*Past Growth*
G/R	1				
(G/R)^2	0.9382	1			
Firm Size	-0.0128	-0.0142	1		
Leverage	0.0243	0.0117	0.0519	1	
Past Growth	-0.0085	-0.0095	0.0583	0.0244	1

<u>The Estimation Sample</u>

For the next sections, I use an estimation sample that covers the period 1995 to 2005. I keep a holdout sample from 2006 to 2008 to test the predictive ability of the model. Table 9 summarizes both samples, as well as the population from which they were taken (the population is the combination of the working and holdout samples). All the variables reported in this descriptive statistics table have been winsorized in both tails of the distribution (0.5% of observations in each tails) prior to forming the estimation and hold-out samples which explains why most variables have identical ranges through the samples. At first glance, the negative leverage may seem odd but these values are due to firms' negative equity on their balance sheet. While this is counterintuitive, a firm with high leverage can sometimes be forced to write off some of its assets enough that they become smaller than its liabilities, thus creating negative equity. Another possible explanation for the negative values includes a massive share repurchase or dividend payment that would reduce the assets value and decrease the equity into negative territory. Last, a drop in equity can be due to firm that reports net losses over the years. Reasons for negative equity in the sample are not investigated in this study.

Table 9. Descriptive Statistics of the Estimation Sample, Holdout Sample and the Population

	Estimation sample						Holdout Sample						Population					
Firm Characteristics	**Obs**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**	**Obs**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**	**Obs**	**Mean**	**Median**	**Std.Dev**	**Min**	**Max**
Total Assets ($M)	74262	1410.2	79.1	5657.1	0.0	58292.7	11302	2643.5	169.1	8320.8	0.0	58292.7	85564	1573.1	86.9	6090.5	0.0	58292.7
Total Debt ($M)	73236	345.0	6.1	1375.9	0.0	13806.5	11082	572.5	9.2	1837.5	0.0	13806.5	84318	374.9	6.4	1447.1	0.0	13806.5
ROA (%)	72802	-45.0	0.8	224.1	-2500.0	46.5	11016	-49.4	2.2	250.8	-2500.0	46.5	83818	-45.6	0.9	227.8	-2500.0	46.5
ROE (%)	63721	-42.0	4.5	211.8	-2118.3	181.5	9821	-27.6	6.5	173.2	-2118.3	181.5	73542	-40.0	4.8	207.1	-2118.3	181.5
BVFirm ($M)	71211	473.1	36.5	1590.6	-114.4	11908.6	10787	866.4	85.7	2288.4	-114.4	11908.6	81998	524.9	40.7	1704.0	-114.4	11908.6
Debt/ Total Assets (%)	72918	34.8	17.6	94.8	0.0	1089.4	11041	36.6	13.9	112.3	0.0	1089.4	83959	35.0	17.1	97.3	0.0	1089.4
Leverage	73931	0.5	0.2	3.1	-18.5	24.3	11272	0.4	0.1	2.7	-18.5	24.3	85203	0.5	0.1	3.1	-18.5	24.3
MTB Ratio	43707	2.8	1.8	10.6	-63.2	79.2	10096	2.8	2.1	8.9	-63.2	79.2	53803	2.8	1.8	10.3	-63.2	79.2
Growth & Resources																		
Average 2yrs sales growth (%)	50311	44.8	10.4	182.4	-79.9	1919.8	13526	43.8	12.7	182.0	-79.9	1919.8	63837	44.6	11.0	182.3	-79.9	1919.8
Average 3yrs sales growth (%)	41102	40.5	10.7	154.6	-59.6	1657.8	12753	40.5	12.9	158.2	-59.6	1657.8	53855	40.5	11.3	155.4	-59.6	1657.8
cash/totass	73745	0.2	0.1	0.3	0.0	1.0	11246	0.3	0.1	0.3	0.0	1.0	84991	0.2	0.1	0.3	0.0	1.0
cash/bv	71211	0.3	0.2	0.8	-4.4	5.8	10787	0.4	0.2	0.8	-4.4	5.8	81998	0.3	0.2	0.8	-4.4	5.8
fcf/totass	73745	-0.1	0.0	0.6	-6.2	0.4	11246	-0.2	0.0	0.8	-6.2	0.4	84991	-0.2	0.0	0.7	-6.2	0.4
Growth-Resources Ratios																		
2yrs/cashtotass	45056	1406.3	93.2	7261.3	-5958.0	79619.6	9115	1335.9	93.2	7508.3	-5958.0	79619.6	54171	1394.5	93.2	7303.4	-5958.0	79619.6
2yrs/cashbv	43949	445.0	43.6	2837.1	-11323.2	28580.4	8777	404.4	44.4	2766.1	-11323.2	28580.4	52726	438.2	43.8	2825.4	-11323.2	28580.4
2yrs/fcftotass	39297	-86.0	18.4	3704.8	-29962.8	23704.5	9046	-20.2	52.7	3168.2	-29962.8	23704.5	48343	-73.7	23.7	3610.5	-29962.8	23704.5
3yrs/cashtoas	36759	1332.5	94.8	6650.3	-4033.7	74088.6	8633	1325.0	99.3	7247.7	-4033.7	74088.6	45392	1331.1	95.8	6767.9	-4033.7	74088.6
3yrs/cashbv	35853	376.0	42.8	2515.9	-11540.6	25301.6	8308	380.9	45.9	2564.6	-11540.6	25301.6	44161	377.0	43.5	2525.1	-11540.6	25301.6
3yrs/fcftotass	36051	-40.7	23.5	3383.1	-26449.6	22877.5	8560	-25.2	56.4	2981.5	-26449.6	22877.5	44611	-37.8	27.1	3309.8	-26449.6	22877.5

Logit Models

This study deals with estimating the probability of the occurrence of certain events that have 2 or 3 different outcomes, depending of the context. It thus requires the use of logit models. The first models predict the probability that a firm will become an acquirer in the year Y+1 where Y is the current year. Since this event has only two categorical responses (acquires next year or does not acquire next year), a binary logit model is used. The same model is also used to test if the firm will become a target in the year Y+1.

In the market for corporate control, a firm isn't limited to a simple yes/no type of decision (like acquiring or not; be acquired or not): it has the freedom to make a choice between these mutually exclusive events: become acquirer, be taken over or do nothing. As the dependant variable isn't binary but has multiple outcomes I use the multinomial logit model to complement the binary logit. However, the multinomial logit model relies on an important assumption: the independence of irrelevant alternatives (IIA). This means that adding or removing an alternative outcome should not alter the odds ratio between the other alternatives. In this case, let's suppose that P(Acquire) is 20% and P(Status Quo) is 80%: the odds ratio is 20/80 = ¼. Now if we add P(Target) with a probability of 20%, then P(Acquire) should become 16% and P(nothing) 64% so that the odds ratio remain constant (16/64 = ¼). However, suppose that the manager of a cash-rich firm would prefer to make an acquisition in order to avoid being taken over, then P(Acquire) will increase relative to P(Status Quo) that will stay the same or (most likely) diminish as the manager fears for the continuity of his position. With P(Target) now a possibility, P(Acquire) is now 20% and P(Status Quo) is 60%. Now the odds ratio dropped to 1/3 (20/60).

If such is the case, then the multinomial Logit model will necessarily make estimation errors on P(Acquire) and P(Target) and the results will be biased. To overcome this violation, it is possible to use a multinomial Probit model, which assumes that the outcomes are jointly normally distributed and can be correlated. These properties thus relax the irrelevant alternative property of logit models.[11] Computing such models used to be very challenging and thus they weren't extensively used, but it has become increasingly feasible with the recent statistical packages. However, the maximum likelihood function usually used in this to estimate the parameters is still difficult as it involves integrating joint normal distributions. Most statistical packages, including Stata (the one used in this study) use *simulated* likelihood techniques relying on random draws and *MonteCarlo* simulations. This is true even for the simplest of cases where 3 outcomes are possible and the methodology gets increasingly complicated and time consuming as more outcomes are added.

It is still unclear if multinomial logit performs better than the multinomial probit. For example Kopko (2007) finds that it performs better in predicting the vote-choice of an elector in the case of multiparty voting (with 3 or more outcomes) despite the violation of the IIA assumption.

In this study, several problems occurred when estimating the multinomial probit model using the growth-resources ratio: the computing time was extreme and the logarithm of the likelihood didn't converge. For that reason, the multinomial probit isn't reviewed here and the few results that could be computed are included in the appendix to compare its performance with the multinomial logit.

[11] For an extensive coverage of the MNP, the reader can refer to McCulloch & Rossi (1994) as the model is not reviewed in this paper.

VII. Results

a. Binary Logit

The logistic function, in its probability form, is described as:

$$P(y = 1) = \frac{e^{\beta x}}{e^{\beta x}+1} \quad (1)$$

$$\text{Or } P(y = 0) = \frac{1}{1+ e^{-\beta x}} \quad (2)$$

Where x is a vector of independent variables and f(x) represents the probability of becoming a bidder in the year Y+1. The model can also be explained with its logit from as:

$$\ln \frac{(P(Y=1)}{1-P(y=1)} = \sum_{k=1}^{k} \beta_k X_k \quad (3)$$

The vector X is defined as:

$$\beta_0 + \beta_1 * \frac{\text{Growth}}{\text{Resources}} + \beta_2 * \left(\frac{\text{Growth}}{\text{Resources}}\right)^2 + \sum_{i=1}^{k} \beta_k X_k + \epsilon \quad (4)$$

where X_k is the set of control variables. Of course this binary logit models only applies when there are two possible outcomes or events for a given situation: the use of this model alone would make an incomplete study that doesn't account all the possibilities of a firm.

Results are presented in this section in two parts: first the binary logit models are exposed for both acquirer and targets where pPcquire) vs P(Status Quo) and P(Target) vs P(Status Quo) are considered to be two exclusive sets of outcomes. Then, I use a 2-step binary logit model to determine if a firm will first be active in the takeover market and in the second step, if it will become an acquirer or a target given the fact that it will become active. The second part reviews the multinomial logit model that is applied to take into account the more realistic approach that a firm has 3 choices in the market for corporate control (acquire, target or nothing) rather than only 2.

An important thing to consider is that only the results where a firm's growth is defined as "average last 2-3 years sales change" are presented. The tables summarizing results where the growth is computed with the firm's market-to-book ratio and change in market-to-book are presented in the appendix for robustness checks. Results with the 3 different definitions of resources are presented for each of the growth variables to facilitate comparisons between the models. The difference is sample size for the different regressions is due to the availability of the data for the different components of the growth-resource ratio. The P-Values are reported between brackets under their respective coefficients.

Table 10. Binary Logit Model Using the Growth-Resources Ratio

This table summarizes the coefficients of the independent variables on the probability to become an acquirer (panel A.) and a target (panel B.) A description of the growth and resources components of the ratio is provided for each regression in the first two rows. The variable *Past Growth* is expressed as the average last 2 years (3 years) market to book ratio, which represents the average past anticipated growth of the firm by the market.

Panel A. Acquirers

Growth Description	**2 Years Sales**	**3 Years Sales**	**2 Years Sales**	**3 Years Sales**	**2 Years Sales**	**3 Years Sales**
Resources Description	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/Total Assets**
G/R	0.000019	0.0000183	0.0001432	0.0001205	0.0000107	0.0000337
	(0.123)	(0.246)	(0)***	(0)***	(0.114)	(0)***
G/R^2	-4.91E-10	-5.10E-10	-8.22E-09	-6.24E-09	8.27E-12	-2.32E-10
	(0.029)**	(0.086)*	(0)***	(0.001)***	(0.643)	(0.606)
Firm Size	0.0000535	0.0000479	0.0000532	0.0000477	0.0000537	0.000048
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	0.0273398	0.0237332	0.0279723	0.0246159	0.0274624	0.0238193
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Leverage	-0.0049798	-0.009141	-0.0077478	-0.120013	-0.0057181	-0.0102716
	(0.587)	(0.386)	(0.411)	(0.271)	(0.536)	(0.337)
Merger Wave	0.1767491	1.752016	0.1517971	1.710129	0.1987219	1.787759
	(0.005)***	(0)***	(0.017)**	(0)***	(0.002)***	(0)***
Recession	-0.1982395	-0.2241861	-0.2042722	-0.2301953	-0.1922233	-0.2263112
	(0.008)***	(0.004)***	(0.006)***	(0.003)***	(0.01)***	(0.004)***
Intercept	-2.750024	-2.68146	-2.751035	-2.684645	-2.751972	-2.681531
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	21509	16162	21230	15932	21277	16023

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Panel B. Targets

Growth Description	2 Years Sales	3 Years Sales	2 Years Sales	3 Years Sales	2 Years Sales	3 Years Sales
Resources Description	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/Total Assets**
G/R	0.0000336	3.83E-06	0.0001368	0.0000743	-1.35E-05	-0.0000179
	(0.224)	(0.912)	(0.097)*	(0.251)	(0.443)	(0.469)
G/R^2	-8.06E-10	-5.26E-11	-1.60E-08	-3.81E-09	-1.07E-10	-5.31E-10
	(0.189)	(0.923)	(0.109)	(0.279)	(0.637)	(0.649)
Firm Size	-0.0000138	-0.0000149	-0.0000144	-0.000015	-0.0000117	-0.0000139
	(0.24)	(0.239)	(0.221)	(0.237)	(0.309)	(0.266)
Past Growth	0.0102447	0.0136028	0.104428	0.0145473	0.0108276	0.0139703
	(0.132)	(0.119)	(0.134)	(0.101)	(0.114)	(0.11)
Leverage	0.0068924	0.01638	0.0058609	0.016002	0.0101451	0.0190978
	(0.73)	(0.464)	(0.776)	(0.491)	(0.614)	(0.395)
Merger Wave	0.0078227	0.7217154	0.0149843	0.7054269	-0.0309154	0.7512796
	(0.959)	(0.037)	(0.921)	(0.041)**	(0.843)	(0.03)**
Recession	-0.085014	-0.1664481	-0.0521469	-0.1397156	-0.0624099	-0.1270732
	(0.599)	(0.346)	(0.747)	(0.429)	(0.702)	(0.471)
Intercept	-4.306088	-4.326525	-4.300962	-4.340157	-4.323016	-4.344835
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	21509	16162	21230	15932	21277	16023

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Table 10 presents the results for the binary logit model. For these preliminary results, the important variables are the growth resources ratios. From panel A. that reports coefficients for future acquirers, half the cases are insignificant. Overlooking the significance, it is always positively related to the probability of a firm to make an acquisition. Firm size is also positively related to making an acquisition, which makes sense since their size makes it easier for them to "digest" the big financial acquisition that are mergers and acquisitions when compared to smaller firms. The variable growth, representing the average past anticipated growth by the market is also positively related to the probability of an acquisition. This relationship is consistent with the view that firms tend to have better performance pre-acquisition assuming that it is anticipated by the market prior to the bid. If the growth component of the ratio is calculated on a 3 year period, the effect of the merger wave control variable increases dramatically on the dependent variable.[12] A possible explanation for this result is that observations that use a 3-year period were computed from 1998 and onwards, whereas observations using a 2-year period started from 1997. Because the merger wave lasted from 1995 to 2000 and the sample ranges from 1995 to 2005, it is possible that the *Merger Wave* effect on the probability of acquisition increased a lot for the 3-year period due to the much smaller amount of observations that were included in a merger wave. Nonetheless, this result is still puzzling.

In contrast, Panel B of Table 10 shows the results for the same models but using the probability of becoming a target as the dependant variable. Not surprisingly, the vast majority of the results lack statistical significance. It is interesting to see the impact of different definitions of the resource component of the growth-resources ratio: ignoring the statistical insignificance, when it is measured as cash, the impact on the probability of becoming a target is positive while it is negative when using free cash flows. This would suggest that a short-term rise in a firm's liquidity is an important criterion for a firm to become a target. Also, firm size is negatively correlated with being a target, which is consistent with the generally accepted view that size acts as a deterrent to takeover activity.

As an alternative approach, I divided the sample into 4 subsamples classified as high or low growth and resources and then estimated the probability models within each

[12] Running the same regressions without the *Merger Wave* variable didn't yield differences in the results: same sign of coefficients and no difference in statistical significance.

subsample. To be considered on the high resources side, a firm must have higher cash over total assets **and** lower leverage than the industry median. The opposite combination applies for the low resources category. To be considered as a high (low) growth firm, the average past 2 years sales growth has to be higher (lower) than the industry median. These subsamples represent each tiers of the aforementioned growth-resource matrix and allow further testing of the growth-resource imbalance on the probability of acquisition. More precisely, this alternative approach can shed light on the relative importance of the growth-resource ratio for both subsamples where there is an imbalance and see how it contrasts with those who don't. Firms that did not fit into either of these subsamples were not included in these models.

Table 11 reports the results for each subsample. The growth variable used in the growth-resources ratio is the past average MTB ratio to avoid a bias in the results since the coefficient of the ratio would most likely be affected by the way each subsamples were divided if the growth definition was kept as the average sales change. The variable past growth is still included in the model so that the regression is consistent with the ones mentioned above: because the growth component of the ratio is computed with the average MTB change, the control variable "past growth" is the average past sales growth, for the same period (2 or 3 years) as the growth component of the ratio.

TABLE 11. Binary Logit Model Using the Split Subsamples

This table summarizes the results of the binary logit model estimated for the following 4 subsamples: high growth-high resources, high-growth-low resources, low growth-high resources and low growth-low resources. To be included in the high growth tiers, a firm must have a higher past average 2 years sales growth than the industry median whereas to be included in the high resource tier, it has to have higher cash over totals assets **and** lower leverage than the industry median. The opposite is also true for the low growth and low resources tiers. The description of the growth component of the ratio is given in the table for each regression. The resources component is "Cash & Short-Term Investments/Total Assets". The *Past Growth* control variable is defined as "average last 2 years (3 years) sales change".

Subsample (Growth-Resources)	**High-High**		**High-Low**		**Low-High**		**Low-Low**	
Growth Description	**Average 2y MTB**	**Average 3y MTB**	**Average 2y MTB**	**Average 3y MTB**	**Average 2y MTB**	**Average 3y MTB**	**Average 2y MTB**	**Average 3y MTB**
G/R	0.025326	0.011039	0.000519	-5.94E-05	0.00024	0.000597	-0.000424	-0.00128
	(0)***	(0.012)**	(0.073)*	(0.859)	(0.89)	(0.831)	(0.244)	(0.007)***
G/R^2	-9.91E-05	-2.49E-05	-2.06E-07	1.11E-08	6.62E-07	1.01E-06	9.16E-08	3.06E-07
	(0.002)***	(0.265)	(0.053)**	(0.919)	(0.821)	(0.863)	(0.388)	(0.044)***
Firm Size	6.66E-05	6.04E-05	5.44E-05	4.42E-05	5.31E-05	2.84E-05	5.71E-05	5.66E-05
	(0)***	(0)***	(0)***	(0)***	(0)***	(0.02)***	(0)***	(0)***
Past Growth	0.000228	-5.32E-05	0.000298	-1.84E-05	0.000214	-0.000154	-0.000103	0.000895
	(0.561)	(0.918)	(0.524)	(0.98)	(0.747)	(0.912)	(0.929)	(0.553)
Leverage	0.082378	0.063254	-0.066296	-0.02938	0.233954	0.207171	-0.051851	-0.077598
	(0.243)	(0.348)	(0.027)**	(0.302)	(0.121)	(0.239)	(0.088)*	(0.046)**
Merger Wave	0.09244	1.499423	0.095141	1.442957	-0.287417	2.25758	0.224097	1.687729
	(0.582)	(0)***	(0.487)	(0)***	(0.188)	(0)***	(0.163)	(0)***
Recession Year	-0.445876	-0.44549	-0.091818	-0.187377	-0.429453	-0.44856	-0.07429	-0.061259
	(0.027)**	(0.035)**	(0.563)	(0.244)	(0.074)*	(0.093)*	(0.679)	(0.742)
Intercept	-2.937069	-2.640864	-2.381884	-2.262991	-2.828245	-2.900479	-2.729022	-2.609209
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	3106	2295	3517	2560	2865	2049	3458	2619

*, ** and *** denote significance of 10%, 5% and 1%, respectively

In the high-high sample, the results are consistent with those reported thus far[13]: positive and significant relationship between the growth-resources ratio and the probability to make an acquisition and negative coefficient of the ratio squared. The growth-resource ratio loses its statistical significance in the “unbalanced” samples which may be due to the use of the average change in market-to-book ratio as the growth variable instead of the average past sales growth, commonly used by similar models in the mergers and acquisitions literature. Results of the robustness check using alternate definitions of *Resource* (reported in the appendix) are consistent for every model: the growth-resource ratio in the high-high sample is significant and positive while it loses its significance in the other subsamples.

Instead of using ratios, Table 12 shows the same model using dummy variables of interest in identifying if a firm has a growth-resource imbalance for the whole estimation sample. High growth firms have a higher average past sales growth than the industry median and thus a value of “1”. For resources, higher cash and short term investments over total assets than industry median has the value “1” while lower leverage than the industry has the value “1” since more capital is accessible. Therefore, for a firm to have high growth and high resources, for example, the dummy variables are equal to 1 for high growth and high cash, and 1 for low leverage. This model has the advantage of capturing the coefficient of every single combination of growth and resources and not excluding firms from the study: firms with high (low) levels of cash *and* leverage that were previously excluded since they didn’t fit the definition of high (low) resources are now taken into account with the dummy variables.

Most of the coefficients are significant at the 1% level: as expected, firms with higher growth have a higher probability to make an acquisition in the next year, when growth is measured on both a 2 and 3 years basis. Higher cash than the industry also means a

[13]As a robustness check, the binary logit model is also estimated using alternate resource definitions. The results are summarized in Table A.4 in the appendix.

higher probability to acquire, which is consistent with my previous expectations. The coefficient of *Merger Wave* is still dramatically higher when using the average growth over a 3 year period.

Table 12. Binary Logit Model With Dummy Variables

This table summarizes the results from the binary logit model using dummy variables to categorize growth and resources. The first column reports the results where growth is measured as the average 2 years sales change and the second column where it is the average 3 years sales change. The dummy variable "high growth" takes a value of 1 if a firm's growth, measured as the average 2 year sales change is greater than the industry median. The dummy variable "high cash" takes a value of 1 if the resource proxy, measured as cash and short term investments over total assets, is greater than the industry median. The dummy variable "leverage" takes a value of 1 if the firm's leverage is lower than the industry median. *Past Growth* is the average MTB for the past period identified for each column.

Variable	2 Years	3 Years
High Growth	0.4556924	0.3998823
	(0)***	(0)***
High Cash	0.108417	0.0908063
	(0.05)**	(-0.15)
Low Leverage	-0.3185705	-0.2966225
	(0)***	(0)***
FirmSize	0.0000533	0.0000483
	(0)***	(0)***
Past Growth	0.0254265	0.0215055
	(0)***	(0)***
Merger Wave	0.1937141	1.709476
	(0.002)***	(0)***
Recession	-0.1923725	-0.2249061
	(0.01)***	(0.004)***
Intercept	-2.932782	-2.829772
	(0)***	(0)***
N=	21877	16400

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

The results become interesting when we include *leverage* in the combination of growth and resources rather than cash only. With its negative coefficient, it undermines the argument of a firm becoming an acquirer when it has high resources since it has a greater impact on the dependant variable than the dummy *Cash* has. This would mean that, according to these results, high resource firms are not as likely to make an acquisition as previously thought[14]. Firms that are the most likely through the less likely to become an acquirer are, in order, firms with high growth, low resources; high growth, high resources; low growth, low resources; and low growth, high resources. These results are consistent with those reported in the 4-quadrants matrix (Table 5).

The impact of leverage is contradictory to my initial prediction: having lower leverage means having relative easiness to obtain financing to do an acquisition but, according to the results, a firm that has lower leverage than its respective industry is *less likely* to make an acquisition. This result is puzzling and an intuitive explanation is that low leverage helps to finance internal growth organically, which may cause an acquisition with the purpose of acquiring resources less necessary. Also, those firms may tend to become targets given their relatively easy access to capital thereby preventing them from making an acquisition themselves. As for the average past anticipated growth, its positive coefficient strengthens the argument that growth is related to acquisition.

Thus far, only the models based on pairs of outcomes were explained and it was assumed that the third alternative was not relevant. Pushing this idea further, I ran a 2 step logistic regression to take into account of the third outcome: the first step, is to estimate the likelihood that the firm will become active in the takeover market or keep the status quo while the second step is to determine if a "takeover market active" firm is more likely to become an acquirer or a target. Panel A. of Table 13 summarizes the probability of a firm to become active in the takeover market and Panel B. summarizes

[14] This holds, of course, assuming that the definition of high resources suggested by Palepu (1982) of high cash **and** low leverage is correct.

the probability of a firm to become an acquirer given that the firm is active (P(Acquire|Active).

Table 13. 2-Step Binary Logit Model

Panel A. Probability of a Firm to Become Active

The growth and resources variables in the ratio are identified in the first 2 rows of the table. The variable *Past Growth* represents the average Market-to-Book ratio for the period identified in each column of the first row.

Growth	**2 Years Sales**	**3 Years Sales**	**2 Years Sales**	**3 Years Sales**	**2 Years Sales**	**3 Years Sales**
Resources	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/ Total Assets**
G/R	0.0000216	0.0000154	0.0001384	0.0001143	0.0000436	0.0001098
	(0.058)*	(0.288)	(0)***	(0)***	(0.133)	(0.018)**
G/R^2	-5.39E-10	-4.07E-10	-8.43E-09	-5.87E-09	1.10E-06	0.000012
	(0.011)**	(0.114)	(0)***	(0)***	(0.88)	(0.273)
Firm Size	0.0000497	0.0000445	0.0000494	0.0000442	0.0000497	0.0000443
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	0.0248715	0.0227413	0.0254437	0.0236818	0.0249723	0.0229925
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Leverage	-0.0028453	-0.0052413	-0.0053528	-0.0079002	-0.0035469	-0.0064171
	(0.738)	(0.592)	(0.541)	(0.436)	(0.68)	(0.518)
Merger Wave	0.1504823	1.728786	0.1307206	1.690154	0.1643762	1.748199
	(0.012)**	(0)***	(0.029)**	(0)***	(0.006)***	(0)***
Recession	-0.1736612	-0.2121072	-0.1729398	-0.2129785	-0.1665245	-0.2065646
	(0.011)**	(0.003)***	(0.012)**	(0.003)	(0.016)**	(0.004)
Intercept	-2.553287	-2.499933	-2.55311	-2.50499	-2.544426	-2.491259
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	21509	16162	21230	15932	21039	15846

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Panel B. Probability of a Firm to Become an Acquirer Given That It Will Become Active

Growth	2 Years Sales	3 Years Sales	2 Years Sales	3 Years Sales	2 Years Sales	3 Years Sales
Resources	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/ Total Assets**
G/R	-0.0000105	0.0000214	0.0001243	0.0001014	0.000018	0.0000588
	(0.752)	(0.602)	(0.243)	(0.384)	(0.382)	(0.059)
G/R^2	2.09E-10	-5.51E-10	-2.81E-09	-4.74E-09	1.12E-09	1.54E-09
	(0.712)	(0.41)	(0.615)	(0.394)	(0.202)	(0.322)
Firm Size	0.0001074	0.000081	0.000107	0.0000801	0.0001038	0.0000801
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	0.0281392	0.009095	0.027603	0.0083921	0.0267779	0.0072591
	(0.007)***	(0.453)	(0.008)***	(0.488)	(0.011)**	(0.552)
Leverage	-0.0179664	-0.0271282	-0.0197205	-0.0271165	-0.0217723	-0.0289877
	(0.488)	(0.338)	(0.449)	(0.341)	(0.398)	(0.298)
Merger Wave	-0.0463796	0.363874	-0.1001718	0.3321792	-0.0021689	0.3640022
	(0.792)	(0.311)	(0.57)	(0.357)	(0.99)	(0.31)
Recession	-0.2070487	-0.1470938	-0.2716912	-0.1907827	-0.2462343	-0.1987319
	(0.253)	(0.455)	(0.134)	(0.333)	(0.177)	(0.311)
Intercept	1.485375	1.60867	1.474663	1.615501	1.493812	1.625549
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	1945	1555	1933	1544	1919	1541

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

The results from panel A. are very similar to those reported in Table 10 when becoming an acquirer or maintaining the status quo are the only options. This may be due to the greater proportion of acquirers than targets in the sample or that the conclusions drawn earlier about acquirers also apply to targets. As for the second step, the model fails to find any significance in the growth-resource ratio. Only *Firm Size* is still significant and positively related to a firm becoming an acquirer given that it will be active. So far, the models have been shown to be significant in predicting acquirers only.

When the third outcome, being a target, is added in the analysis, the model is unable to distinguish between firms that become targets from those that become acquirers. This result is not completely surprising and requires further testing using models designed to test multiple outcomes.

b. Multinomial Logit and Probit

As discussed earlier, the multinomial logit models are similar to binary logit but they account for more than 2 possible outcomes of the dependent variable. In this case there are three different scenarios that can describe the dependent variable: P(Status Quo) is the base outcome where it is equal to 0 and the firm maintains the status quo, P(Acquire) is equal to 1 and P(Target), 2. The multinomial logit equation is:

$$P(y_i = j) = \frac{e^{(\sum_{i=1}^{N} \beta_{ij} X_i)}}{1 + \sum_{j=1}^{J-1} e^{(\sum_{i=1}^{N} \beta_{ij} X_i)}} \quad (5)$$

and

$$P(y_i = 0) = \frac{1}{1 + \sum_{i=1}^{J} e^{(\sum_{i=1}^{N} \beta_{ij} X_i)}} \quad (6)$$

From which Y_i is defined as an outcome and X_i is a vector of explanatory variables for that outcome. The multinomial and binary logit have very similar equations and computation, but the multinomial explains unordered and discreet polytomous dependent variables instead of dichotomous, like the binary logit . The logit form of the equation is:

$$\ln \frac{(P(Y=j)}{P(Y=J)} = \sum_{\mathrm{k}=1}^{\mathrm{K}} \beta_{\mathrm{jk}} X_{\mathrm{k}} \quad (7)$$

If J=2, then the equation simplifies to the binary logit equation (3). Replacing j and J, we get the probability functions for both the probability that a firm will be an acquirer and a target:

$$\frac{P_{(\mathrm{Acquire})}}{P_{(\mathrm{SQ})}} = e^{\sum_{\mathrm{k}=1}^{\mathrm{K}} \beta_{\mathrm{Acq,k}} * X_{\mathrm{k}}} \quad (8)$$

$$\frac{P_{(\mathrm{Target})}}{P_{(\mathrm{SQ})}} = e^{\sum_{\mathrm{k}=1}^{\mathrm{K}} \beta_{\mathrm{Tar,k}} * X_{\mathrm{k}}} \quad (9)$$

where βAcq and βTar are the coefficients for the different vector of independent variables explaining the likelihood of a firm becoming either an acquirer or a target conditional on being active in the takeover market. The parameters β are the coefficients estimates of interest estimated by maximum likelihood. Just like the binary logit model, the estimated values of the multinomial logit are not absolute probability values but rather the logarithm of the odds ratio of event j relative to the base outcome, the status quo.

Table 14 presents the results from the multinomial logit[15] for the 2 outcomes of interest using the dummy variables representing high growth and high resources. For predicting both acquirers and targets, the coefficients are similar and of the same sign, but they have a significantly greater influence on the dependent variable for bidders. These results are very similar to those presented using the binary logit model: firms with higher growth, cash *and* leverage than the industry median are more likely to make a bid while those with low growth, low cash and low leverage are the less likely. Qualitatively similar conclusions can be drawn for targets.

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[15] A complementary table reporting results from the multinomial Probit model using the dummy variables is available in the appendix if the reader wishes to compare results of both models. However, the multinomial Probit is not reviewed here due to the convergence issues: while the computer found a solution to the model using dummy variables, it ran calculations for several hours without finding results when using the growth-resource ratio, preventing this study to benefit from the input of such a model.

The coefficients of *leverage* are always significant at the 1% level and negative. Firms with higher leverage than their peers are more likely to become either a target or a bidder. The relationship is stronger for targets, which suggests that firms with high leverage or potential financial difficulties are more likely to become targets. This makes sense, since a firm in trouble with too many debts resulting from poor managerial decisions is a good acquisition prey.

Table 14. Multinomial Logit Model With Dummy Variables

This table summarizes the results from the multinomial logit model using dummy variables to categorize growth and resources. The first column reports the results for acquirers where growth is measured as average 2 years sales change and the second column reports the results for targets. The dummy variable "high growth" takes a value of 1 if a firm's growth, measured as the average 2 year sales change is greater than the industry median. The dummy variable "high cash" takes a value of 1 if the resource proxy, measured as cash and short term investments over total assets, is greater than the industry median. The dummy variable "leverage" takes a value of 1 if the firm's leverage is lower than the industry median. *Past Growth* is the average MTB for the past 2 year period.

Variable	Acquirers	Targets
High Growth	0.4501954	0.1725072
	(0)***	(0.153)
High Cash	0.093586	0.0272758
	(0.094)*	(0.83)
Low Leverage	-0.313069	-0.5535483
	(0)***	(0)***
Firm Size	0.0000534	-0.0000145
	(0)***	(0.316)
Past Growth	0.0248566	0.0127377
	(0)***	(0.075)*
Merger Wave	0.1770498	0.0886396
	(0.005)	(0.556)
Recession	-0.1886495	-0.0681559
	(0.011)**	(0.676)
Intercept	-2.911022	-4.166654
	(0)***	(0)***
N=	21877	21877
	# of Acquirers = 1661	# of Targets = 291

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

The following table summaizes the results using the growth-resources ratio instead of the dummy variables. The growth variables measured by the average MTB ratio and change in MTB ratio were not included in the multinomial regressions because of their insignificance in the binary logit models. The probit estimations were run but the results are not presented because the likelihood function didn't- converge and there was no output generated by the statistical software used. Therefore, only the multinomial logit is included. [16]

Table 15. Multinomial Logit Model Using the Growth-Resources Ratio

This table summarizes the results of the multinomial logit model. The growth component of the growth-resources ratio is identified in the first row and the resource component is measured by cash / book value of the firm. The variable *Past Growth* is defined as the average market-to-book ratio for the period identified for each column by the growth variable.

Growth	2 Years Sales	2 Years Sales	3 Years Sales	3 Years Sales
Resources	Cash / Book Value of Firm	Cash / Book Value of Firm	Cash / Book Value of Firm	Cash / Book Value of Firm
Variable	**Acquirer**	**Target**	**Acquirer**	**Target**
G/R	0.0001364	0.0001971	0.0001209	0.0000832
	(0)***	(0.031)**	(0)***	(0.214)
G/R ^2	-7.89E-09	-1.99E-08	-6.25E-09	-4.12E-09
	(0)***	(0.077)*	(0.001)***	(0.253)
Firm Size	0.0000533	-0.0000105	0.0000476	-0.0000053
	(0)***	(0.447)	(0)***	(0.699)
Past Growth	0.0273203	0.013375	0.0249778	0.015314
	(0)***	(0.065)*	(0)***	(0.106)
Leverage	-0.0071251	0.0048559	-0.0118044	0.0150933
	(0.451)	(0.817)	(0.28)	(0.527)
Merger Wave	0.1368542	0.0910808	1.746563	1.206615
	(0.033)**	(0.549)	(0)***	(0)***
Recession	-0.1989199	-0.0401628	-0.2294642	-0.1219492
	(0.008)***	(0.807)	(0.003)***	(0.497)
Intercept	-2.737124	-4.297553	-2.674381	-4.333386
	(0)***	(0)***	(0)***	(0)***
N	21230	21230	15932	15932
	# Acquirers = 1666	# Targets = 287	# Acquirers = 1344	# Targets = 212

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

[16] The table included for the discussion uses the ratio of average sales growth / (cash/book value of firm) because it yielded extremely significant results compared to the other two definitions and it is the one used to predict future acquirers in the holdout sample. The other tables using alternate definitions of the growth-resource ratio are available in the appendix.

Results from table 15 are essentially the same as those in the binary logit model for both the 2 and 3 years average growth period: as the growth-resources ratio, firm size and average past anticipated growth increase, so does the probability of acquiring. The coefficient of the squared ratio is still negative and leverage is insignificant for each regression. A recession obviously decreases the probability of either acquiring or being acquired. Once again, we see the dramatic and puzzling increase in the effect of the variable *Merger Wave* is present when using a 3 year rather than 2 year period for the growth component in the growth-resources ratio. As for the targets, most results lack statistical significance. Using 2-year growth, the relationship of the ratio and the ratio squared are of the same sign and relatively similar. However, this result is isolated, given that all previous effects of the ratio on the probability to become a target aren't significantly different than 0.

Discussion and Comparison

The Growth-Resource Ratio

The study of the growth-resource imbalance when defined as a **ratio** has been found to significantly affect the probability of becoming an acquirer but not a target. More specifically, when the ratio is measured as the average sales growth over the relative cash and short term investments to the size of the firm, it has a positive impact on the probability of becoming an acquirer. This means that a relative increase in growth (the numerator of the ratio) always lead to an increase in the probability of acquisition. Measuring the influence on the dependent variable of the firms' resources, in the denominator, is ambiguous: if the firms' growth is negative, making the ratio negative, then an increase in resources will increase the probability to make an acquisition. If however, growth is positive, the same increase in resources will now negatively affect that probability. For this reason, it is necessary to isolate both components of the ratio to shed light on their true impact.

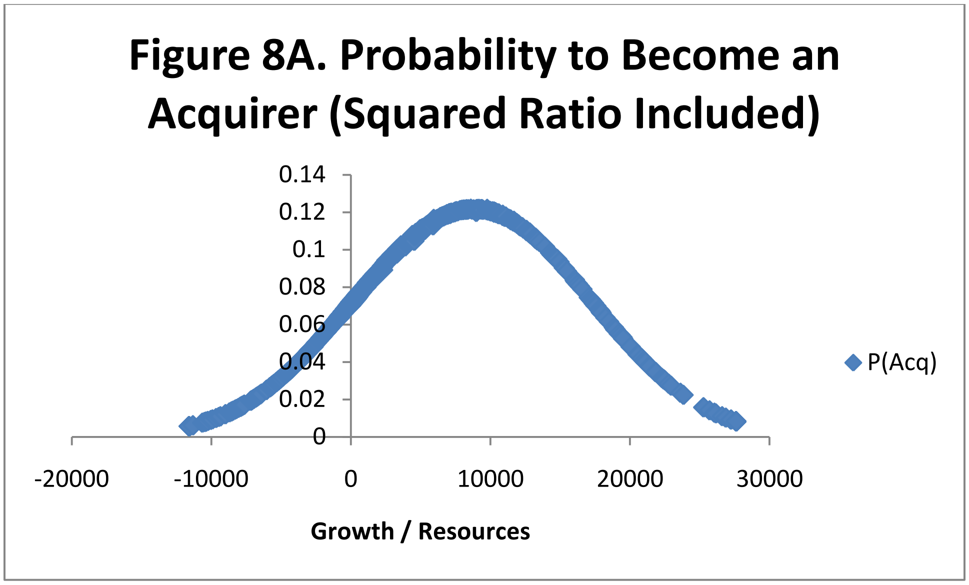
When high growth and high resources are used as dummy variables, they are both found to positively affect the probability to make a bid in the coming year. However, the impact of *high growth* is more important than *high cash*, which strengthens the argument discussed regarding the growth-resources ratio and the fact that growth, rather than resources, seem to be driving acquisition decisions.

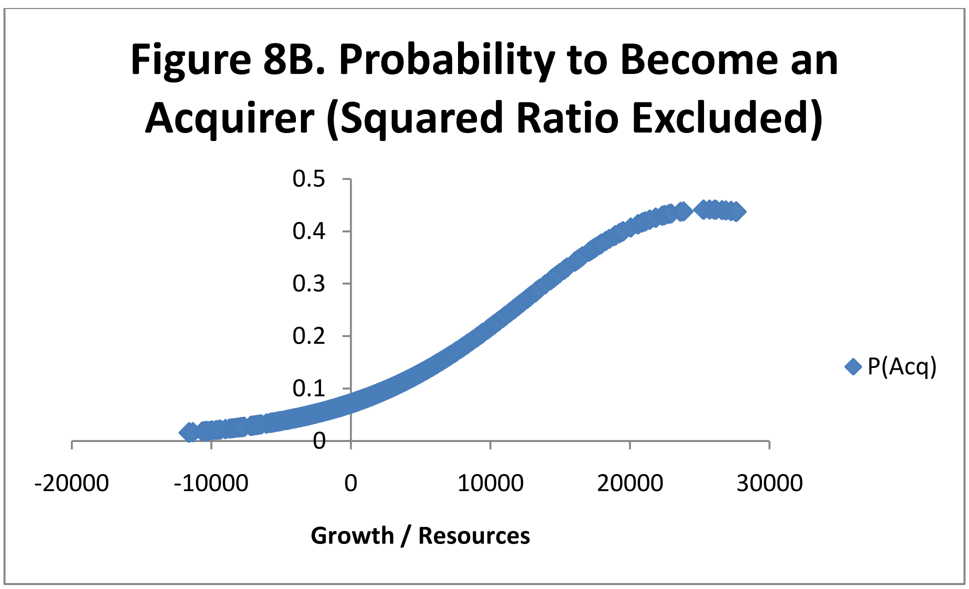
<u>The Growth-Resource Ratio Squared</u>

Another variable of interest to review is the growth-resource ratio squared. In every case but one, when the coefficient is significant, the sign is negative. While the coefficients are low in absolute value, the impact on the distribution of probabilities of acquisition cannot be neglected. Figure 8A. plots the distribution of the estimated probabilities using the multinomial logit model where the coefficients were the most significant[17]. The graph illustrates the parabolic shape obtained when the ratio squared is included in the models. In contrast, Figure 8B. plots the same distribution without the squared ratio. The probability values were computed with the multinomial logit[18] model using the definition of growth as the average past 2 year sales growth and the definition of resources as cash and short term investments over book value of the firm as both component of the growth-resource ratio[19]. The average values of each control variable were used to isolate the effects of the ratio on the probability of acquisition. It is

[17] The model that uses 2 years past sales growth over cash and short term investments relative to the book value of the firm as the definition of the ratio was the most significant and is the one used here.
[18] The same figures using the binary logit model are available in the appendix.
[19] The equation used to compute the probabilities is: $P(y_i = j) = \frac{e^{(\sum_{i=1}^{N} \beta_{ij} X_i)}}{1+\sum_{j=1}^{J-1} e^{(\sum_{i=1}^{N} \beta_{ij} X_i)}}$, which is the multinomial logit equation.

important to note that the figures are both probability density functions and *not* cumulative probability distributions.





Holding everything else constant, the influence of the squared-ratio is dramatic. In the model excluding the squared ratio we see that the impact of increasing the ratio reaches a limit in its effect – at a ratio of approximately 25,000. In contrast, with the squared ratio model we see that the impact of increasing the growth resource ratio increases until the ratio reaches approximately 10,000 and thereafter the impact decreases. The squared ratio model allows the investigation of the impact of the growth resource ratio to see if it exhibits a symmetrical pattern more reminiscent of a normal distribution than of the logistic distribution.

Results of the Hypothesis Tests

The evidence in this paper suggests that the growth-resources imbalance hypothesis holds partially for acquirers when the restrictive (Palepu; 1986, Ambrose et al.; 1992, Powell; 1997; 2004) definition of resources is used (high cash level and low leverage). Referring back to Table 12 and Table 14 that use the dummy variables to determine a firm's growth and resource levels, results suggest that *High Growth* is the variable that has the most positive and significant impact on the probability to become an acquirer. On the other hand, *High Resources* has a significant negative effect on the dependent variable. Thus, firms with high growth and low resources (low cash level and high leverage) relative to the industry median have the highest chance of making an acquisition, and they don't exhibit any preference between paying cash or stock (Table 5). These results are consistent with my hypothesis that managers want to correct the imbalance for the good of the firm and the shareholders. Firms with low growth and high resources are the less likely to become an acquirer. This finding is very interesting as it contradicts my hypothesis and is consistent with the theory of agency: managers prefer to keep the firms' high cash level rather than spending it on an acquisition which would improve the firm's growth potential and reduce the imbalance. This also means that the managers keep the firm's leverage low and don't exploit the available internal financing optimally: capital could be raised through debt to feed extra growth for the firm. Furthermore, they don't exhibit any preference for stocks or cash as the method of payment.

Firms having both high growth and high resources are the second most likely to make an acquisition. This is contrary to what I expected since these firms are assumed to be “balanced’’: internal funding can fuel the high growth without the need of drastic measures. However, they are very likely to acquire and have much higher propensity to finance their acquisition with stocks (41.25% of the deals) rather than cash (14.79% of deals). This further confirms the agency theory for firms in the high resources tier and is consistent with the market timing theory. First, managers prevent the cash flows from being invested in a project in order to keep them for their own benefit. At the same time, they strengthen their relative importance to the firm by making an acquisition using most likely (because of the high growth) overvalued stocks.

The firms with low growth and resources are second less likely to make an acquisition but almost as likely as firms in the high-high category. They have a preference for cash (27.93% of cases) rather than stocks (12.3%) that is most likely due to a probable low stock valuation. While they don’t technically show an “imbalance”, firms in the low-low category are those who perform the worst and the fact that they make an acquisition can be interpreted as either a genuine attempt by managers to improve the firm’s condition or, conversely, as a way to increase the firm’s dependence on them and to secure their job. The motives are unclear and thus are difficult to interpret.

If we relax the restrictive definition of *Resources* used in the literature for takeover target models, we are able to predict the most likely future acquirers, using the models of Table 12 and 14. Large firms (high total assets) with high growth, high cash position *and* high leverage during a merger wave year (and not a recession year) are the ones with the highest probability of acquisition. These results make sense, as these firms have exhausted their internal funding but still need to fuel their high growth. The positive coefficient of *high Cash* is consistent with Harford (1999) and the generally accepted view that high cash levels lead to acquisition. However, its impact is lesser than *Growth*, which is contrary to the evidence of Harford (1999). Inversely, smaller firms with low growth, low cash *and* low leverage are the less likely to become acquirers.

VIII. Prediction Ability of the Models

This section explores the actual ability of the different models to effectively predict which firms will become an acquirer in the next year. The models presented here are those who yielded the most significant results in the estimation section of the paper: two binary logit and two multinomial logit models were selected. For each type of model, two versions were used: one using the dummy variable definitions of high/low growth and resources and one using the continuous definition and the growth / resource ratio.[20]The fifth model, the 2-step binary logit model, although statistically insignificant for the most part in the second step, was kept for comparison purposes with the multinomial logit models.

To successfully assess a model's performance, it is necessary to find a probability cut-off that is reasonable. This cut-off is the percentage value used to determine if a firm is classified as an acquirer or not by the model. For example, choosing a cut-off of 10%, all firms with a predicted probability of becoming an acquirer higher than 10% will be classified as future acquirers while those with a lower probability than 10% will be classified as non acquirers. Of course, the models are not perfect and there are two types of errors that they can make. Type 1 error consists of misclassifying a firm that will become an acquirer as a firm who will not; while a type 2 error would put a non-acquiring firm in the acquirers-to-be category. Table 16 shows the representation of these errors in a simple matrix.

Table 16. Errors Matrix

Selection Criterion	***Did Acq***	***Didn't Acq***
P(Acquire) > Cutoff (Classifed as Acquiror)	**OK**	Type 2 Error
P(Acquire)< Cutoff (Classified as Non-Acquiror)	Type 1 Error	**OK**

[20] The ratio is measured as (average last 2 years Δ sales)/ (cash and short term investment / book value of the firm) for both models.

The choice of a good cut-off for the estimated models' probability is challenging because it depends on the level and type of misclassification that can be admitted. There is a direct relationship between the importance of type 1 and type 2 errors and the cut-off used in the estimated probabilities of the models. By choosing a very high cut-off probability, the model will classify a low proportion of firms as future acquirers but will inevitably omit a lot of them in the process. This would lead to low type 2 errors and high type 1 errors.

On the other hand, if the cut-off is too low, the model will identify a lot of firms as future acquirers. Of these, many will not become acquirers and the model will have high type 2 errors and low type 1 errors. The optimal cut-off to choose comes down to the perceived cost of both type of errors and minimizing the one we find the more costly.

Empirically, using target-prediction models, different rules were applied: Palepu's (1986) classification rule, predicting target firms, attributed the same weights (and costs) to type 1 and type 2 errors in his model. He sought to minimize type 1 errors so that most future target firms were correctly classified using a low cut-off probability. Thus, in a portfolio created of all the predicted future targets, the positive abnormal returns generated by the real targets were nullified by the "normal" returns of all the other incorrectly classified firms (in his portfolio, 24 out of 625 firms are correctly classified as targets). Powell (2004) points that the cost of classifying a target into a non-target (type 1 error) is greater than the opposite, since the abnormal returns generated by the target are forfeited. Thus, he uses a rule of minimization of type 1 errors and a high cut-off for his portfolio to earn the highest returns. However, his model did marginally better than chance alone.

When predicting acquiring firms, the cost of a misclassification is not as high as for models where categorizing a future target is the purpose since the aim of this study is not to maximize a portfolio's return but to create a model to pinpoint potential bidding firms thereby supporting the decisions of investment bankers when giving advice on possible acquisitions. Where, in the case of targets, a misclassification strongly impacts a portfolio's performance, it wouldn't in the case of acquirers since they tend to have little to no abnormal return on the announcement date, and negative returns afterwards. If maximizing the portfolio returns is the goal, then the focus should clearly be on targets, which explains the vast literature on target prediction. This is not the objective here.

If this model is used as a support tool for investment bankers, advising a firm to make an acquisition while it shouldn't (type 2 error) could have several repercussions on the firm's performance, its stakeholders, and the reputation of the investment bankers. Inversely, passing on the opportunity of gaining an extra client when it would be advised to do so (type 1 error) would be costly for the investment banks and but necessarily the firm. However, these costs are not possible to measure. For these reasons, I report the model's performance using three different cut-offs calculations, and propose that the model with the lowest type 2 and type 1 errors will perform the best.

The first method to determine the cut-off probability is to use the actual fraction of acquirers in the estimation sample. In this case, the estimation sample consists of 4281 acquirers in a total of 107 066 firm-years.[21]This gives a probability cut-off of 3.9985%, assuming that there should be a similar proportion of acquirers in the holdout sample. Results for the binary logit models presented in panel A. of table 17 are all very similar, although measuring the imbalance as a ratio seems a little more efficient with 1.57% of type 1 error against 3.28% when using the dummy variables. These results also apply to the multinomial logit models. When comparing the multinomial with the binary logit using the ratio, it is surprising to see that their performance is almost identical.

Because the probability cut-off is very low, it is normal that the models do well in classifying future acquirers in the correct category, but at the cost of a high type 2 error: the proportion of non acquirers incorrectly classified as acquirers is consequently very

[21] In the case where a firm makes more than 1 acquisition in a given year, only the first deal was kept in the sample since the logit model doesn't take into consideration the subsequent bids.

high. Using this cut-off probability, even if the error rate is high, the models still perform twice better than chance, which is noteworthy.

Table 17: Model Performance Matrixes Using the Estimation Sample Cut-off

These tables present the classification of each firm the models. Panel A. reports Binary logit models only while Panel B reports the multinomial logit as well as the 2-steps binary logit. Bolded observations correspond to correct classifications. Relative frequencies are reported under the actual numbers to get a better idea of the models' predictive power.

Panel A. Binary Logit Models *(cutoff = 3.99%)*

	Binary Dummy			Binary Ratio		
Cutoff Probability	***Acq***	***Didn't Acq***	***Total***	***Acq***	***Didn't Acq***	***Total***
P(A) > 3.99%	**583**	6783	*7366*	**614**	7034	*7648*
	7.91%***	92.09%		**8.03%*****	91.97%	
P(A)< 3.99%	52	**1533**	*1585*	4	**251**	*255*
	3.28%	**96.72%*****		1.57%	**98.43%*****	
Total	*635*	*8316*	*8949*	*618*	*7285*	*7903*
	7.10%	*92.90%*		*7.82%*	*92.18%*	

Panel B. Multinomial Logit And 2 steps Binary Logit Models *(cutoff = 3.99%)*

	Multilogit Dummy			Multilogit Ratio			Acquire Given Active		
Cutoff Probability	***Acq***	***Didn't Acq***	***Total***	***Acq***	***Didn't Acq***	***Total***	***Acq***	***Didn't Acq***	***Total***
P(A) > 3.99%	**588**	6893	*7481*	**613**	7044	*7657*	**611**	6985	*7596*
	7.86%***	92.14%		**8%*****	92%		**8.04%*****	91.96%	
P(A)< 3.99%	47	**1423**	*1470*	5	**241**	*246*	7	**300**	*314*
	3.20%	**96.80%*****		2.03%	**97.97%*****		2.23%	**97.77%*****	
Total	*635*	*8316*	*8951*	*618*	*7285*	*7903*	*618*	*7285*	*7903*
	7.09%	*92.91%*		*7.82%*	*92.18%*		*7.82%*	*92.18%*	

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

It is important to note that the cut-off percentage of 3.99% was obtained using the frequency of acquirers in the entire estimation sample regardless of data availability. The second method used to test the model is to use the percentage of acquirers actually included in the samples *used by the models* as the probability cut-off. It is equal to the number of acquirers (whether they made one or several acquisitions) in the sample divided by the total number of firm-years in each of the models' respective sample. Because some variables used in the logit regressions are missing for many firms, the true number of observations considered decreases sharply. Table 18 displays the results using different cut-offs for each model, depending on the proportion of acquirers in the sample that was used to estimate the probability of acquisition. The probabilities of the model *Binary Acquire Given Active,* which is the 2-step binary logit model, were computed from both steps of the model. First, the probability to become active in the takeover market (step 1) was computed and then this probability was multiplied by the probability to become an acquirer (step 2) given that the firm would become active. This model used the same sample of available data as the multinomial logit model with the ratios. A test on proportions indicates that the proportions of correct classifications are all significantly different than the actual proportions of acquirers and non-acquirers in the sample, at the 1% level.

Table 18: Model Performance Matrixes Using Models' Actual Sample Cut-off

This table summarizes the classification of each firms by models. Panel A. reports Binary logit models only while Panel B reports the multinomial logit as well as the 2-steps binary logit. Bold observations correspond to correct classifications. The cut-offs for each model are defined by the number of acquirers divided by the total number of firm-years, both reported as well. Relative frequencies are reported under the actual numbers to get a better idea of the models' predictive power.

Panel A. Binary Logit Models

Binary Dummy			
#Acquirers:		1385	
#Firm-Years:		21286	
Cutoff:		**6.51%**	
Probability Cut-off	**Acq**	**Didn't Acq**	***Total***
P(A) > 6.51%	**368**	2984	*3352*
	10.98%***	89.02%	
P(A)< 6.51%	267	**5332**	*5599*
	4.77%	**95.23%*****	
Total	*635*	*8316*	*8951*
	7.09%	*92.91%*	

Binary Ratio			
#Acquirers:		1370	
#Firm-Years:		20642	
Cutoff:		**6.64%**	
Probability Cut-off	**Acq**	**Didn't Acq**	***Total***
P(A) > 6.64%	**376**	2698	*3074*
	12.23%***	87.77%	
P(A)< 6.64%	242	**4587**	*4829*
	5.01%	**94.99%*****	
Total	*618*	*7285*	*7903*
	7.82%	*92.18%*	

Panel B. Multinomial Logit and 2-steps Binary Logit Models

Multinomial Logit Dummy			
#Acquirers:	1418		
#Firm-Years:	21345		
Cutoff:	6.64%		
Cut-Off Probability	***Acq***	***Didn't Acq***	***Total***
P(A) > 6.64%	**385**	3013	*3398*
	11.33%***	88.67%	
P(A)< 6.64%	250	**5253**	*5553*
	4.50%	**95.5%*****	
Total	*635*	*8266*	*8901*
	7.13%	*92.87%*	

Multinomial Logit Ratio			
#Acquirers:	1403		
#Firm-Years:	20700		
Cutoff:	6.78%		
Cut-Off Probability	***Acq***	***Didn't Acq***	***Total***
P(A) > 6.78%	**344**	3273	*3617*
	9.51%***	90.49%	
P(A)< 6.78%	274	**5012**	*5286*
	5.18%	**94.82%*****	
Total	*618*	*8285*	*8903*
	6.94%	*93.06%*	

Binary Acquire Given Active			
#Acquirers:	1403		
#Firm-Years:	20700		
Cutoff:	6.78%		
Cut-Off Probability	***Acq***	***Didn't Acq***	***Total***
P(A) > 6.78%	**353**	2280	*2633*
	13.41%***	86.59%	
P(A)< 6.78%	265	**5005**	*5270*
	5.03%	**94.97%*****	
Total	*618*	*8285*	*8903*
	6.94%	*93.06%*	

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

From this table, we get a better idea of the differences in each model's prediction ability. For the binary logit models, using the growth-resources ratio still outperforms the use of dummy variables. While the type 1 error is slightly higher, using a higher cut-off reduced the type 2 error by a considerable margin: the model now correctly identified 12.23% of the future acquirers. As for both multinomial logit models, the dummy variable version clearly outperforms the ratio: 11.33% of the acquirers were correctly identified against 9.51%. This result is contrary to when the lower cut-off of the estimation sample was used. Results from the 2-steps binary model are still superior to those using the multinomial logit models with both lower type 1 and 2 errors. The insignificance of the coefficients in step 2 of the model suggests that using a 2-step binary model is very useful for identifying which firm will become active in the takeover market, but doesn't differentiate firms becoming acquirers from targets. Once again, the models perform better than chance in identifying acquirers by a few percentage points ranging from 2.57% to 6.47%: even though these values may seem marginal, they represent an increase ranging from 37.03% to 93.23% in efficiency.

At first glance, the performance of these models can seem marginal to the reader when compared to those in the literature. This big difference in performance is explained by the way the prediction abilities are computed. In prior papers, (Palepu; 1986, Powell; 1999, Espahbodi & Espahbodi; 2003), where prediction performance of the models range from 46% to 63%, the method of computation of the models' accuracy is referred to as the ratio of the total number of firms correctly classified over the total sample size. In this case, correctly predicted future acquirers *and* future non-acquirers over the total sample size would reflect the prediction performance of the models. Table 19 reports the models' performance using this definition. As one can see, when using the estimation sample's proportion of acquirers as the cut-off, the prediction accuracy is fairly low. This is due to the fact that, with such a low cut-off, most firms are classified as future acquirers, which explains the high type 2 errors. However, when using the actual proportion of acquirers in each model's respective sample used to compute the aforementioned results, the models' prediction accuracy, ranging from 60.16% to

63.68%, are comparable to the takeover targets prediction models of the literature. Using this method of performance assessment, the models using dummy variables outperform those using the ratio.

Table 19. Prediction Accuracy of the Models Using the Empirical Definition

This table summarizes the performance of the different models built in this study using the empirical definition of prediction accuracy: (Total number of correctly classified acquirers + Total number of correctly classified non-acquirers) / Total sample size. Panel A displays the performance for the models using the cut-off equal to the proportion of acquirers in the estimation sample and Panel B displays the performance for the model using the proportion of acquirers in their own sample used to compute the results.

Panel A. Models Performance Using the Estimation Sample Cut-Off (3.99%)

Model:	Binary Dummy	Binary Ratio	Multinomial Dummy	Multinomial Ratio	2 Steps Binary
Correctly Predicted Acquirers	583	614	588	613	611
Correctly Predicted Non-Acquirers	1533	251	1423	241	300
Total Sample Size	8949	7903	8951	7903	7903
Prediction Accuracy	**23.65%**	**10.95%**	**22.47%**	**10.81%**	**11.53%**

Panel B. Models' Performance Using the Each Model's Own Sample

Model:	Binary Dummy	Binary Ratio	Multinomial Dummy	Multinomial Ratio	2 Steps Binary
Correctly Predicted Acquirers	368	376	385	344	353
Correctly Predicted Non-Acquirers	5332	4587	5253	5012	5005
Total Sample Size	8951	7903	8901	8903	8903
Prediction Accuracy	**63.68%**	**62.80%**	**63.34%**	**60.16%**	**60.18%**

The third method consists of dividing the samples into deciles and reporting the prediction ability for each of them, making it easier to pinpoint the best range of cut-off to use in order to minimize type 2 errors. Results from this method are reported in table 20. Only the values for the binary logit models are reported since the results are not significantly different for the multinomial logit models.[22] When using both the growth-resources ratio and the dummy variables, the cut-off point with the highest proportion of future acquirers correctly identified is in the top deciles, ranging from ≥9.59% and ≥9.57% for the dummy and ratio: they take values of 19.42% and 20.51% of correct classification, respectively. While this method of classification gives the highest percentage of correctly identified future acquirers, the type 1 error is still important as almost three quarters of the total acquirers are not correctly identified. However, it is still much lower than when using the cut-off values from the previous methods.

This section shows that building a very efficient model is hard and that researchers always face a trade-off between both types of errors. It is also surprising that the multinomial models **do not** outperform binary logit models, which is contrary to Powell's (2004) findings in his study on targets. The most surprising result is that the 2-step binary model performs very well even though the most important variables of the model are statistically insignificant in the second step (identifying acquirers from a sample consisting of acquirers and targets exclusively). This conclusion is interesting as the use of the growth-resource imbalance is widely used in empirical work to predict targets. Results from the models reported here open the door to the hypothesis that the imbalance may cause a firm to become a target ***or*** an acquirer rather than a target exclusively. The fact that the binary models perform as well or better than the multinomial logit for predictions also put an emphasis on the effect of the IIA assumption's violation for the latter on the predictive power of the model.

[22] Refer to the Appendix for the tables reporting the multinomial logit models and the 2-steps binary logit model.

Table 20 : Model Performance Sensitivity to Probablity Cut-Off by Decile

This table summarizes the estimated probability that a firm becomes an acquirer by different models. Results are reported in deciles from the highest estimated probability to the lowest. *% of Acquirers Correctly Classified* is calculated as the number of *Acquirers Correctly Classified* over the *Total Firms Classified as Acquirer* .The *Cumulative % of Total Acquirers Correctly Classified* in the whole sample is reported in the last column.

Model:		***Binary Logit dummy***				**Model:**		***Binary Logit Ratio***			
Estimated Probability Decile	**Acquirers correctly classified**	**Non-Acquirers Incorrectly Classified as Acquirers**	**Total Firms Classified as Acquirers**	**% of Acquirers Correctly Classified**	**Cumulative % of Total Acquirers Correctly Classified**	**Estimated Probability Decile**	**Acquirers correctly classified**	**Non-Acquirers Incorrectly Classified as Acquirers**	**Total Firms Classified as Acquirers**	**% of Acquirers Correctly Classified**	**Cumulative % of Total Acquirers Correctly Classified**
9.59-100%	**174**	**722**	**896**	**19.42%**	**27.40%**	**9.57-100%**	**162**	**628**	**790**	**20.51%**	**26.21%**
8.06-9.59%	86	809	895	9.61%	40.94%	7.56-9.57%	75	715	790	9.49%	38.35%
6.99-8.06%	66	829	895	7.37%	51.34%	6.93-7.56%	78	713	791	9.86%	50.97%
6.27-6.99%	62	833	895	6.93%	61.10%	6.61-6.93%	71	719	790	8.99%	62.46%
5.66-6.27%	55	840	895	6.15%	69.76%	6.35-6.61%	44	746	790	5.57%	69.58%
5.19-5.66%	54	841	895	6.03%	78.27%	6.03-6.35%	37	754	791	4.68%	75.57%
4.6-5.19%	42	853	895	4.69%	84.88%	5.63-6.03%	61	729	790	7.72%	85.44%
4.2-4.6%	34	861	895	3.80%	90.24%	5.37-5.63%	42	748	790	5.32%	92.23%
3.6-4.2%	50	845	895	5.59%	98.11%	5.14-5.37%	31	760	791	3.92%	97.25%
0-3.6%	12	883	895	1.34%	100.00%	0-5.14%	17	773	790	2.15%	100.00%
Total	635	8316	8951			Total	618	7285	7903		

IX. Anticipation of the Deal and CARs

When a firm becomes a target, there is typically an abnormal return earned over the 42 days prior to the announcement (see Schwert; 1996) which may be attributed to information leakages or to market anticipation. Information leakages include insider information, unusual trading patterns or higher insider trading activity than usual. In contrast, market anticipation refers to the ability of the market to use publically available information to assess the likelihood of an acquisition and to trade accordingly. In this section, I examine the relationship between the abnormal return earned by the acquirer and the acquisition probability estimated by the models of this study.

In the sample, the average CAR before the announcement date is negative, and it is only slightly positive around the announcement date, as shown in table 21. Post-merger performance is significantly negative, which is similar to that reported in most previous studies. Other descriptive statistics are also included in the table. An interesting fact is that the Eventus-computed precision weighted CAR is not statistically significant while, when the distribution is standardized, the Patell Z measure is significant: this shows that all acquirers are drawn from different distributions and may not exhibit similar behaviours.

Table 21. Descriptive Statistics of Daily CARs

This table reports the test statistics for both the daily event study (in Panel A.) and the cross-sectional daily event study (in Panel B.) as reported from Eventus.

Panel A. Daily Event Study

Window	N	Mean CAR	Precision Weighted CAR	Positive : Negative	Patell Z	Portfolio Time-Series (CDA)t	Generalized Sign Z
(-42,-2)	5148	2.51%	1.27%	2675:2473***	3.846***	6.663***	7.010***
(-5,+5)	5147	1.08%	0.76%	2677:2470***	4.439***	5.506***	7.080***
(-1,+1)	5147	0.80%	0.62%	2658:2489***	6.991***	7.848***	6.549***
(+2,+40)	5148	-2.13%	-2.30%	2397:2751	-7.158***	-5.800***	-0.752

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Panel B. Cross-Sectionnal Daily Event Study

Window	N	Mean CAR	Mean CAR / StDev	Positive : Negative	Patell Z	Median CAR	Generalized Sign Z	Standard Error of Mean
(-42,-2)	5148	-0.745%	-2.212%	2511:2637**	-0.687	-0.521%	-1.735**	0.0046957
(-5,+5)	5147	0.503%	3.194%	2642:2505**	3.297***	0.293%	1.936**	0.002194
(-1,+1)	5147	0.666%	6.589%	2662:2485***	6.623***	0.199%	2.511***	0.0014098
(+2,+40)	5148	-4.717%	-11.518%	2285:2863***	-9.645***	-2.241%	-7.639***	0.0057074

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

As the abnormal return reflects the surprise element of an announcement, I expect to observe a negative relationship between the probability and the acquirer's abnormal return. The CARs were computed using four different event windows (-42;-2), (-5;5), (-1;1) and (2;40) days around the event's announcement date and the expected probability was computed using the two models with the best performance and statistical significance. Following Malatesta and Thompson (1985) I use three different models to examine the relationship between the CAR and the expected probability of acquisition. The first is a simple OLS regression:

$$CAR = \sum_{i=1}^{n} \beta i X i + \epsilon \qquad (10)$$

where X is the vector of the deal's characteristic which are described in table 22, which excludes the estimated probability of acquisition (Table 23, Panel A.). In panel B and C, the estimated probability of acquisition is added to the models: results using two slightly different equations that are used in both panels.

The equation of the second model is the CAR expressed as:

$$CAR = \sum_{i=1}^{n} \beta i X i + \epsilon \qquad (11)$$

where the estimated probability of acquisition *P(Acq)* is included in the vector of variables X. In the third model, the dependent variable is divided (1 – estimated P(Acq)):

$$\frac{CAR}{(1-P(acq)} = \sum_{i=1}^{n} \beta i X i + \epsilon \ , \qquad (12)$$

so that the anticipated part of the total CAR (the runup in stock price) is taken into account in the dependent variable. By dividing by (1-P(Acq)), the CAR should be a more appropriate measure of the value of the deal. For example, consider a deal where the total cumulative abnormal return is $100M and there is a 25% probability of the deal's occurrence. During the trading days leading to the announcement, $25M (25%) of the total gains will be incorporated in the firm's stock price so that only a $75M gain materializes at announcement. Thus, by dividing the CAR at announcement, $75M by 1-P(A), 75%, we get the whole $100M gain. The coefficients of the regressions thus reflect more accurately the relationship between the value of the deal and the independent variables. The models chosen to estimate the probabilities are: the binary logit model using the growth-resource ratio[23] (Table 23, Panel B.) and the multinomial logit model (Table 23, Panel C.) using that same ratio. Results for both types of models (binary and multinomial logit) are reported for the ease of comparison.

[23] The ratio = (Average 2-year Sales Growth)/ (Cash & Short Term Investment / Book Value of the Firm)

Table 22. Description of the Variables

Variable	Description
Merger Wave	Dummy Variable, equals to 1 if the year of the deal is included in a merger wave
Recession	Dummy variable, equals to 1 if the year of the deal is considered as a recession year according to the NBER
Stock Deal	Dummy variable, equals to 1 if the deal was paid for with stocks only
Cash Deal	Dummy variable, equals to 1 if the deal was paid for with cash only
Private	Dummy variable, equals to 1 if the target firm is private
Public	Dummy variable, equals to 1 if the target firm is public
Friendly	Dummy variable, equals to 1 if the takeover is friendly
Value	Value of the deal, in Millions of $
Firm Size	Size of the firm expressed as Ln(Total Assets)
P(Acq)	The probability to make an acquisition as estimated by the chosen models

Table 23. OLS Results for the Anticipation of the Deal Before Announcement

This table summarizes results from the three OLS regression models that predict a deal's CAR. Results from the first model, where the dependent variable is explained by a vector of deal characteristics, are reported in Panel A. The second model incorporates the estimated probability of acquisition in the vector of explanatory variables. The third model is computed by dividing the CAR by (1 - estimated probability of acquisition) so that the dependent variable is expressed as (CAR / 1-P(Acq)). The estimated probabilities of acquisition are computed by a binary logit model (Panel B.) and a multinomial logit model (Panel C.). Results from the second and third models are clustered together to facilitate comparison. The difference is sample size between Panel A. and the others is due to the lack of availability of the predicted probability of acquisition.

Panel A. CAR Excluding the Estimated Probability of Acquisition

Window	(-42;-2)	(-5;5)	(-1;1)	(2;40)
Merger Wave	0.0001	0.0017	0.0086	-0.0325
	(0.993)	(0.774)	(0.023)**	(0.08)
Recession	-0.0246	-0.0176	-0.0054	-0.0384
	(0.356)	(0.094) *	(0.425)	(0.25)
StockDeal	-0.0270	-0.0200	-0.0118	-0.0647
	(0.059)*	(0) ***	(0.001)***	(0) ***
Cash Deal	-0.0117	0.0092	0.0123	-0.0025
	(0.488)	(0.164)	(0.004)***	(0.906)
Private	0.0074	0.0012	-0.0019	0.0042
	(0.888)	(0.955)	(0.888)	(0.95)
Public	0.0378	-0.0132	-0.0246	0.0106
	(0.477)	(0.528)	(0.069)*	(0.874)
Friendly	0.0432	0.0077	-0.0016	0.0003
	(0.241)	(0.596)	(0.867)	(0.996)
Value of Deal	0.0000	0.0000	0.0000	0.0000
	(0.608)	(0.037)**	(0.017)**	(0.481)
Firm Size	-0.0010	-0.0043	-0.0030	0.0112
	(0.742)	(0.001)***	(0)***	(0.005)***
Intercept	-0.0525	0.0315	0.0324	-0.0843
	(0.451)	(0.252)	(0.067)*	(0.333)
N=	3526	3525	3525	3525
Adjusted R-Square	0.0001	0.0139	0.0303	0.0074

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Panel B. Binary Logit Model

Window	(-42;-2)		(-5;5)		(-1;1)		(2;40)	
Dependent Variable	CAR	CAR / 1-P(Acq)	CAR	CAR / 1-P(Acq)	CAR	CAR / 1-P(Acq)	CAR	CAR / 1-P(Acq)
Merger Wave	0.0037	-0.0004	-0.0068	-0.0109	-0.0016	-0.0007	-0.0402	-0.0520
	(0.806)	(0.979)	(0.414)	(0.243)	(0.769)	(0.901)	(0.006)	(0.002)***
Recession	-0.0395	-0.0373	-0.0279	-0.0286	-0.0057	-0.0067	-0.0397	-0.0418
	(0.042)*	(0.092)	(0.009)***	(0.017)**	(0.402)	(0.386)	(0.036)**	(0.052)*
StockDeal	-0.0219	-0.0271	-0.0124	-0.0140	-0.0039	-0.0037	-0.0334	-0.0397
	(0.174)	(0.14)	(0.162)	(0.159)	(0.496)	(0.562)	(0.034)**	(0.026)**
Cash Deal	0.0034	0.0093	0.0096	0.0108	0.0131	0.0154	0.0138	0.0139
	(0.832)	(0.609)	(0.272)	(0.27)	(0.019)**	(0.014)**	(0.374)	(0.43)
Private	0.0056	0.0234	0.0052	0.0051	-0.0069	-0.0069	0.0567	0.0944
	(0.912)	(0.686)	(0.852)	(0.871)	(0.698)	(0.732)	(0.252)	(0.093)*
Public	0.0334	0.0493	-0.0054	-0.0044	-0.0287	-0.0290	0.0633	0.1039
	(0.513)	(0.398)	(0.846)	(0.889)	(0.112)	(0.152)	(0.205)	(0.067)*
Friendly	0.0374	0.0430	0.0025	-0.0028	-0.0060	-0.0086	-0.0013	0.0010
	(0.332)	(0.33)	(0.904)	(0.906)	(0.66)	(0.574)	(0.972)	(0.982)
Value of Deal	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.971)	(0.576)	(0.082)*	(0)***	(0.046)**	(0)***	(0.969)	(0.738)
Firm Size	0.0032	-0.0007	-0.0013	-0.0029	-0.0029	-0.0021	0.0089	0.0069
	(0.392)	(0.845)	(0.508)	(0.128)	(0.026)**	(0.08)*	(0.014)**	(0.04)**
P(Acq)	-0.1058	-	-0.0249	-	0.0347	-	-0.0489	-
	(0.153)	-	(0.54)	-	(0.184)	-	(0.498)	-
Intercept	-0.0666	-0.0764	0.0130	0.0267	0.0348	0.0354	-0.1289	-0.1624
	(0.324)	(0.322)	(0.726)	(0.523)	(0.145)	(0.186)	(0.051*)	(0.031)**
N=	1549	1549	1548	1549	1548	1549	1548	1549
Adjusted R-Square	0.0021	0.0007	0.0101	0.0184	0.0234	0.028	0.0138	0.0153

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

Panel C. Multinomial Logit Model

Window	(-42;-2)		(-5;5)		(-1;1)		(2;40)	
Dependent Variable	CAR	CAR / 1-P(Acq)	CAR	CAR / 1-P(Acq)	CAR	CAR / 1-P(Acq)	CAR	CAR / 1-P(Acq)
Merger Wave	0.0066	0.0038	-0.0035	-0.0072	-0.0021	-0.0010	-0.0289	-0.0404
	(0.654)	(0.823)	(0.669)	(0.438)	(0.69)	(0.862)	(0.046)**	(0.014)**
Recession	-0.0401	-0.0386	-0.0264	-0.0266	-0.0050	-0.0058	-0.0423	-0.0439
	(0.035)**	(0.075)*	(0.013)**	(0.026)**	(0.459)	(0.442)	(0.023)**	(0.038)**
StockDeal	-0.0223	-0.0273	-0.0157	-0.0187	-0.0051	-0.0055	-0.0333	-0.0416
	(0.159)	(0.129)	(0.076)*	(0.059)*	(0.364)	(0.386)	(0.032)**	(0.018)**
Cash Deal	-0.0008	0.0044	0.0081	0.0086	0.0121	0.0141	0.0092	0.0086
	(0.959)	(0.806)	(0.355)	(0.38)	(0.028)**	(0.023)**	(0.544)	(0.621)
Private	-0.0077	0.0044	0.0028	0.0027	-0.0099	-0.0103	0.0497	0.0853
	(0.877)	(0.938)	(0.919)	(0.931)	(0.576)	(0.602)	(0.307)	(0.123)
Public	0.0238	0.0337	-0.0089	-0.0082	-0.0324	-0.0333	0.0605	0.1009
	(0.636)	(0.554)	(0.751)	(0.796)	(0.069)*	(0.096)*	(0.218)	(0.071)*
Friendly	0.0395	0.0459	0.0040	-0.0015	-0.0064	-0.0090	0.0042	0.0073
	(0.296)	(0.287)	(0.849)	(0.951)	(0.635)	(0.554)	(0.911)	(0.863)
Value of Deal	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.908)	(0.571)	(0.09)*	(0)***	(0.044)**	(0)***	(0.986)	(0.855)
Firm Size	0.0026	-0.0006	-0.0004	-0.0023	-0.0026	-0.0017	0.0095	0.0064
	(0.478)	(0.852)	(0.848)	(0.227)	(0.047)**	(0.157)	(0.008)***	(0.055)*
P(Acq)	-0.0840	-	-0.0363	-	0.0369	-	-0.0838	-
	(0.248)		(0.372)		(0.153)		(0.239)	
Intercept	-0.0541	-0.0603	0.0097	0.0252	0.0362	0.0370	-0.1285	-0.1558
	(0.414)	(0.423)	(0.794)	(0.545)	(0.124)	(0.161)	(0.048)**	(0.034)
N=	1558	1558	1557	1558	1557	1558	1557	1558
Adjusted R-Square	0.0023	0.0009	0.01	0.0179	0.024	0.0283	0.0114	0.018

*, ** and *** denote significance of 10%, 5% and 1%, respectively.

From Panel A, the results show that the characteristics of the deal are not significantly related to the CAR during the run-up period. Only the dummy variable “stock” has a significantly negative relationship with the dependent variable for all the windows. This means that the market can partially anticipate an event if they suspect that the stock’s price is overvalued. Obviously, when the deal is announced, that signal sent by managers confirms the suspicions, since they are likely to use overvalued equity to finance the acquisition rather than cash. When cash is used, as opposed to stock as the means of payment, the CAR in the (-1;1) window increases, which is contrary to the view that managers prefer to use the firm’s resources to make value reducing deals rather than distribute them to shareholders. Also, given the results, it appears that bigger doesn’t mean better: as deal value and firm size increase, the abnormal returns generated by the event are expected to decrease. As deals and firms increase in size, assessing the true value of synergies and expected performance become more complicated and forecasting errors are much harder to avoid, which can explain why the stock price performance decreases, especially at the announcement date. On the other hand, for the period after the event, larger firms will tend to have higher CARs, which could be explained by the increased coverage by analysts and monitoring control of the managers.

When controlling for the probability of making an acquisition, in Panel B and C, the recession dummy variable becomes significantly and negatively correlated with the deal CAR. If the acquisition was anticipated, one would see an increase in the run-up prior to the deal and a lower abnormal return at the date of announcement. However, the coefficients of the predicted probability estimated by both the binary and the multinomial logit models are negative, as expected, but aren’t significantly different than zero. Therefore, the interpretation of this finding is that the estimated probability of the models doesn’t reflect the anticipation of the market before the deal’s announcement, if such a deal is anticipated.

Because these deals may not anticipated by investors, it is not surprising to see that the results in both Panel B and C are not different than in Panel A. Even when we correct the deal's CAR by its expected probability of occurrence, most deal characteristics still lack statistical significance.

X. Summary and Concluding Remarks

The growth-resources imbalance hypothesis is generally accepted to be a good predictor of future targets. In this paper, the focus was the opposite: how the imbalance relates to the probability of becoming an acquirer for a sample of 6976 US acquirers who made acquisitions during the period 1995 to 2008. The growth-resource imbalance was hypothesized to be positively related to the probability of acquisition and was tested using binary, 2-step binary and multinomial logit models. This implies that high-growth, low resource firms and low growth, cash hungry firms would be more likely to make an acquisition than more "balanced" firms.

The evidence presented showed that the majority of acquiring firms tended to outperform their industry peers in the 3 to 5 years prior to their first bid, which is consistent with the work of Bradley & Sundaram (2004). Contrary to popular belief, the growth component of the firm is the one driving acquisition rather than the resources. Using the traditional definition of resources as a combination of cash and leverage, I find that only growth has a positive effect on the probability to make a bid. When the definition of resources is relaxed to cash only, growth has a greater impact than resources on the probability of acquisition. As such, I find that firms with high growth relative to the industry median are the most likely to become bidders while those with low growth are the less likely.

The growth-resources imbalance hypothesis was partially confirmed. Firms with high growth and low resources are the most likely to become an acquirer while firms with low growth and high resources, which were expected to be the most likely to acquire, were, in fact, less likely to make a deal. This lack of action from management to correct the imbalance raises suspicions on a possible agency conflict with regards to what they are supposed to do in order to keep the firm balanced between a steady growth and the necessary resources to fuel it, and thus make it prosperous.

From the models used, both the binary and multinomial logit models performed well in predicting future acquirers in the holdout sample with a success rate nearly double that of simple chance and a predictive accuracy ranging from 60.16% to 63.68%[24]. However, contrary to Powell (2004), the binary logit outperformed its multinomial counterpart with its higher prediction accuracy. This finding can partially be explained by the fact that the multinomial logit violates the IIA assumption, and this argument is further strengthened by the fact that the 2 step binary model has a much higher ability to correctly classify future acquirers.

While this study adds a piece to the puzzle of acquirers in the M&A literature, it still has its weaknesses. The models used are simple and may not account for each element that affects the acquisition decisions of firms and managers. Bringing other aspects of corporate governance such as managerial incentives and characteristics of the board could also prove useful. In addition, the use of a proportional hazard model would add significantly to the robustness of the results by considering the time dimension in the model. More precisely, such a model would estimate the probability of a firm to make a bid given that it is not an acquirer at a given day. This dynamic model would complement the logit models reported in this study. For the methodology, the cut-offs used to define high (low) growth and high (low) resources are arbitrary and ambiguous. The use of a different cut-off (i.e. the top 25% of growth or resources, for example) could strengthen the evidence provided. These improvements, however, are left for future studies.

[24] These percentages are based on the empirical definition of predictive accuracy defined as: (% of future acquirers correctly classified + % of non-acquirers correctly classified) / Total sample size.

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Appendix – Robustness Checks

This section presents all figures and tables that were not reported in the discussion part of the paper that are used for the sake of completeness and robustness check. First the figures are included and then the tables, both in order of appearance in the paper.

Figure A-1. Probability to Become an Acquirer (Squared Ratio Included)

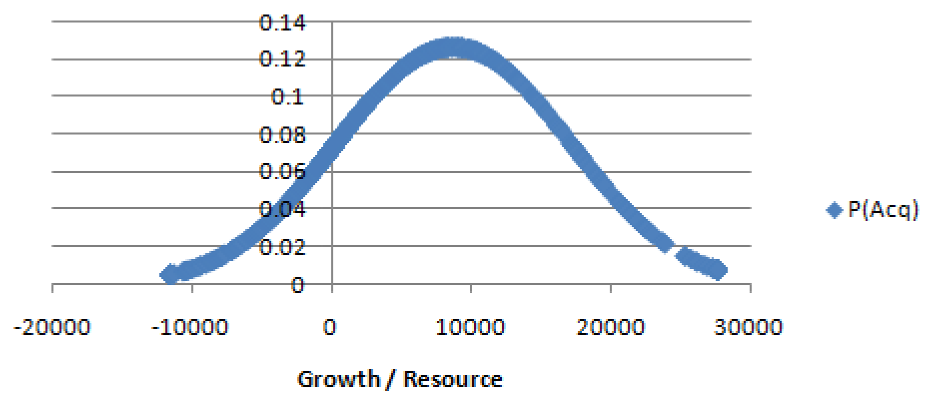

Figure A-2. Probability to Become an Acquirer (Squared Ratio Excluded)

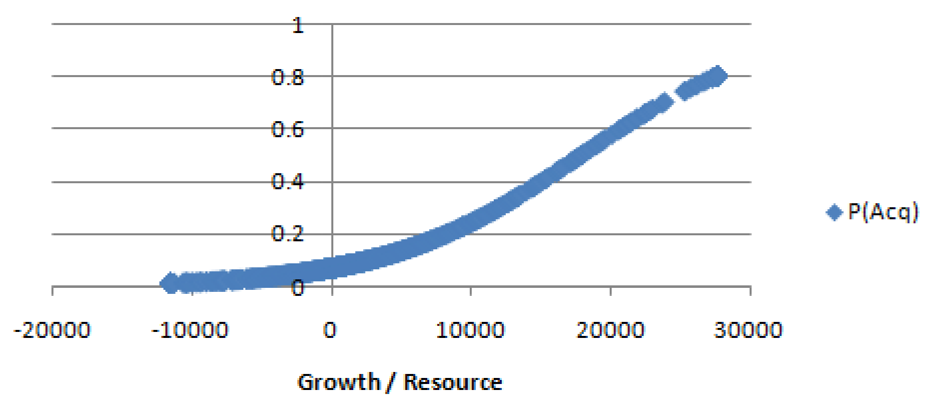

Figure A-1 and A-2 plot the probability to become an acquirer computed by the binary logit model using the average past 2 years sales growth and cash and short term investments over book value of the firm for the growth and resource components of the ratio, respectively. All the other variables were held constant using their mean value for each observation. This way, the effect of the ratio on the dependent variable is isolated. Both figures are similar to those computed with the multinomial logit model and no significant difference exists between the two. The figures represent a probability density function and are not a cumulative probability distribution.

Table A.1 Growth-Resources Matrix Using Alternate Definitions

In this table, the probability of firms to become an acquirer or a target is reported according to their growth and resources level. High (low) growth means higher (lower) than the industry median measured by the average last 2 years sales growth. In panel A. for a firm to be in the high (low) resources category, it has to have higher (lower) cash over total assets **and** lower (higher) leverage than the industry median. In panel B., a firm has to have lower (higher) leverage than the industry median only to be in the high (low) resources category.

Panel A. Resources defined as high (low) cash over total assets and low (high) leverage.

Resource		**Growth** High	**Growth** Low
	High	P(A): 6.77% P(T): 2.82%	P(A): 4.45% P(T): 3.94%
	Low	P(A): 8.89% P(T): 4.37%	P(A): 6.23% P(T): 4.13%

Panel B. Resources defined as high (low) leverage.

Resource		**Growth** High	**Growth** Low
	High	P(A): 7.23%% P(T): 3.76%	P(A): 4.11% P(T): 3.58%
	Low	P(A): 8.86% P(T): 4.48%	P(A): 6.46% P(T): 3.97%

When the definition of resources is tightened to include both of cash and leverage, the results vary slightly. The high-high tier has lower probabilities to become both an acquirer and a target than when using cash-only as reported in the paper. In the high growth-low resources quadrant, results here indicate an increased probability to become an acquirer and a target by more than around 1.5% and 0.5% respectively. The other significant difference is in the low-low quadrant, where north of 6% of firms will become acquirers while this proportion is only 4.45% when using cash only: when leverage is higher than the industry median, it has a positive effect on the probability to make an acquisition. However, the most prominent firms to become an acquirer are still in the high growth quadrants, and each quadrant retains the same order of probability to make an acquisition across each matrix.

Table A.2. Binary Logit Model for Acquirers Using the Growth-Resources Ratio

This table summarizes the results of the binary logit model where the dependent variable is the probability to become an acquirer in the next year. Both panels summarize the results using alternate definitions of growth. In Panel A., growth is measured as the past growth in the firms' market-to-book ratio which represents the average *change* in expected growth from the market. Panel B. reports results using the definition of growth as the average past market-to-book ratio which represents the average anticipated growth by the market. The variable *Past Growth* is measured by the average past 2 (3) years sales growth.

Panel A. Growth Measured as the Past 2 (3) Years Growth in the Market-to-Book Ratio

Growth Description	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth**	**3y MTB Growth**
Resources Description	**Cash/ Total Assets**	**Cash/ Total Assets**	**Cash/ Book Value of Firm**	**Cash/ Book Value of Firm**	**Free Cash Flows / Total Assets**	**Free Cash Flows / Total Assets**
G/R	0.0009317	0.0013333	0.0001951	0.0004833	0.0000353	-0.0001664
	(0.061)	(0.075*)	(0.808)	(0.661)	(0.941)	(0.78)
G/R^2	-1.15E-06	-1.82E-06	-3.24E-06	-4.34E-06	-5.79E-11	-4.80E-10
	(0.045)**	(0.058)*	(0.09)*	(0.136)	(0.639)	(0.489)
Firm Size	0.0000515	0.0000524	0.0000512	0.0000521	0.0000517	0.0000523
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	-6.96E-06	0.0000556	-6.25E-06	0.0001176	-4.29E-06	0.0003227
	(0.829)	(0.882)	(0.817)	(0.753)	(0.859)	(0.383)
Leverage	-0.008239	-0.0198273	-0.0118422	-0.0228083	-0.0108007	-0.0236223
	(0.482)	(0.172)	(0.325)	(0.123)	(0.364)	(0.108)
Merger Wave	1.3918	collinearity	1.37577	collinearity	1.789692	collinearity
	(0.231)		(0.236)		(0.147)	
Recession Year	-0.1638202	predict	-0.1666788	predict	-0.1670791	predict
	(0.038)**		(0.036)**		(0.036)**	
Intercept	-2.659065	-2.641029	-2.64674	-2.631237	-2.66051	-2.642904
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	14244	9674	14028	9561	14003	9539

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively. ''Collinearity'' means that the variable was found to have a multicollinearity problem and was dropped from the equation by the statistical package. ''Predict'' means that the variable predicted successes of the dependent variable perfectly and was also dropped from the equation by the software.

Panel B. Growth Measured as the Past 2 (3) Years Average Market-to-Book Ratio

Growth Description	Avg 2 Years MTB	Avg 3 Years MTB	Avg 2 Years MTB	Avg 3 Years MTB	Avg 2 Years MTB	Avg 3 Years MTB
Resources Description	**Cash/ Total Assets**	**Cash/ Total Assets**	**Cash/ Book Value of Firm**	**Cash/ Book Value of Firm**	**Free Cash Flows / Total Assets**	**Free Cash Flows / Total Assets**
G/R	0.0003744	0.0000163	0.0011592	0.0004558	0.0001634	0.000134
	(0.021)**	(0.937)	(0.001)***	(0.286)	(0.062)*	(0.199)
G/R^2	-1.31E-07	-6.16E-09	-8.84E-07	-3.82E-07	6.62E-08	2.01E-08
	(0.016)**	(0.928)	(0.001)***	(0.219)	(0.21)	(0.75)
Firm Size	0.0000568	0.0000517	0.0000566	0.0000513	0.0000572	0.0000517
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	-2.95E-06	0.0002297	-2.85E-06	0.0002826	-2.98E-06	0.0002296
	(0.806)	(0.338)	(0.809)	(0.239)	(0.805)	(0.335)
Leverage	-0.0042902	-0.0071872	-0.0045295	-0.0096722	-0.0028251	-0.0082168
	(0.656)	(0.52)	(0.645)	(0.401)	(0.768)	(0.468)
Merger Wave	0.2564771	1.902299	0.2440523	1.87529	0.2853377	1.926757
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Recession Year	-0.1414824	-0.184444	-0.1363172	-0.1831759	-0.1263557	-0.1773268
	(0.061)*	(0.019)**	(0.072)*	(0.021)**	(0.096)*	(0.025)**
Intercept	-2.719799	-2.649518	-2.718723	-2.649127	-2.721819	-2.658323
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	19856	14575	19598	14361	19647	14456

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

Results in this table summarize the probability of acquisition using alternate definitions of growth. The growth-resources ratio loses most of its significance when past MTB growth is used as a proxy for growth and it remains significant only for the 2-year period when using the past average market-to-book. The sign of the coefficients of the ratio and the ratio squared are constant across all tables and for all measures of resources as well. Firm size is always significantly and positively related to the probability to make a bid.

An interesting difference from the table in the discussion is that the variable past growth (defined as average past sales growth in these tables) is not significant in any regression, as opposed to when it is defined as the average past market-to-book ratio in the discussion table, where it is always positive and significant. Finally, I have no explanation for the fact that ‘’merger wave’’ and ‘’recession year’’ suffer of multicollinearity and perfectly predicts failures respectively when using the 3 years MTB growth variable. .

Table A.3 Binary Logit Model for Targets Using the Growth-Resources Ratio

This table summarizes the results of the binary logit model where the dependent variable is the probability to become a target in the next year. Both panels summarize the results using the alternate definitions of growth. In Panel A., growth is measured as the past 2 (3) years growth in the firm's market-to-book ratio which represents the change in expected growth from the market. Panel B. reports results using the definition of growth as the average past market-to-book ratio which represents the average anticipated growth by the market. The variable *Past Growth* is measured by the average past 2 (3) years sales growth.

Panel A. Growth Measured as the Past 2 (3) Years Growth in the Market-to-Book Ratio

Growth Description	2y MTB Growth	3y MTB Growth	2y MTB Growth	3y MTB Growth	2y MTB Growth	3y MTB Growth
Resources Description	Cash/ Total Assets	Cash/ Total Assets	Cash/ Book Value of Firm	Cash/ Book Value of Firm	Free Cash Flows / Total Assets	Free Cash Flows / Total Assets
G/R	-0.000251	0.0006573	0.0011291	0.0039979	0.0016996	0.0021727
	(0.63)	(0.485)	(0.367)	(0.274)	(0.068)*	(0.043)*
G/R^2	8.76E-07	1.63E-07	2.30E-07	-7.43E-06	-5.01E-11	-4.47E-10
	(0.123)	(0.878)	(0.935)	(0.483)	(0.796)	(0.765)
Firm Size	-0.0000241	-0.0000282	-0.0000247	-0.0000281	-0.0000232	-0.0000263
	(0.153)	(0.158)	(0.145)	(0.158)	(0.162)	(0.179)
Past Growth	-0.0011998	-0.0035024	-0.0011718	-0.0035689	-0.000931	-0.0031096
	(0.246)	(0.128)	(0.263)	(0.13)	(0.349)	(0.181)
Leverage	0.0203756	0.0268498	0.0226173	0.0284109	0.0230979	0.0293587
	(0.363)	(0.305)	(0.335)	(0.301)	(0.308)	(0.261)
Merger Wave	Predicts Perfectly	Collinearity	Predicts Perfectly	Collinearity	Predicts Perfectly	Collinearity
Recession Year	-0.2997192	3.609676	-0.2723559	3.600289	-0.2588945	3.612268
	(0.089)*	(0.004)***	(0.122)	(0.004)***	(0.143)	(0.003)***
Intercept	-4.135325	-4.056392	-4.126241	-4.052982	-4.146241	-4.079477
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	14240	9677	14024	9564	14000	9542

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively. ''Collinearity'' means that the variable was found to have a multicollinearity problem and was dropped from the equation by the statistical package. ''Predict'' means that the variable predicted successes of the dependent variable perfectly and was also dropped from the equation by the software.

Panel B. Growth Measured as the Past 2 (3) Years Average Market-to-Book Ratio

Growth Description	Avg 2 Years MTB	Avg 3 Years MTB	Avg 2 Years MTB	Avg 3 Years MTB	Avg 2 Years MTB	Avg 3 Years MTB
Resources Description	**Cash/ Total Assets**	**Cash/ Total Assets**	**Cash/ Book Value of Firm**	**Cash/ Book Value of Firm**	**Free Cash Flows / Total Assets**	**Free Cash Flows / Total Assets**
G/R	0.0001615	0.0003712	0.0007273	0.0009506	-0.000283	-0.0000646
	(0.648)	(0.384)	(0.334)	(0.303)	(0.203)	(0.762)
G/R^2	-5.61E-08	-7.39E-08	-6.08E-07	-5.51E-07	-1.88E-09	1.26E-07
	(0.61)	(0.59)	(0.251)	(0.394)	(0.989)	(0.32)
Firm Size	-0.0000164	-0.0000183	-0.0000169	-0.0000183	-0.0000138	-0.0000168
	(0.172)	(0.163)	(0.162)	(0.163)	(0.239)	(0.191)
Past Growth	-0.0007683	-0.0011533	-0.0007648	-0.0011799	-0.0007986	-0.0011467
	(0.061)*	(0.076)*	(0.066)*	(0.082)*	(0.052)*	(0.077)*
Leverage	0.0081933	0.0141844	0.0081746	0.0161332	0.0122359	0.0186536
	(0.682)	(0.534)	(0.689)	(0.494)	(0.54)	(0.409)
Merger Wave	-0.0907879	0.6772595	-0.0923519	0.681726	-0.1450315	0.692134
	(0.542)	(0.047)**	(0.535)	(0.046)**	(0.345)	(0.042)**
Recession Year	-0.231668	-0.2973962	-0.2083534	-0.2658932	-0.2220361	-0.2588985
	(0.151)	(0.089*)	(0.196)	(0.128)	(0.172)	(0.138)
Intercept	-4.107372	-4.135517	-4.110677	-4.135813	-4.117091	-4.139203
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	19856	14575	19598	14361	19647	14456

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

For the targets, results are consistent across all tables with the lack of statistical significance of the coefficients. This means that all models fail to accurately predict future targets.

Table A.4-1 Binary Logit Model Using the Split Subsamples

This table summarizes the results of the binary logit model ran for the 4 subsamples: high growth-high resources, high-growth-low resources, low growth-high resources and low growth-low resources. The period of the growth component of the ratio is given in the table for each regression. The resources component is **"Cash & Short-Term Investments/Book Value of Firm".** The past growth control variable is defined as "average last 2 (3) years sales change".

Subsample (Growth-Resources)	**High-High**		**High-Low**		**Low-High**		**Low-Low**	
Growth Description	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth2**	**3y MTB Growth3**	**2y MTB Growth3**	**3y MTB Growth4**	**2y MTB Growth5**	**3y MTB Growth6**
G/R	0.0365437	0.0232521	0.0009678	-0.0000216	0.0002404	-0.0003815	-0.0002781	-0.0019592
	(0)***	(0.001)***	(0.177)	(0.979)	(0.89)	(0.951)	(0.794)	(0.176)
G/R^2	-0.0001742	-0.000095	-1.01E-06	-2.70E-07	6.62E-07	-0.0000135	-1.14E-06	-3.18E-06
	(0)***	(0.066)*	(0.099)*	(0.661)	(0.821)	(0.761)	(0.457)	(0.422)
Firm Size	0.0000669	0.0000595	0.0000546	0.0000439	0.0000531	0.000028	0.0000561	0.0000553
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	0.0002556	0.0000549	0.0003008	4.73E-06	0.0002136	-0.0002194	-0.0000611	0.0009001
	(0.532)	(0.92)	(0.516)	(0.995)	(0.747)	(0.88)	(0.957)	(0.545)
Leverage	0.0641959	0.044101	-0.0602013	-0.0278505	0.233954	0.1915093	-0.0545052	-0.0838025
	(0.4)	(0.507)	(0.039)**	(0.33)	(0.121)	(0.264)	(0.08)*	(0.039)**
Merger Wave	0.0381298	1.296985	0.0974062	1.424951	-0.2874165	2.338945	0.222935	1.646653
	(0.823)	(0)***	(0.476)	(0)***	(0.188)	(0)***	(0.165)	(0)***
Recession Year	-0.4735071	-0.4518419	-0.07683	-0.1682871	-0.4294531	-0.4112248	-0.0555182	-0.0567582
	(0.019)**	(0.033)**	(0.629)	(0.296)	(0.074)*	(0.124)	(0.758)	(0.761)
Intercept	-2.940069	-2.700713	-2.36467	-2.253094	-2.828245	-2.88788	-2.734741	-2.608369
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	3081	2276	3471	2520	2833	2020	3421	2592

*,** and *** denote statistical level of significance of 10%, 5% and 1%, respectively

Table A.4-2 Binary Logit Model Using the Split Subsamples

This table summarizes the results of the binary logit model ran for the 4 subsamples: high growth-high resources, High-growth-low resources, low growth-high resources and low growth-low resources. The period of the growth component of the ratio is given in the table for each regression. The resources component is **"Free Cash Flows / Total Assets".** The past growth control variable is defined as "average last 2 (3) years sales change".

Subsample (Growth-Resource)	**High-High**		**High-Low**		**Low-High**		**Low-Low**	
Growth Description	**Average 2y MTB**	**Average 3y MTB**	**Average 2y MTB**	**Average 3y MTB**	**Average 2y MTB**	**Average 3y MTB**	**Average 2y MTB**	**Average 3y MTB**
G/R	0.0022143	0.0008263	0.0000659	0.0001125	0.0009353	0.0003669	-0.0000963	-0.0001717
	(0)***	(0.033)*	(0.669)	(0.539)	(0.141)	(0.599)	(0.616)	(0.438)
G/R^2	-1.25E-06	-2.39E-07	1.06E-07	2.88E-08	3.57E-08	1.19E-07	1.14E-07	3.82E-08
	(0.002)***	(0.335)	(0.26)	(0.801)	(0.924)	(0.761)	(0.335)	(0.779)
Firm Size	0.0000848	0.0000696	0.0000546	0.0000442	0.0000527	0.0000292	0.0000575	0.0000562
	(0)***	(0)***	(0)***	(0)***	(0)***	(0.014)**	(0)***	(0)***
Past Growth	0.0003856	0.0002015	0.0002222	-0.0000155	0.000347	-0.0002674	-0.0000596	0.0010064
	(0.285)	(0.687)	(0.633)	(0.982)	(0.613)	(0.863)	(0.957)	(0.493)
Leverage	0.1118082	0.0714649	-0.0655634	-0.0303371	0.2121755	0.1823512	-0.0549899	-0.0819061
	(0.185)	(0.315)	(0.027)**	(0.291)	(0.13)	(0.273)	(0.076)*	(0.043)**
Merger Wave	0.3576294	1.851917	0.1405361	1.480379	-0.2493335	2.26386	0.2501779	1.579812
	(0.026)**	(0)***	(0.302)	(0)***	(0.253)	(0)***	(0.118)	(0)***
Recession Year	-0.2761709	-0.3846699	-0.0778653	-0.1984879	-0.3672307	-0.3748057	-0.0589486	-0.0798415
	(0.164)	(0.067)*	(0.626)	(0.219)	(0.128)	(0.161)	(0.744)	(0.668)
Intercept	-2.654796	-2.498941	-2.347252	-2.272364	-2.85606	-2.923511	-2.804205	-2.724935
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	3021	2240	3483	2545	2776	1990	3461	2619

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

This table summarizes the results of the regressions when the samples are divided into quadrants defined by the growth and resources levels of the firms. The subsamples are the same across each table and the difference between them is the definition of resources in the ratio used. In table A.4-1, resources is defined as ‘’cash and short-term investments / book value of the firm’’ while it is ‘’free cash flows / total assets’’ in table A.4-2.

Once again, the results are similar for each definition of resources as only the high growth-high resource quadrant yields significant results while the ratios are mostly insignificant for other subsamples. Firm size is positively related to acquisition, and the puzzling inflated coefficient of ‘’merger wave’’ for the 3 years growth period is still present. Past growth and leverage are still insignificant.

Table A.5-1 Binary Logit Model and the Probability to Be Active

This table summarizes the results of the logit regressions on the probability of a firm to become active in the takeover market (as an acquirer or a target). Panel A. summarizes the results when growth is measured as the ''average past growth in the market-to-book ratio'' (2 and 3 years), while Panel B. displays the results when it is defined as the ''average past market-to-book'' for the 2 and 3 years period. Past growth is defined by the average past 2 (3) years sales growth.

Panel A. Past Average Growth of Market-to-Book Ratio

Growth	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth**	**3y MTB Growth**
Resources	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/ Total Assets**
G/R	0.0005049	0.0011374	0.0004695	0.0010707	0.0003693	0.0003636
	(0.171)	(0.057)*	(0.487)	(0.283)	(0.399)	(0.547)
G/R^2	-4.48E-07	-1.14E-06	-2.28E-06	-4.00E-06	-1.42E-07	-1.40E-06
	(0.278)	(0.115)	(0.147)	(0.135)	(0.877)	(0.299)
Firm Size	0.0000469	0.0000474	0.0000466	0.0000471	0.0000473	0.0000474
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	-0.0000169	-0.000191	-9.01E-06	-0.0001383	-0.0000319	-0.0001768
	(0.93)	(0.617)	(0.848)	(0.718)	(0.894)	(0.633)
Leverage	-0.0028733	-0.0110359	-0.0057461	-0.0137108	-0.0035776	-0.0125796
	(0.787)	(0.403)	(0.602)	(0.312)	(0.742)	(0.352)
Merger Wave	1.197258	Collinearity	1.184352	Collinearity	1.59396	Collinearity
	(0.302)		(0.307)		(0.196)	
Recession Year	-0.1838889	1.362414	-0.1798861	1.361831	-0.1742965	1.371964
	(0.012)**	(0.269)	(0.014)**	(0.27)	(0.018)*)	(0.266)
Intercept	-2.452313	-2.422945	-2.440983	-2.413603	-2.460884	-2.425031
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	14244	9677	14028	9564	14131	9619

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively. ''Collinearity'' means that the variable was found to have a multicollinearity problem and was dropped from the equation by the statistical package. ''Predict'' means that the variable predicted successes of the dependent variable perfectly and was also dropped from the equation by the software.

Panel B. Past Average Market-to-Book Ratio						
Growth	**Avg 2 Years MTB**	**Avg 3 Years MTB**	**Avg 2 Years MTB**	**Avg 3 Years MTB**	**Avg 2 Years MTB**	**Avg 3 Years MTB**
Resources	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/ Total Assets**
G/R	0.0003413	0.0000616	0.0010903	0.0005136	0.0001091	0.0000607
	(0.023)**	(0.745)	(0.001)***	(0.194)	(0.184)	(0.515)
G/R^2	-1.18E-07	-1.11E-08	-8.33E-07	-3.86E-07	5.55E-08	5.00E-08
	(0.017)**	(0.858)	(0.001)***	(0.173)	(0.267)	(0.376)
Firm Size	0.0000524	0.0000475	0.0000522	0.0000472	0.000053	0.0000478
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	-4.87E-06	0.0000595	-4.62E-06	0.0001115	-4.91E-06	-5.77E-06
	(0.782)	(0.802)	(0.78)	(0.64)	(0.782)	(0.79)
Leverage	-0.0017275	-0.0037028	-0.0019776	-0.0055862	0.0001663	-0.0035415
	(0.845)	(0.719)	(0.826)	(0.598)	(0.985)	(0.729)
Merger Wave	0.1962352	1.847605	0.1855374	1.824018	0.2168981	1.901843
	(0.001)***	(0)***	(0)***	(0)***	(0)***	(0)***
Recession Year	-0.1519142	-0.1981508	-0.1432275	-0.1918677	-0.1364168	-0.1748543
	(0.028)**	(0.006)***	(0.04)**	(0.009)***	(0.05)**	(0.016)**
Intercept	-2.497944	-2.440924	-2.497518	-2.440896	-2.501219	-2.453254
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	19856	14575	19598	14361	19647	14622

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

Results for the regressions on the probability to be active are consistent across all definitions of growth both in the discussion and the appendix. The main difference is the variable *past growth*, defined in table A.5-1 as the average past sales growth is not significant in both panels. In the discussion table, when it is defined as the past average market-to-book ratio, the results are significant and positive, once again meaning that the market can partially anticipate an event such as an acquisition.

For the dummy variables controlling for merger waves and recessions, results from both panels are much different. In panel A, results from ''Merger Wave'' are insignificant or were dropped due to multicollinearity while ''Recession'' is only significant for the 2-year growth period. On the other hand, results from panel B are consistent with those in the discussion. ''Merger Wave'' and ''Recession'' share consistent coefficients and significance levels.

Table A.5-2 Binary Logit Model on the Probability to Become an Acquirer Given the Probability to be Active.

This table summarizes the results of the second step of the 2-steps logit regressions for the probability of a firm to become an acquirer given the probability to be active (reported in table A.5-1) in the takeover market. Panel A. summarizes the results when growth is measured as the past variation in the market-to-book ratio (2 and 3 years), while Panel B. displays the results when it is defined as the ''average past market-to-book'' for the 2 and 3 years period. The variable *Past Growth* is defined by the average past 2 (3) years sales growth.

Panel A. Past Average Growth of Market-to-Book Ratio

Growth	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth**	**3y MTB Growth**	**2y MTB Growth**	**3y MTB Growth**
Resources	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/ Total Assets**
G/R	0.00102	0.0001562	-0.000995	-0.0023995	-0.0014911	-0.0047087
	(0.15)	(0.888)	(0.497)	(0.333)	(0.146)	(0.072)
G/R^2	-1.73E-06	-1.15E-06	-3.58E-06	-5.65E-07	-1.94E-06	4.19E-06
	(0.025)**	(0.396)	(0.28)	(0.937)	(0.37)	(0.479)
Firm Size	0.0001442	0.0001217	0.0001432	0.0001183	0.0001442	0.0001215
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	0.0041917	0.0108962	0.0038466	0.0112185	0.0039093	0.0125661
	(0.06)*	(0.006)***	(0.08)*	(0.005)***	(0.084)*	(0.003)***
Leverage	-0.0124649	-0.0376883	-0.0274847	-0.0482071	-0.0285288	-0.0564878
	(0.663)	(0.317)	(0.337)	(0.176)	(0.308)	(0.116)
Merger Wave	Predicts	Collinearity	Predicts	Collineartiy	Predicts	Collineartiy
Recession Year	0.0361262	Predicts	-0.0051623	Predicts	-0.0121706	Predicts
	(0.856)		(0.979)		(0.951)	
Intercept	1.298903	1.216009	1.320103	1.233136	1.324821	1.215479
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	1222	888	1213	882	1208	877

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively. ''Collinearity'' means that the variable was found to have a multicollinearity problem and was dropped from the equation by the statistical package. ''Predict'' means that the variable predicted successes of the dependent variable perfectly and was also dropped from the equation by the software.

Panel B. Past Average Market-to-Book Ratio						
Growth	**Avg 2 Years MTB**	**Avg 3 Years MTB**	**Avg 2 Years MTB**	**Avg 3 Years MTB**	**Avg 2 Years MTB**	**Avg 3 Years MTB**
Resources	**Cash/Total Assets**	**Cash/Total Assets**	**Cash/Book Value of Firm**	**Cash/Book Value of Firm**	**Free Cash Flow/ Total Assets**	**Free Cash Flow/ Total Assets**
G/R	0.0000943	-0.0005662	0.0001411	-0.001016	0.0006467	0.0002201
	(0.844)	(0.315)	(0.894)	(0.435)	(0.042)	(0.349)
G/R^2	-3.93E-08	1.28E-07	-8.93E-08	4.86E-07	3.03E-07	-5.49E-08
	(0.781)	(0.463)	(0.895)	(0.577)	(0.177)	(0.711)
Firm Size	0.0001269	0.0000998	0.0001265	0.0000976	0.0001217	0.0000959
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Past Growth	0.004032	0.0062096	0.0040961	0.0062578	0.0039473	0.0062285
	(0.007)***	(0.008)***	(0.006)***	(0.007)***	(0.009)***	(0.009)***
Leverage	-0.005885	-0.0115344	-0.0068437	-0.0179064	-0.0070333	-0.0197164
	(0.819)	(0.68)	(0.789)	(0.532)	(0.782)	(0.478)
Merger Wave	0.0741604	0.2775271	0.0593922	0.2583818	0.1311649	0.2843125
	(0.678)	(0.451)	(0.741)	(0.484)	(0.474)	(0.441)
Recession Year	-0.0323034	-0.0380518	-0.0567618	-0.065385	-0.0423531	-0.0703258
	(0.858)	(0.846)	(0.755)	(0.739)	(0.817)	(0.72)
Intercept	1.269787	1.35948	1.277019	1.365429	1.261148	1.342056
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
N=	1801	1420	1790	1410	1777	1407

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

These tables report the results of the regressions of the second step of the 2-step binary logit model testing the probability to make an acquisition given the probability to become active in the takeover market. No significant difference exists between the different definitions of growth: except firm size and past growth, most results are insignificant. Results for past growth in table A.5-2 are the only one to provide significance in predicting the probability of acquisition from the average past sales growth. While this can be a simple anomaly, it is still interesting to observe that, using a sample of future acquirers and future targets exclusively, the level of past sales growth is strongly and positively related to the probability to make a bid.

Table A.6 Multinomial Logit and Probit Models Using Dummy Variables

This table summarizes the results from the multinomial logit and probit models using dummy variables to define growth and resources. The dummy variable *High Growth* takes a value of 1 if a firm's growth, measured as the average past 2 years sales growth is higher than the industry median. The dummy variable *High Cash*, measured as cash and short term investments over total assets is also equal to 1 if it is greater than the industry median. The dummy variable *Low Leverage* takes a value of 1 if the firm's leverage is *lower* than the industry median. The variable past growth is the average MTB for the past period identified for each column. Results from the logit models are the same as reported in discussion part of the paper. They are displayed here for the ease of comparison with the probit model.

Model	**Logit**		**Probit**	
Variable	**Acquirer**	**Target**	**Acquirer**	**Target**
High Growth	0.4501954	0.1725072	0.3011444	0.122304
	(0)***	(0.153)	(0)***	(0.05**)
High Cash	0.093586	0.0272758	0.0673934	0.0235948
	(0.094*)	(0.83)	(0.082*)	(0.721)
Low Leverage	-0.313069	-0.5535483	-0.2179882	-0.3075684
	(0)***	(0)***	(0)***	(0)***
Firm Size	0.0000534	-0.0000145	0.0000432	-4.60E-07
	(0)***	(0.316)	(0)***	(0.946)
Growth (MTB)	0.0248566	0.0127377	0.0183175	0.0089902
	(0)***	(0.075*)	(0)***	(0.021**)
Merger Wave	0.1770498	0.0886396	0.0928109	0.0663811
	(0.005***)	(0.556)	(0.041**)	(0.397)
Recession	-0.1886495	-0.0681559	-0.1371544	-0.0517333
	(0.011**)	(0.676)	(0.007***)	(0.539)
Intercept	-2.911022	-4.166654	-2.29128	-2.964834
	(0)***	(0)***	(0)***	(0)***
N=	21877	21877	21877	21877
	# Acquirers=1661	# Targets=291	# Acquirers=1661	# Targets=291

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

This table exposes the differences in results from the multinomial logit and multinomial probit models with the purpose of facilitating the comparison between both. The coefficients always have the same sign and similar significance. The relationship of the independent variables on the dependent variable is always weaker for the probit model. This model also reports a significantly positive link between higher growth than the industry median and the probability to become a target, although weaker than to become an acquirer. Except from this coefficient, results are essentially the same and the multinomial probit slightly increases the significance of the results over the multinomial logit.

Table A.7 Multinomial Logit Model Using the Growth-Resources Ratio

This table summarizes the results of the multinomial logit model using the growth-resource ratio. Panel A. summarizes the results when resources is defined as "Free Cash Flows / Totals Assets" and Panel B., when it is defined as "Cash / Total Assets". The growth component of the growth-resources ratio is identified in the first row. The variable *Past Growth* is the average market-to-book ratio for the period identified for each column by the growth variable.

Panel A. Resources defined as "Free Cash Flows / Total Assets".

Growth	**2 Years Sales Growth**	**2 Years Sales Growth**	**3 Years Sales Growth**	**3 Years Sales Growth**
Resources	**Free Cash Flows / Total Assets**	**Free Cash Flows / Total Assets**	**Free Cash Flows / Total Assets**	**Free Cash Flows / Total Assets**
	Acquirer	**Target**	**Acquirer**	**Target**
G/r	0.0000185	-0.0000423	0.0000333	-0.0000197
	(0.009)***	(0.011)**	(0.001)***	(0.453)
G/R ^2	1.57E-11	-2.72E-10	-2.32E-10	-6.07E-10
	(0.509)	(0.199)	(0.605)	(0.623)
Firm Size	0.0000539	-7.01E-06	0.000048	-3.66E-06
	(0)***	(0.601)	(0)***	(0.786)
Growth	0.0268844	0.0131892	0.0241577	0.0146445
	(0)***	(0.064)*	(0)***	(0.116)
Leverage	-0.0051833	0.0093697	-0.0100053	0.0185692
	(0.577)	(0.647)	(0.35)	(0.42)
Merger Wave	0.1831975	0.053553	1.824991	1.263467
	(0.004)***	(0.732)	(0)***	(0)***
Recession	-0.1892019	-0.0437679	-0.2254367	-0.1073377
	(0.012)**	(0.791)	(0.004)	(0.549)
Intercept	-2.740723	-4.319713	-2.671505	-4.338767
	(0)***	(0)***	(0)***	(0)***
N=	21277	21277	16023	16023
	# Acquirers=1658	# Targets=280	# Acquirers=1342	# Targets=211

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

Panel B. Resources defined as "Cash / Total Assets".

Growth	2 Years Sales Growth	2 Years Sales Growth	3 Years Sales Growth	3 Years Sales Growth
Resources	**Cash / Total Assets**	**Cash / Total Assets**	**Cash / Total Assets**	**Cash / Total Assets**
	Acquirer	**Target**	**Acquirer**	**Target**
G/r	0.0000179	0.0000429	0.0000181	7.03E-06
	(0.147)	(0.124)	(0.252)	(0.841)
G/R ^2	-4.73E-10	-9.77E-10	-5.06E-10	-1.03E-10
	(0.035)**	(0.137)	(0.088)**	(0.852)
Firm Size	0.0000536	-9.72E-06	0.0000478	-5.00E-06
	(0)***	(0.48)	(0)***	(0.715)
Growth	0.0267295	0.0130162	0.0240653	0.0142101
	(0)***	(0.065)*	(0)***	(0.126)
Leverage	-0.0043971	0.0061913	-0.00892	0.0158205
	(0.633)	(0.761)	(0.398)	(0.49)
Merger Wave	0.1609187	0.0881744	1.788395	1.222392
	(0.012)**	(0.561)	(0)***	(0)***
Recession	-0.1938925	-0.0709109	-0.2237863	-0.1496428
	(0.009)***	(0.665)	(0.004)***	(0.404)
Intercept	-2.737278	-4.297191	-2.670995	-4.319392
	(0)***	(0)***	(0)***	(0)***
N=	21509	21509	16162	16162
	# Acquirers=1675	# Targets=290	# Acquirers=1352	# Targets=215

*, ** and *** denote statistical level of significance of 10%, 5% and 1%, respectively.

Results from the multinomial logit models using the growth-resources ratio are reported in Table A.7. The definition of resources is different in Panel A. and Panel B. and the variable *Past Growth* remains the average past sales growth. In panel A., results are consistent with those in the discussion part of the paper, except that the ratio squared is insignificantly different than zero. However, when the empirical definition of resources is used (cash and short term investments / total assets) in panel B, the coefficients from the growth-resources ratio become insignificant. Other than that, results are consistent across all tables.

Table A.8 Models' Performance by Decile

This table summarizes the estimated probability that a firm become an acquirer by different models. It is the continuation of table 20 that is reported here since the results were essentially the same across all models. Results are reported in deciles from the highest probability to the lowest.% of Acquirers Correctly Classified is calculated as the number of Acquirers Correctly Classified over the Total Firms Classified as Acquirer. The Cumulative % of Total Acquirers Correctly Classified in the whole sample is reported in the last column.

Model : 2 Steps Binary Logit

Estimated Probability Decile	Acquirers correctly classified	Non-Acquirers Incorrectly Classified as Acquirers	Total Firms Classified as Acquirers	% of Acquirers Correctly Classified	Cumulative % of Total Acquirers Correctly Classified
9.97-100%	**161**	**629**	**790**	**20.38%**	**26.05%**
7.64-9.97%	80	710	790	10.13%	39.00%
6.92-7.64%	75	716	791	9.48%	51.13%
6.55-6.92%	76	714	790	9.62%	63.43%
6.27-6.55%	42	748	790	5.32%	70.23%
5.94-6.27%	36	755	791	4.55%	76.05%
5.49-5.94%	59	731	790	7.47%	85.60%
5.19-5.49%	42	748	790	5.32%	92.39%
4.94-5.19%	31	760	791	3.92%	97.41%
0-4.94%	16	774	790	2.03%	100.00%
Total	**618**	**7285**	**7903**		

Model: Multinomial Logit Dummy

Estimated Probability Decile	Acquirers correctly classified	Non-Acquirers Incorrectly Classified as Acquirers	Total Firms Classified as Acquirers	% of Acquirers Correctly Classified	Cumulative % of Total Acquirers Correctly Classified
9.66-100%	**179**	**716**	**895**	**20.00%**	**28.19%**
8.2-9.66%	95	800	895	10.61%	43.15%
7.16-8.2%	69	826	895	7.71%	54.02%
6.48-7.16%	51	844	895	5.70%	62.05%
5.78-6.48%	66	829	895	7.37%	72.44%
5.29-5.78%	44	851	895	4.92%	79.37%
4.71-5.29%	32	863	895	3.58%	84.41%
4.29-4.71%	40	855	895	4.47%	90.71%
3.65-4.29%	43	853	896	4.80%	97.48%
0-3.65%	16	879	895	1.79%	100.00%
Total	**635**	**8316**	**8951**		

Model: Multinomial Logit Ratio

Estimated Probability Decile	Acquirers correctly classified	Non-Acquirers Incorrectly Classified as Acquirers	Total Firms Classified as Acquirers	% of Acquirers Correctly Classified	Cumulative % of Total Acquirers Correctly Classified
9.45-100%	**161**	**629**	**790**	**20.38%**	**26.05%**
7.49-9.45%	77	713	790	9.75%	38.51%
6.89-7.49%	77	714	791	9.73%	50.97%
6.58-6.89%	73	717	790	9.24%	62.78%
6.34-6.58%	41	749	790	5.19%	69.42%
6.02-6.34%	42	749	791	5.31%	76.21%
5.63-6.02%	57	733	790	7.22%	85.44%
5.38-5.63%	41	749	790	5.19%	92.07%
5.17-5.38%	33	758	791	4.17%	97.41%
0-5.17%	16	774	790	2.03%	100.00%
Total	**618**	**7285**	**7903**		

Table A.9 reports the remaining models' performances by deciles that were not included in the discussion because of redundancy. As one can see, the models behave essentially the same: around 20% of the firms are correctly classified as acquirers in the first decile~~s~~ and then the proportion decreases substantially in the next deciles.