MARKETS TALK, FIRMS LISTEN: THE DYNAMICS OF REPEAT ACQUIRERS*

KENNETH R. AHERN†
UNIVERSITY OF CALIFORNIA — LOS ANGELES

*** JOB MARKET PAPER ***

Abstract

Prior studies have shown that repeat acquirers' early abnormal returns are higher than the returns from later acquisitions. Using new econometric techniques with a panel dataset over two decades, I find that this pattern of declining returns is not caused by market anticipation of later deals. Instead, announcement returns are deal-specific, rather than firm-specific, and thus provide valuable feedback to acquirers about their M&A choices. In a novel approach, I find that firms consider this feedback when making current decisions, providing new evidence of learning in M&As. Finally, I find no support for explanations of declining returns based on agency, hubris, or diminishing opportunity sets. Instead, I propose a cost minimization hypothesis consistent with shareholder wealth maximization through M&As. Balancing search and integration costs leads larger firms to demand larger targets, though of small relative sizes, leading to declining returns.

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† Please direct correspondence to Kenneth R. Ahern, 8283 Bunche Hall, 405 Hilgard Avenue, P.O. Box 951477, Los Angeles, California, 90095-1477. Telephone: (310) 283-9605. Fax: (310) 450-6151. Email: ahern@ucla.edu. Webpage: http://ahern.bol.ucla.edu.

1. Introduction

Though the majority of acquisitions are made by firms that have acquired before, there is little evidence on the dynamics of repeat acquirers. The one prevalent finding in the prior literature is a pattern of declining event returns over successive deals (Fuller, Netter, and Stegemoller, 2002; Conn, Cosh, Guest, and Hughes, 2004; Aktas, de Bodt, and Roll, 2006). This raises many questions. In particular, 1) Do markets anticipate future acquisition returns? 2) Do firms adjust current M&A activities based on the returns of prior deals? And 3) Do repeat acquirers develop a standardized acquisition model? This paper addresses these questions empirically by examining the interaction between the acquisition decisions of repeat acquirers and the resulting market responses. My analysis of a large panel dataset over two decades provides sharply different explanations than those presented in prior cross-sectional studies. Though firms do learn from market responses, returns decline because later deals are smaller in relative size though targets are larger in absolute value, both of which yield lower returns.

Understanding the interaction between acquisition history and current abnormal returns can provide important insights into the decision-making processes of firms. First, a positive relation between experience and acquisition returns would support a widely-held belief in the business press and among consulting firms that learning can lead to better acquisitions (Harding and Rovit, 2004; Palter and Srinivasan, 2006). Second, acquisition returns have been shown to be negatively related to the likelihood of CEO dismissal (Mitchell and Lehn, 1990; Lehn and Zhao, 2006). However, if returns are low because the value of an acquisition has been capitalized by investors at an earlier acquisition announcement, made perhaps by a former CEO, blame may be incorrectly placed on the current executive. In addition, a better understanding of the information conveyed by acquisition announcements may be obtained by an examination of repeat acquirers. In a dynamic setting, later deals may more likely convey information about the target and deal structure instead of the acquirer, since investors have already received prior signals about the bidder (Hietala, Kaplan, and Robinson, 2003). Finally, since firm size may be related to M&A experience, panel data may help us to understand why large firms have lower acquisition returns in the cross-section (Moeller, Schlingemann, and Stulz, 2004).

I addresses these dynamic effects by first examining two theories of repeat acquirers. The *anticipation theory* posits that the value of a current acquisition may have been reflected in price changes surrounding prior acquisition announcements if markets correctly anticipate future M&A activity. Second, the *organizational learning theory* states that firms make better acquisitions by learning from their histories of prior acquisitions.

With an understanding of these two dynamic effects, I then investigate the determinants of the pattern of declining returns found in the prior literature, controlling for the forward-looking nature of markets and the backward-looking nature of firms.

To test the anticipation theory, I control for the endogenous relationship between current returns and the likelihood of future acquisition activity. Market anticipation of future deals implies that current abnormal returns should be positively related to the expected value of future acquisitions, and hence, the probability of completing future acquisitions (Schipper and Thompson, 1983). However, the probability of future acquisitions is expected to be higher if the returns to the current acquisition are high. Using a large panel data set of acquisitions between 1981 and 2004, I estimate a simultaneous equations model of this endogenous interaction and find that markets do not capitalize the expected value of later deals following the announcements of early acquisitions. Though repeat acquirers have higher first announcement returns than firms that do not make subsequent acquisitions, these higher returns are not related to the likelihood of future acquisitions. To my knowledge, this is the first paper that directly controls for this endogeneity problem in the econometric analysis.

The anticipation theory also suggests that the amount of information conveyed in acquisitions should be decreasing with deal order (Asquith, Bruner, and Mullins, Jr., 1983). After a firm has made many acquisitions, the amount of new information revealed from a subsequent announcement should be only marginal if investors have anticipated the later deals. I use quantile regression to identify the effect acquisition experience has on the distribution of returns while holding other confounding variables fixed. I find that information, as measured by the dispersion in returns for a cross section of acquisitions, is constant for all deals in a sequence, in contrast to the anticipation theory. Thus the information provided by an acquisition is deal-specific, rather than acquirer-specific.

These results imply that histories of acquisition returns provide clear and valuable feedback to repeat acquirers about the value of their prior M&A choices. I test whether firms make current acquisition decisions based on this information, as predicted by the learning theory (Lubatkin, 1983). Using a dynamic panel data framework that controls for unobserved firm-specific heterogeneity, I analyze three key decisions that acquirers make: target organizational status (public or private), method of payment (majority cash or majority stock), and the decision to make diversifying acquisitions (same industry or not). I hypothesize that firms will select the options that have generated the best returns historically for the firm.

My results show that on average repeat acquirers are sensitive to prior returns when deciding the public status of targets and method of payment, but not whether to make diversifying acquisitions. Moreover, I find that the firms that are more responsive to prior acquisition performance have higher returns across all deals than do firms that are not responsive. Thus the firms that adjust subsequent M&A activities due to market signals perform better than those that do not. These results are consistent with the hypothesis of shareholder wealth maximization through organizational learning.

The above results suggest that the pattern of declining abnormal returns found in the prior literature is not caused by market anticipation of later deals. Furthermore, all else constant, organizational learning implies returns should be increasing. Thus it seems important to reconsider the determinants of the pattern of returns in a dynamic setting. Using panel data to control firm-specific unobserved heterogeneity, I identify the determinants of abnormal returns for a fixed deal number. Then I determine if these factors are changing with acquisition experience. I find that returns decline because larger firms with less managerial oversight are buying larger targets, though of smaller relative sizes. Agency problems, hubris, or declining investment opportunity sets could explain this pattern, as others have suggested (Conn, Cosh, Guest, and Hughes, 2004; Aktas, de Bodt, and Roll, 2006; Klasa and Stegemoller, 2006). However, my empirical analysis rejects these explanations, consistent with my finding of shareholder wealth maximization through M&As.

Instead, I posit that the pattern of declining returns is due to considerations of post-merger integration costs and the pre-merger costs of M&A activities including search, legal, and financial advice. Larger targets incur greater integration costs, but targets that are too small do not provide enough value to offset the search and transaction costs of the acquisition. Balancing these costs leads to an optimal relative size of target to acquirer. In my sample, average acquirer size continues to grow over subsequent acquisitions, but the relative size of the target is a stable 10% on average (3% at the median) for fifth and later deals. Thus later deals are dominated by acquisitions of increasingly large targets which are more likely public, though of a small relative size. The liquidity premium on public targets (Officer, 2006) and the lesser impact created by relatively small targets leads to decreasing acquirer returns. In sum, my results imply that on average, firms are learning from their histories and minimizing acquisition costs in order to maximize shareholder value.

In contrast to the vast literature on the cross-section of acquirer returns, this paper provides new contributions by examining acquisition behavior in the context of a firm's acquisition history. This is important because firms learn from their histories to adjust current activities, a result not evident in cross-sectional studies. Also, by examining the dispersion of returns across deal number, controlling for other factors than experience, I provide new evidence about the informativeness of acquisition announcements over a deal sequence. Finally, I propose a new hypothesis to explain the pattern of declining acquisition returns based on a minimum target size constraint and the desire to acquire relatively small targets.

This paper also contributes to the small, but growing literature on repeat acquirers by examining the interaction between acquisition *decisions* and market responses, as opposed to a simple analysis of abnormal returns. Also, because I only include firms in my sample that were publicly listed after 1980, the first year my merger data is available, I establish a solid benchmark from which to measure acquisition experience. This produces less bias in measures of experience than the arbitrary definitions of M&A program starts commonly used in the prior literature.

The remainder of the paper is organized as follows. Section 2 presents the theoretical arguments of repeat acquirers and prior empirical results. The data are described in Section 3. The tests and results of market anticipation are described in Section 4. Section 5 presents results on firm learning from historical market responses. Section 6 examines the determinants of the pattern of returns over deal sequences. Section 7 concludes.

2. Related Literature

2.1. Market Anticipation

Schipper and Thompson (1983) propose a capitalization theory where markets reflect the entire benefit of an acquisition sequence in the first announcement of the program. Later acquisition returns only reflect surprises, which are zero on average. A related signaling theory proposed in Asquith, Bruner, and Mullins, Jr. (1983) suggests that each acquisition announcement provides less information to the market about the true value of the firm than the preceding announcement. Since the signaling theory is equivalent to the capitalization theory with uncertainty, I group them together in a theory called the *anticipation theory*. This theory predicts that acquisition returns will be declining as uncertainty is resolved and later deals will reflect less new information.

The empirical evidence presented in these two seminal papers on repeat acquirers is mixed, finding support for capitalization in Schipper and Thompson (1983), but no support for signaling in Asquith, Bruner, and Mullins, Jr. (1983). However, both studies use very small samples (55 and 70 firms) and do not control for many possible confounding variables explaining abnormal returns, such as the organizational status of the target or payment method. Subsequent studies have tested the anticipation theory by comparing the first deal returns (as opposed to program announcements as in Schipper and Thompson (1983)) of single acquirers to those of repeat acquirers using larger samples and holding other factors constant. The results present mixed support for anticipation, finding either no difference or that repeat acquirers do significantly better (Loderer and Martin, 1990; Haleblian and Finkelstein, 1999; Rosen, 2004; Conn, Cosh, Guest, and Hughes, 2004).

However, no prior study controls for the endogeneity between the likelihood of future acquisition activity and the returns to a current deal. This implies that the high first deal returns of repeat acquirers may simply reflect a survival bias, where successful firms continue to make acquisitions. This is a very different story than market anticipation. Thus it is an open question whether higher returns on the first deal reflect future acquisition returns or simply lead firms to become repeat acquirers. To explicitly control for this endogeneity problem, I use a simultaneous equations framework with panel data which allows me to control for the likelihood of future acquisition activity at the current deal.

2.2. Organizational Learning

In an early paper, Lubatkin (1983) hypothesizes that firms may learn from experience in M&As, with frequent acquirers outperforming less active firms. In a more recent theoretical paper, Bernardo and Chowdry (2002) develop a model of firm learning where firms specialize initially, then experiment in new lines of business, then depending upon the results of the experimentation, either expand across segments or expand in a focused industry. In a merger context, this theory suggests that a learning firm would first exhibit small exploratory acquisitions, and then a pattern of either multisegment or focused acquisitions of larger scale targets. Aktas, de Bodt, and Roll (2005) develop a model of CEO learning in the context of acquisitions. Rational CEOs learn to bid more aggressively over deals in order to win private benefits associated with deal completion. Hubris-infected CEOs learn to bid less aggressively for fear of replacement. Rational CEOs exhibit higher early returns that diminish as premiums paid increase, whereas hubris CEOs overpay early and have increasing returns as they learn to pay smaller premiums. Thus learning may produce declining returns, consistent with prior empirical findings, because CEOs are learning how to maximize private benefit, rather than firm value.[1]

Empirical tests of learning in M&As have been primarily restricted to testing the relationship between abnormal returns and acquisition experience. The majority of the evidence contradicts learning, finding a negative relationship after controlling for acquirer size, relative size, and method of payment (Haleblian and Finkelstein, 1999; Hayward, 2002; Conn, Cosh, Guest, and Hughes, 2004), though Aktas, de Bodt, and Roll

[1]Though I empirically control for CEO effects, I focus on organizational learning, as opposed to CEO learning, because repeat acquirers are typically large firms that have M&A departments as well as legal and finance departments with specialized knowledge in M&As. Repeat acquirers also tend to buy relatively small targets. Thus the decisions of the CEO in M&As, though important, are only part of the process. Aktas, de Bodt, and Roll (2006) focus on CEOs since the theoretical model they test describes a tradeoff between private benefits of control and the risk of being replaced.

(2006) report an insignificant relationship after including control variables. A number of studies have shown that early losses lead to higher returns later in a deal sequence (Hayward, 2002; Conn, Cosh, Guest, and Hughes, 2004; Aktas, de Bodt, and Roll, 2006). This evidence is consistent with the hypothesis that when firms have early acquisition losses, they learn from their mistakes and perform better subsequently. It is also consistent with the model of Aktas, de Bodt, and Roll (2005), where hubris-infected CEOs are identified by early acquisition losses. However, as Conn, Cosh, Guest, and Hughes (2004) point out, this evidence is also consistent with mean-reversion, or simply chance.

The common shortcoming of all these prior empirical tests is that learning is observed only by looking at acquisition returns, rather than the decisions that firms make. Because many variables affect returns, this indirect method is open to conflicting explanations. In contrast, Jennings and Mazzeo (1991) and Luo (2005) study whether announcement returns affect firm *decisions*, in particular, the decision to complete, renegotiate, or abandon a deal. Jennings and Mazzeo do not find any evidence that firms change their actions based on the information provided by the market response to the announcement. Using a larger dataset and a more robust econometric procedure, Luo (2005) find that firms are responsive to announcements. Higher bidder-target combined announcement returns are significantly and positively related to the likelihood of closing a deal and the likelihood of a renegotiated higher offer price. This result suggests that firms learn from the market and adjust behavior accordingly.

I adopt this more direct approach to tests of learning in M&As. In particular, I test whether prior performance affects current acquirer decisions of three key choices: target public status, method of payment, and bidder-target relatedness. To my knowledge, no prior study has ever tested the relationship between acquisition history and current decisions. This is a substantial improvement as this method overcomes the shortcoming of identifying learning through abnormal returns. As opposed to Jennings and Mazzeo (1991) and Luo (2005), I investigate firm decision-making based on a firm's entire acquisition history, rather than the first announcement return of a current deal. This provides a richer information source and allows tests of firm sophistication in learning, where firms may learn only from the last deal returns, the returns to all prior deals, and the returns controlling for other factors. This is discussed in greater detail in Section 5.

2.3. Acquirer, Target, and Deal Characteristics

Prior research has identified a variety of factors related to acquisition returns that may be changing with deal number and so must be controlled when investigating the dynamic effects of learning and market anticipation. I divide these effects into acquirer, target, and deal structure factors.

Moeller, Schlingemann, and Stulz (2004) report that small acquirers generate larger announcement returns than do large acquirers. They suggest this effect may be caused by agency issues of large firms. Thus a measure of managerial monitoring may help explain returns (Shleifer and Vishny, 1997; Field and Karpoff, 2002). High prior returns and low book-to-market ratios may signal overvaluation, leading to lower acquisition returns (Rhodes-Kropf, Robinson, and Viswanathan, 2005). These factors have also been used to proxy for a firm's investment opportunity set (Billett, King, and Mauer, 2006). Klasa and Stegemoller (2006) find results that the start of an acquisition program is associated with increased investment opportunities and the end of the program with decreased opportunities.

An acquirer's industry may also affect the motivation for mergers and hence their abnormal returns. Neoclassical theory states that mergers are profit maximizing responses to unanticipated forces such as regulatory changes and technological progress (Gort, 1969). Empirical tests have supported the theory, showing that merger waves are industry specific and are typically initiated by an external shock (Mitchell and Mulherin, 1996; Harford, 2005). To control for this effect I include a dummy variable for acquisitions made as part of a merger wave.

The organizational structure of the target has also been shown to affect acquirer abnormal returns. Private and subsidiary targets generate positive returns, whereas public targets generate negative returns (Fuller, Netter, and Stegemoller, 2002). Studies have also documented both discounts and premiums for diversification (Campa and Kedia, 2002). Thus acquirer-target similarity may affect abnormal returns.

Significant relationships have been reported between acquirer returns and the method of payment and relative size of the target to the acquirer. Cash deals have higher returns than equity deals overall, though equity purchases of private targets have higher returns than those of public targets, whereas equity purchases of public targets have lower returns than public targets. A larger relative size of the target to the acquirer magnifies the absolute value of the returns (Chang, 1998; Fuller, Netter, and Stegemoller, 2002; Moeller, Schlingemann, and Stulz, 2004).

It is likely that acquisitions made later in a firm's series of acquisitions will be made by a larger firm with less managerial share ownership and greater managerial entrenchment which will reduce the abnormal returns relative to earlier deals. Larger firms may also wish to purchase larger targets which are more likely to be publicly listed. Thus, these factors may explain the pattern of declining returns. Conversely, these prior results in the literature may be due to deal order effects, because the results were found without controlling for acquisition experience. Thus, the use of panel data is imperative to separate experience from these other factors that explain abnormal returns.

3. Data and Methodology

To test theories of repeat acquirers it would be ideal to have returns data and complete acquisition histories of all acquiring firms. However, comprehensive merger data begins in 1980 and returns data are only available for public firms. Thus to produce the most complete acquisition histories I limit my sample to firms that publicly list after 1980. This may produce two types of bias. First, firms may have extensive acquisition histories as private firms that would not be captured in my data. However, it is likely that acquisitive private firms will also be acquisitive public firms and this bias will affect all firms equally. Second, the post-1980 listing restriction may bias my sample towards firms in certain industries. I address this problem below and find little bias.[2] The following presents a detailed description of the data.

The sample data are taken from Securities Data Corporations's (SDC) U.S. Mergers and Acquisitions database. Only acquisitions worth at least $1 million announced between 01/01/1980 and 12/23/2004 that were completed within 1,000 days are included in the sample.[3] Because repeat acquirers may be more likely to acquire many small firms, rather than fewer large firms, no restriction is placed on the relative value of the target to the acquirer as is commonly done in prior studies. Also, acquirers have to own less than 50% of the target before the acquisition, and 100% after the acquisition. This prevents the inclusion of partial acquisitions of the same target. Acquirers have to be public firms with data available on the Center for Research in Security Prices (CRSP) and CompuStat databases. Targets are restricted to public, private, or subsidiaries of a public or private firm. Also, multiple acquisition announcements by the same firm within five days of each other are excluded.

Finally, as noted above, to ensure acquisition experience is correctly measured, I exclude all acquirers that were listed on CRSP before 01/01/1980. This exclusion is not typically done in prior research on multiple acquirers but provides a solid benchmark from which to order acquisitions. If no benchmark is used, acquisition data limitations will lead to a downward bias in the measurement of acquisition experience for older firms. Using this restriction also avoids defining the beginning of a merger program by an arbitrary no-acquisition hiatus of between two and eight years, as is commonly done in prior studies (Loderer and Martin, 1990; Rosen, 2004; Conn, Cosh, Guest, and Hughes, 2004).

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[2] Future research could include firms listing before 1980, while controlling for date of first-listing. In this way, cohorts of firms by listing date could be compared in the post-1980 period.

[3] I restrict attention to completed deals because data on incomplete deals will likely be biased towards public targets which may affect my results on learning. However, only using completed deals may lead to a misproportional small number of hostile deals, as hostile deals are more likely to fail (Walkling, 1985).

This sampling procedure produces 12,942 acquisitions made by 4,879 acquirers. The prototypical repeat acquirer, Cisco Systems, completed 50 acquisitions, the largest number in the sample, though the average firm completed 2.7 deals over the sample 15 year period. If a 1% relative value restriction had been placed on the sample, Cisco would only have 10 deals in the sample. A 5% cutoff would have left only one deal in the sample. Thus, imposing relative value restrictions may alter the sample significantly. Table 1 presents a summary description of the sample by year. Total deals peaked in 1997 with 1,437 announcements, though total transaction value peaked in 2000 with $615,382 million. The median transaction value for all years is $25.38 million, considerably less than the average value of $571 million, reflecting the positive skewness of the distribution of transaction values.

Though I limit the sample to firms not listed before 1980, the distribution of deals by industry shifts only slightly towards high technology industries. In a sample where acquirers are not restricted to being listed after 1980, using the 49 Fama French Industry Classifications,[4] banking accounts for the largest number of deals without restricting acquirer listing dates (13.9% of all deals). Computer software (9.9%), business services (6.9%), electronic equipment (5.8%), and communication (5.5%) round out the top five industries which together account for 42% of all deals in the unrestricted sample. The top five industries for the sample used in this paper, where acquirers must be first listed after 1980, are software (13.9%), banking (10.8%), business services (8.6%), communication (6.5%), and electronic equipment (6.2%), totalling 46% of all deals. Thus the industry clustering in merger activity reported in prior work is confirmed here, and relatively unchanged by my sample restrictions (Mitchell and Mulherin, 1996; Harford, 2005). This suggests that the 1980 listing requirement will not produce extensive bias in my results.

Because prior acquisitions may affect any event study prediction method which estimates abnormal returns using firm historical returns, I calculate abnormal returns using a market-adjusted model with the equally-weighted CRSP index as a market proxy. For each day in the event period, market returns are subtracted from firm returns (Brown and Warner, 1985). Cumulative abnormal returns (CARs) are computed over the five days surrounding the announcement because the announcement dates listed on SDC are not always accurate. Significance tests of CARs are conducted with a sign test (Corrado and Zivney, 1992). Table 2 reports CARs grouped by total number of deals in a firm's series, acquisition order in series, and target organizational status.

[4]Generously provided on Kenneth French's website.
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

There are 2,212 firms that made only one acquisition in the sample period, while there are 503 with over five acquisitions. These 503 firms account for 10% of all firms in the sample, but complete 35% of all the deals. The average CAR for all firms and all deals is a significant 1.98%. Subsidiary targets yield higher returns (3.09%) than do private targets (2.30%), which yield higher returns than public targets, which are statistically negative (-0.86%). Consistent with prior studies, CARs are declining with deal order, regardless of target status. Public targets yield an insignificant 0.35% for first deals declining to a significant −2.06% for sixth and later deals. First acquisitions of private targets generate 3.39%, declining to 0.72% for sixth and later deals.[5]

The sample sizes reported for each CAR in Table 2 also reflect that the type of target is changing with deal order. For the first through third deals, roughly 16% are public targets, 55% are private, and 29% are subsidiaries. For fourth and higher deals, public targets become more prevalent, increasing to 25% of the sample for the sixth or later deals, while private targets decrease to 48%. Subsidiary targets first increase to 33% then decline to 27% for the later deals. This supports the idea that changing firm characteristics may explain part of the decline in abnormal returns with deal order.

For later tests, I define three subsamples from the total sample as follows. *Frequent* acquirers are the 503 firms that completed more than five deals during the sample period. The 2,667 firms that made at least two acquisitions are defined as *Repeat* acquirers. Of these repeat acquirers, 90% completed their second acquisition within 1,168.8 trading days, or roughly 4.6 years after the first acquisition. I define *Single* acquirers as those firms that complete only one acquisition in the sample period and also had stock that was actively traded for 1,169 trading days following their single deal. This yields a sample of 662 firms. These restrictions ensure with 90% confidence that the *Single* subsample excludes would-be repeat acquirers had the sample period extended further in the future.

4. Do Markets Anticipate Future Acquisition Returns?

4.1. Capitalization Theory

The capitalization theory posits that early acquisition returns reflect the value of future M&A activity. I begin with a naïve test of the capitalization hypothesis by comparing the returns to the first acquisition announcement of the *Frequent* and *Repeat* acquirer samples to the acquisition returns of the *Single* acquirer

[5]In unreported calculations, average (median) abnormal dollar returns are −\$19.5 million (\$0.4 million) in 2005 dollars, consistent with the same calculations in Moeller, Schlingemann, and Stulz (2004). However, the abnormal dollar returns do not exhibit a strong pattern of decline over deals, as do the equally-weighted abnormal returns. Nevertheless, I replaced CARs with dollar returns in all of the following analyses as a robustness check and found no qualitative difference in the results.

group. Insignificantly different returns to multiple and single acquirers is evidence against the capitalization hypothesis. I label this the naïve approach because higher first deal returns to repeat acquirers are consistent with capitalization, but are not proof, as other explanations are possible, such as a survival bias, where successful first deals lead to future deals. Table 3 presents the results from this naïve test. All variable definitions are provided in the Appendix.

The first three columns present mean values of acquirer, target, and deal characteristics. The five-day CAR is not significantly different between the three sub-samples, with all realizing abnormal returns around 3%. However, the characteristics of the bidder, target, and deal, are quite different between the three sample groups. In particular, at the time of the first deal, repeat acquirers are significantly larger, have higher prior year returns, lower book-to-market ratios, and higher values of Tobin's q on average than do single acquirers. First targets of repeat acquirers are more likely private and less likely public compared to single acquirer targets. Finally, repeat acquirers are also more likely to use an all stock deal structure than are single acquirers. Since many of these factors have been shown to affect abnormal returns, a direct comparison of the single and repeat acquirer CARs is misleading.

The final two columns of Table 3 present ordinary least squares (OLS) regressions of these factors on the CAR including variables indicating future acquisition activity. The first regression shows that controlling for firm and deal characteristics, firms that go on to complete more than five deals yield CARs that are a significant 1.64 percentage points higher than the CARs of single acquirers. Regression (2) includes a variable for total deals completed during the sample period, 1981-2004, and finds that one more future deal is associated with an increase in the first deal CAR of 0.14 percentage points. These results are robust to time effects and industry effects, as I include both in the regressions. This evidence is consistent with the capitalization hypothesis. Holding firm and deal characteristics fixed, repeat acquirers have significantly higher returns than do single acquirers. However, since the results from this naïve approach can not reject other theories, further tests are necessary.

4.1.1. Simultaneous Equations Model

The above results support the capitalization hypothesis, but they could also be the consequence of an entirely different process. In particular, firms that have high early acquisition returns are likely to continue making deals, as they attempt to repeat their early successes. This will produce the same positive correlation between current CARs and future acquisitions. Thus, to control for the possible market anticipation of future deals, we must account for the endogenous relationship between the likelihood of future deals and the returns to the current deal. All else constant, higher current returns are hypothesized to increase the likelihood of acquiring again. At the same time, the capitalization hypothesis states that current returns reflect the probability of future acquisitions.

To empirically control for this endogeneity, I define these relationships in the following simultaneous equations model.

$$CAR_{it} = \alpha_1 EVF_{it} + \mathbf{X_{1it}}\boldsymbol{\beta_1} + c_{1i} + u_{it} \qquad t = 1, \ldots, T \tag{1}$$

$$EVF_{it} = \alpha_2 CAR_{it} + \mathbf{X_{2it}}\boldsymbol{\beta_2} + c_{2i} + v_{it} \qquad t = 1, \ldots, T \tag{2}$$

where

$$EVF = \text{Expected Value of Future Deals}$$

This model allows for a simultaneous relationship between the present CAR and the expected value of future acquisitions. The c_{1i} and c_{2i} terms capture assumed time-invariant unobserved firm heterogeneity that may affect returns and the value of future deals. This would include such attributes as corporate culture and organizational ability. The variables in the $\mathbf{X}$'s reflect other explanatory variables in the equations including size, valuation, deal number, and time elapsed between deals.

To estimate the expected value of future deals (EVF) I must account for both the probability of completing more deals and the value of the deals. First, prior studies have shown that the value of acquisitions are dependent upon a number of factors, such as payment method and the public status of the target. Even after controlling for numerous factors, cross-sectional studies usually report R^2 measures of less than 10%, indicating that much of the variance in returns is unexplained. Thus, to reduce noise, I assume all firms would realize a common gain if they carried out a future deal. Second, the current probability of making a future deal is declining in the deal number due to compounding probabilities. In other words, the probability of making a subsequent deal is much higher than the probability of making ten more deals. Compounding probabilities implies that the likelihood of the immediately subsequent deal captures the greatest portion of the uncertainty of future M&A activity. Thus the uncertainty of the value and likelihood of future deals motivates the following simplifying assumption,

$$EVF_{it} = P_{it} \cdot V_{t+1} \tag{3}$$

where the value of the future deal, V_{t+1} is common to all firms, but the probability of making a subsequent deal, P_{it}, varies by the firm and deal characteristics of the current deal, t. According to the CARs presented above, V_{t+1} is non-negative on average, and so there should exist a positive relationship between EVF_{it} and CAR_{it} in Equations (1) and (2).

The use of panel data provides an important benefit over pooling all observations, because unobserved firm heterogeneity can be controlled by directly comparing each firm to itself across subsequent acquisition announcements. Taking the first differences of each Equation (1) and (2), cancels out all time-invariant variables, observed or not, including firm heterogeneity. Under the assumption that the variables in $\mathbf{X_{1it}}$ and $\mathbf{X_{2it}}$ are correlated with the unobserved firm heterogeneity variables, c_{1i} and c_{2i}, standard OLS would produce biased estimates of their corresponding coefficients. This assumed correlation is plausible, as it is likely that firm size, book-to-market ratios, and governance, among others may be correlated with unobserved firm ability or corporate culture. First differencing the equations eliminates this bias. Thus the equations to be estimated are,

$$\Delta CAR_{it} = \alpha_1 \Delta P_{it} + \Delta \mathbf{X_{1it}} \boldsymbol{\beta_1} + \Delta u_{it} \qquad t = 1, \ldots, T \tag{4}$$

$$\Delta P_{it} = \alpha_2 \Delta CAR_{it} + \Delta \mathbf{X_{2it}} \boldsymbol{\beta_2} + \Delta v_{it} \qquad t = 1, \ldots, T \tag{5}$$

where

$$\Delta Z_{it} = Z_{it} - Z_{i,t-1} \quad \text{where } Z \text{ is any variable in Equation (4) or (5)}$$

$$P_{it} = \text{Probability of completing a subsequent deal for firm } i \text{ at deal } t$$

There are various approaches to estimating these equations. Estimating both equations simultaneously in a generalized method of moments (GMM) framework provides the most efficient estimators. However, this approach allows model misspecification in one equation to bias the results in the other. Therefore, I estimate the system, equation-by-equation, rather than simultaneously to reduce the potential for bias at the cost of reduced efficiency. Second, since Equation (4) is the equation of interest I use a linear probability model to estimate Equation (5). Linear probability models, as opposed to probit or logit models, have the unappealing quality that fitted probabilities may not fall in the range $[0, 1]$. However, the advantage of a linear probability model is that no distributional assumptions need to be made about the error term, v_{it}. This allows me to use a GMM estimation procedure for both equations permitting heteroskedasticity as well as serial correlation in the return distributions, both of which are likely in this setting.

To estimate the probability model I record for each acquisition announcement whether a subsequent deal is made. In order to prevent biasing these numbers downwards due to upper year restrictions on the sample, i.e. only deals announced by the end of 2004 are included, or from sample attrition, I only record no subsequent deal if the firm had enough time to complete another deal at the 90% level. For each deal number I find the 90th percentile of trading days until the next announcement across all firms that made a subsequent deal. If a firm does not complete a subsequent deal, but is listed on CRSP for this number of days after its terminal deal, I record this as not making a deal. If the firm is not listed this many days or the sample period ends before the number of days has elapsed I record the observation as missing. I use this dummy variable as the dependent variable P_{it} in Equation (5).

To identify each equation there must be valid instruments for the endogenous variables, $\text{CAR}_{(-2,+2)}$ and Pr(Future Deal), present only in the alternate equations. In other words, to identify Equation (4), I must have at least one exogenous variable that is correlated with P_{it}, but is not correlated with CAR_{it}. This variables proxies for P_{it} but does not introduce bias as it is uncorrelated with u_{it}, the error term. Likewise, I need instrumental variables (IVs) for CAR_{it} in Equation (5). These variables provide a means to exogenously vary P_{it} without varying CAR_{it} and vice versa.

I use *Net Payout Yield* and *Internal*/(*Total Investment*) to instrument for P_{it} in Equation (4). Net payout yield is a simplified measure of the one used in Boudoukh, Michaely, Richardson, and Roberts (2006), and is defined as dividends plus net purchases of common stock normalized by market equity. Internal to total investment is defined as net capital expenditures divided by net capital and acquisition expenses. I assume these variables are correlated with the probability of completing a future deal, but not with the CAR of the current deal. The relation between payout yield to the probability of future acquisitions is intuitive. On average, firms with high payout yields have less attractive investments (internal or external) than those firms who are retaining their earnings and thus are less likely to be making external investments. The ratio of internal to total investment is also likely to be correlated with future acquisition activity. Large external investments may require complementary future internal investments. For these to be valid instruments they must also be uncorrelated with current CARs. Given a firm is making an acquisition, there is not a clear link between current CAR and payout yields or internal-to-total investment ratios. Though it is less likely that high payout firms would engage in M&As, there is no reason to believe that if they do acquire, that their prior payout or investment is systematically linked to current acquisition CARs.

To instrument for CAR_{it} in the probability model (Equation (5)), I use NYSE prior returns, public and private target dummies, transaction value, toehold, and interaction terms between equity and public and private target dummies. These are assumed to be correlated with the CAR of the current deal but not with the probability of completing a future deal. Prior returns, public and private dummy variables, and toeholds should only be relevant for the current acquisition as they do not predict any future activity. Whereas relative size of a target to a bidder is likely to be related to future activity, as very large deals may make it less likely that firms will acquire again, transaction value is not likely to have a strong relation to future M&A activity because my sample includes a wide variation of acquirer size. These variables, however, will be related to the current CAR and so they are suitable instruments to use in the simultaneous equations framework.

Formal tests of the over-identifying restrictions of the instrumental variables (IVs) is tested with Hansen's J-statistic and the null of group exogeneity can not be rejected for both equations ($p-$values of 0.865 and 0.280 are found for Equations (4) and (5) respectively). Anderson canonical correlations likelihood-ratio tests of whether the excluded instruments are relevant finds that the IVs are sufficiently correlated with their corresponding endogenous regressors ($p-$values of 0.001 and 0.000 for Equations (4) and (5) respectively). Thus the economic motivations for the above assumptions of exogeneity and relevance of the IVs are statistically sound.

The results of the simultaneous equations model is presented in Table 4. Neither endogenous variable, $\text{CAR}_{(-2,+2)}$ or Pr(Future Deal), is significant, contradicting the capitalization theory. This implies that the endogenous relationship between CARs and future acquisition activity has no explanatory power. In particular, Pr(Future Deal) is not significantly related to the current CAR. Furthermore, deal number is not a significant determinate of abnormal returns, in contrast to the indication of the univariate results. Instead, the significant determinants of current deal CARs are acquirer size, and prior returns, the public status of the target firm, and the form of payment used in the transaction, all variables reported as significant determinants in the prior literature (Moeller, Schlingemann, and Stulz, 2004; Moeller, Schlingemann, and Stulz, 2005). Since book-to-market and Tobin's q are often used to proxy for growth opportunities, this finding shows no support for the hypotheses that investment opportunity sets are related to merger activity (Billett, King, and Mauer, 2006; Klasa and Stegemoller, 2006).

Though not central to the goals of this paper, Table 4 also presents the determinants of the likelihood of making future acquisitions. Large firms with low book-to-market ratios are more likely to acquire again, as are firms who have made fewer prior acquisitions (Deal Number) and firms who acquire quickly (Deals/Year). As hypothesized, payout yield is negatively related to making future acquisitions. Also, firms that have higher ratios of internal to total investment are more likely to acquire in the future, suggesting that external investment is counter-cyclical to internal investments. In unreported tests, I include a dummy variable which indicates if the current deal was made by a new CEO, with data taken from the Compustat Execucomp database, and find that CEO changes do not affect CARs, but significantly increase the likelihood of making a future acquisition. However, the introduction of this variable does not change any of the qualitative results reported above.

4.2. Signaling Theory

The signaling theory of Asquith, Bruner, and Mullins, Jr. (1983) posits that each subsequent deal conveys less information than prior deals. In other words, if a firm has already made multiple acquisitions, a new announcement will only be marginally informative. For a given deal number, assuming individual deals in the cross section have individual and unique true values, a widely dispersed distribution of abnormal returns reflects more information is being revealed, whereas less dispersion would be associated with less information. Dispersion in this case is not noise because each deal does not have a common true value. Thus the signaling theory predicts that the dispersion of returns is decreasing with deal number.

To test this theory I use quantile regression to check for heteroskedasticity in returns over deal number. Whereas OLS fits a line through the data at the conditional expectation, quantile regression fits a line through any specific quantile, or percentile, if whole numbers are used as quantiles. Thus fitted lines can be computed for various quantiles. The quantile regression through the 0.50 quantile fits a line through the conditional median of the sample, analogous to OLS's conditional expectation line. The quantile regression through the 75th percentile fits a line through the data that predicts the 75th percentile conditional on the regressors. See Buchinsky (1998) for details on quantile regression.

If the slopes of the quantile regression estimates of CAR on deal number at different quantiles are unequal, then the returns are heteroskedastic, as the dispersion of returns is not constant. The signaling hypothesis suggests that the difference between the deal number slope of an upper tail quantile and a lower tail quantile is negative, implying dispersion is decreasing in deal number. A stylized representation of this is presented in Figure 1, where the slope of the 90th percentile is smaller than the slope of the 10th percentile. Quantile regression is an ideal method to test dispersion for financial returns because it is robust to outliers and independent of any Gaussian assumption.

Panel A of Table 5 presents quantile regression results for a simple model where deal number is regressed on the five-day CAR and a constant for the quantiles $0.10, 0.25, 0.50, 0.75,$ and 0.90. The sample observations are the first six deals announced by the *Frequent* acquirer subsample so that there exist the same number of observations for each deal number, one through six. This insures that sample size does not distort the estimate of dispersion. The slope coefficient for deal number at the 25th percentile is a significant -0.003. At the 75th percentile, the slope is -0.007. The difference in slopes is tested by Wald tests in the last three columns of Table 5. These tests show that in the simple model, the dispersion of CARs is becoming significantly less dispersed, consistent with the signaling hypothesis.

However, this simple model is a weak test of the signaling theory because it does not control for factors other than deal number that may affect the dispersion of returns. If later deals have less variation in such factors as bidder size, relative value, and the public status of targets, dispersion may be diminishing, but not due to the order of the deal. The appeal of using quantile regression to test the shift in dispersion, versus standard deviation measures, is that these other factors can be controlled in the test of heteroskedasticity. Panel B of Table 5 presents quantile regressions controlling for firm and deal characteristics. Now the estimated upper quantile slopes are not significantly different than the lower quantile slopes. This contradicts the signaling hypothesis and indicates that information dispersion does not significantly change over deal number, at least for the first six deals.

The finding against the signaling hypothesis is consistent with the findings above against a capitalization hypothesis. New information is revealed with each announcement, regardless of its order in a deal sequence. Markets are unable to anticipate this new information and the returns generated by each deal are deal specific and do not reflect future acquisition activity. Acquisitions are judged on a deal by deal basis by the characteristics of the bidder, the target, the deal structure, and the interaction between the three.

A second interpretation of the results on the dispersion in returns is that firms do not learn to do better deals. If experience leads to better returns, we would expect that the lower tail of the distribution of returns should be getting smaller as firms learn to avoid poor acquisitions in later deals. This is not the case however, as the dispersion is not changing with deal number. A more robust test of learning is presented next.

5. Do Firms Adjust M&As Based On The Returns Of Prior Deals?

The above results show that abnormal returns are deal specific market responses to the particular characteristics of an acquisition. Thus, a firms's acquisition history provides valuable feedback that can be used to improve future performance, i.e., firms can learn from history. To test the theory of organizational learning I define "learning" similarly to Luo (2005): Learning firms are those that consider the returns to prior acquisition choices when making current decisions. I hypothesize that firms make M&A decisions that are consistent with their histories, such that the past choices that yielded the best historical returns are more likely to be chosen again. This means firms are attempting to maximize shareholder wealth through M&As.

Ideally I would like to be able to relate current M&A decisions to prior performance changes caused by a specific form of synergy gains, such as reduced costs, access to new markets, or financial benefits. If a learning firm is good at capturing a certain type of synergy, we would expect it to make future acquisitions that offer the same type of synergy potential. However, this approach involves two large obstacles to a researcher. First, it is not possible for the econometrician to identify the change in operating performance arising from one out of many acquisitions. Second, the sources of gains from mergers are likely to be debatable and difficult to precisely identify. To address these issues I assume that on average, short-run returns are the best indicator of the economic value of a specific deal and second, I analyze three M&A decisions with clear outcomes. Specifically, I examine the relationship between prior CARs and the current choice of the organizational form of the target, the method of payment, and whether targets are in the same industry as the acquirer. It is possible that firms have special skills for finding and integrating private targets that are different than the skills needed to buy a public target. A similar argument can be made for focusing or diversifying acquisitions. Finally, some firms may find that they are better able to secure loans to finance cash purchases, whereas others are better at 'selling the deal' to stockholders in order to get approval to issue equity as payment.

This method of testing learning is a more direct approach than an analysis of the pattern of CARs as is done in prior studies (Hayward, 2002; Conn, Cosh, Guest, and Hughes, 2004). By looking directly at decision-making, rather than returns to firm decisions, I remove the possibly confounding effects of market responses. Furthermore, panel data allows me to control for unobserved firm-specific heterogeneity such as corporate culture and organizational flexibility which is likely to be related to the capacity to learn. Thus by holding these factors fixed, I can determine whether the average firm responds to its acquisition history when making current decisions in a way consistent with the interests of shareholders.

5.1. An Empirical Model of Responsiveness

I define the following dynamic choice model of organizational form of the target for deal t. I will describe the model for public versus non-public targets in detail. The other choice models of payment and industry are analogous.

$$
\begin{aligned}
\text{Public}_{it} =& \alpha + \beta_1 \text{Public}_{i,t-1} + \beta_2 \text{Public}_{i,t-1} \times \text{CAR}_{i,t-1} + \beta_3 \text{CAR}_{i,t-1} + \\
&+ \beta_4 \text{Public } \overline{\text{CAR}}_{i,t-1} + \beta_5 \text{Private } \overline{\text{CAR}}_{i,t-1} + \beta_6 \text{Subs.} \overline{\text{CAR}}_{i,t-1} + \\
&+ \beta_7 \text{Public } t\text{-stat}_{i,t-1} + \beta_8 \text{Private } t\text{-stat}_{i,t-1} + \\
&+ \delta \mathbf{X}_{it} + c_i + \varepsilon_{it} \qquad (6)
\end{aligned}
$$

where

$$\text{Public } \overline{\text{CAR}}_{i,t} \equiv \frac{1}{D_t} \sum_{d=1}^{t} PUB_{i,d} \cdot CAR_{i,d} \qquad (7)$$

$$PUB_{i,d} = 1 \text{ if the target is public in deal } d \text{ for firm } i, \text{ 0 otherwise} \qquad (8)$$

$$D_t = \sum_{d=1}^{t} PUB_{i,d} \qquad (9)$$

and

$$\text{Public } t\text{-stat}_{i,t} \equiv t\text{−statistic on the variable Public}_{i,t} \text{ in the following:} \qquad (10)$$

$$
\begin{aligned}
CAR_{i,t} =& \gamma_0 + \gamma_1 Size_{i,t} + \gamma_2 RelVal_{i,t} + \gamma_3 Public_{i,t} + \gamma_4 Private_{i,t} + \\
&+ \gamma_5 Cash_{i,t} + \gamma_6 Stock_{i,t} + \gamma_7 SameInd_{i,t} + \nu_{i,t} \qquad (11) \\
&\text{for observations } 1, \ldots, \text{t}
\end{aligned}
$$

$\mathbf{X}_{it}$ is a vector of acquirer, target, and deal characteristics. Private $\overline{\text{CAR}}_{i,t}$, Subs. $\overline{\text{CAR}}_{i,t}$, and Private t-stat$_{i,t-1}$ are defined similarly.

This model states that the current choice of a public target is dependent upon the same choice made by the firm in its prior acquisition (Public$_{i,t-1}$), three measures of historical performance (Public$_{i,t-1}$ $\times$ CAR$_{i,t-1}$, Public $\overline{\text{CAR}}_{i,t-1}$, and Public t-stat$_{i,t-1}$), contemporaneous control variables ($\mathbf{X}_{i,t}$), and a firm-specific heterogeneity factor c_i. The lagged choice variable, Public$_{i,t-1}$ measures whether firm decisions are influenced by experience, or convention, independent of the returns produced. The three measures of prior performance are designed to capture increasing sophistication of responsiveness. The first, Public$_{i,t-1}$ $\times$

$\text{CAR}_{i,t-1}$, simply measures the change in the prior CAR for acquiring a public target. Firms may be myopic and look only at the latest deal, or they may simply weight the most recent acquisition heavily in their current decision. Public $\overline{\text{CAR}}_{i,t-1}$ is the average CAR for all prior acquisitions of public firms. This measure incorporates more information than the first, but does not control for other factors that may have affected returns. The most sophisticated measure of prior performance is Public $t\text{-stat}_{i,t-1}$, which controls for acquirer, target, and deal characteristics, as well as the number of prior acquisitions made, as $t-$statistics are increasing in the number of observations in the regression. Each of these three measures of prior performance of public targets are expected to have a non-negative relationship with the current choice of a public target.

As in the prior model of firm fixed effects, I first difference Equation (6) to remove the firm heterogeneity factor c_i. However, this creates endogenous variables as the first-differenced lag of the dependent variable is correlated with the differenced error term. To correct this, I follow Arellano and Bond (1991) and use the lagged levels of the dynamic variables as instruments in a GMM estimation of the first-differenced equation. I only use the second and third lagged levels to reduce the number of instruments to the smallest number possible, while using the most recent exogenous lags to increase the strength of the instruments. I use a one-step procedure to estimate the variance-covariance matrix, which assumes homoskedasticity, because prior literature has shown that the two-step heteroskedasticity robust method may be severely biased in small samples. See Bond (2002) for more information on the estimation of dynamic panel data models.

These models are binary choice models where the dependent variable takes the value of one or zero. As before, I assume a linear probability model, rather than a probit or logit model, as I am more interested in the relative size and signs of the coefficients, rather than predicting probabilities. Finally, only observations of deal five or higher are included in the regression, as the $t-$statistic will be meaningless without sufficient observations and the average CARs will also exhibit greater variation with longer acquisition histories.

5.2. Firm Responsiveness Results

The results of this estimation procedure are reported in Table 6. Column one reports the results for the choice of a public target. The coefficients on both the Public $\overline{\text{CAR}}_{i,t-1}$ and Public $t\text{-stat}_{i,t-1}$ measures of firm responsiveness are significantly positive, indicating that the likelihood of acquiring a public target increases with the average and adjusted prior performance of public target acquisitions. This means that firms are sophisticated in their analysis of prior deals, controlling for other variables, while not placing significant weight on only the last deal. Finally, there is no indication of state dependence, as the lagged value, Public_{t-1} is insignificantly related to the current choice. In contrast, the choice of a private target in column two of Table 6 is not significantly related to prior performance measures.

Table 6 also shows that experience affects decision making. The likelihood of acquiring a public target is increasing with deal number, after controlling for acquirer size, transaction and relative values, and the form of payment, whereas private targets are becoming less likely. This is consistent with the idea that acquisitions of public targets are more complicated than private targets. Inexperienced acquirers may be hesitant to purchase a public target due to the uncertainties of a more complicated shareholder approval process, or perhaps because it lacks the necessary relationships with legal and financial advisors needed to undertake a more complicated purchase.

In the choice of cash versus stock, firms are again sensitive to prior performance, as the coefficients on Cash $\overline{\text{CAR}}_{i,t-1}$ are significantly related to the current method of payment choice. The $t-$statistic variables are insignificant, though their signs are consistent with learning. Also, the positive coefficient on Cash_{t-1} indicates that firms display some form of convention or habit, even after controlling for acquirer size, transaction value, free cash flow, leverage, and the debt/equity ratio. It is possible that prior experience with a particular payment method reduces the transaction costs in a current deal. For example, the firm may have relationships in place with lenders that lower its cost of debt-financed cash, versus the costs of issuing stock. It is also possible that firms are habitual and choose payment method based on the most recent procedures used.

Finally, the results on the decision to acquire a target in the same Fama-French 49 industry class as the acquirer provides evidence contrary to the hypothesis of learning. The value of the $t-$statistic on the same industry variable is negative and significant. This may be because the $t-$statistics on Same Industry in Equation (11) display very little variation, or because other factors affecting this decision are omitted from the equation, such as CEO effects, which may influence firm sensitivity.

To account for CEO effects, I re-run the above analyses including a dummy variable for CEO changes taken from the Execucomp Database. In unreported results, including this variable reinforces the firm-sensitivity findings above. In particular, the dynamic variables in the choice of private targets and same industry become significant and display signs consistent with learning to maximize shareholder wealth. However, the dynamic variables in the choice of payment method models become insignificant. This suggests that CEOs influence the choice between private and public targets, and focusing or diversifying acquisitions relatively more than does the organization as a whole, whereas sensitivity to prior market returns at the firm level is relatively more important for financing considerations.[6]

In summary, I find that firms are responsive in a sophisticated way to their histories of abnormal returns when making current decisions about the public status of a target and the method of payment. Moreover, firms are making decisions that are consistent with shareholder wealth maximization. This is consistent with organizational learning, though a direct causal link can not be determined as it is possible that firms make decisions based on other criteria which are related to market responses, but do not actually use prior returns in their decision-making process.

5.3. Does Responsiveness Pay?

If on average, firms are responsive to their history of abnormal returns, it makes sense to ask if those firms that are the most responsive have higher returns than the least sensitive firms. To answer this question I divide firms into two responsiveness categories and test if the more responsive firms have higher average returns. For each acquisition I record if the firm makes a choice consistent with the $\overline{\text{CAR}}_{i,t-1}$ variables. For example, if a firm acquires a public target at deal t and the average CAR for prior acquisitions of public firms is greater than both the average CAR for private and subsidiary targets, then I record a 1, for responsiveness, and 0 otherwise. I create three dummy variables of sensitivity, one for each of target public status, payment method, and same industry, which are either 1 or 0 for each deal in my sample except the first deal. Then for each firm in the sample, I calculate the percentage of responsive deals versus non-responsive deals.

I find that 42% of all deals are responsive to payment method, though the average number of responsive deals per firm is 34%. For public status of targets, 35% of deals are responsive for a firm average of 29%. Same industry sensitivity across all deals is 54% and the mean firm average is 45%. For each of payment, public status, and industry, I divide firms by the median firm percentile of sensitive deals, such that firms that have a proportion of responsive deals higher than the median firm proportion are considered *Responsive*, and those with less than the median are *Non-Responsive*. Restricting my sample to only Frequent acquirers who have made at least six acquisitions, I find that for payment method, the responsive firms have average five day CARs of 1.53%, significantly larger than the 0.09% average for Non-Responsive firms ($t = 4.54$).

[6]These results are unreported because they may be affected by selection bias. Of 12,942 deals in my full sample, only 2,930 have data on CEO identity. Out of 4,879 firms in the full sample, 1,580 firms have CEO data. Moreover, there are relatively few CEO changes over deal sequences. 77% of the firms have the same CEO for all deals, 21% have 2 CEOs, and 1% have 3 or more CEOs over the sample period.

For public status, the Responsive firms have average CARs of 1.56% significantly larger than 0.33% of Non-Responsive firms ($t = 4.01$). Finally, for same industry, again the Responsive firms have significantly higher average returns than the Non-Responsive firms (1.68% versus 0.28%, $t = 4.92$).

I next conduct multivariate regressions to control for the possibility that other confounding variables, such as target organizational status and method of payment, are explaining the higher performance associated with the most responsive firms. Because I am interested in firm effects, I do not first difference the data, which would erase my responsiveness variable. Instead I conduct pooled OLS controlling for year and industry effects. The results are presented in Table 7.

Column one reports the effects of the dummy variables for Responsive Firms on five day CARs. Firms in the Responsive categories for payment, public status of target, and target industry, have returns that are significantly higher than the non-responsive category, controlling for bidder, target, and deal characteristics. Responsiveness to payment choice results in returns that are higher by 1.6% percentage points on average. Column two of Table 7 replaces the dummy variables with the firm percentage of responsive deals. Results are similar. Abnormal returns are increasing in a firm's responsiveness to market signals. Thus those firms that make acquisition choices that are consistent with learning from prior acquisition histories perform better than those firms that do not. This implies that there is a benefit to adjusting current M&A decisions based on prior outcomes.

6. Do Repeat Acquirers Develop A Standardized Acquisition Model?

The preceding sections find that acquisition returns do not incorporate the value of future deals and that firms are responsive to their acquisition performance histories. These two results are in direct contrast to the pattern of declining returns presented in Table 2. In this section I propose a new hypothesis based on considerations of post-merger integration costs and the pre-merger costs of M&A activities including search, legal, and financial advice. Larger targets certainly incur greater integration costs. However, targets that are very small may not provide enough value to offset the search and transaction costs of the acquisition. In particular, since the fee structure of financial and legal advice contains a fixed cost component, firms have an incentive to acquire larger targets to reduce their average costs (McLaughlin, 1990; McLaughlin, 1992; Ma, 2006). Balancing these costs leads to an optimal relative size of target to acquirer. I propose that returns are declining because targets are getting larger in absolute size, but smaller in relative size as targets approach an optimal relative size.

Alternative theories that may explain declining returns include agency, hubris, and diminishing opportunity sets. First, since later deals are likely to be made by larger firms, agency problems may be more acute. Entrenched managers may simply be making worse acquisitions over a M&A program (Aktas, de Bodt, and Roll, 2005). Also, hubris may lead managers to overpay for targets, driving down returns (Conn, Cosh, Guest, and Hughes, 2004). Finally, investment opportunity sets may diminish as good targets are acquired first, leaving poorer target for later deals, yielding declining returns (Klasa and Stegemoller, 2006). I test these three alternative theories by first identifying the factors that significantly affect returns in the cross-section and then testing whether these factors are changing over deal sequences. Only factors that both explain cross-sectional variation and that vary systematically over a deal sequence can explain the pattern of declining returns.

6.1. Determinants of Abnormal Returns

I test the agency, hubris, and opportunity set theories in the firm fixed effects regressions presented in Table 8. The first column regresses the five day CAR on acquirer, target, and deal characteristics, controlling for unobserved firm heterogeneity and time effects. First, deal number is not significantly related to abnormal returns. Second, acquirer size and deals/year are negatively and significantly related to CARs, though time elapsed since the prior deal is positively related. Firms that make many acquisitions quickly have lower CARs than firms that do not. This may be related to the indigestion hypothesis of Conn, Cosh, Guest, and Hughes (2004), where integration between target and bidder is hampered by a subsequent acquisition. Third, public targets and particularly those purchased with stock, generate significantly lower returns, consistent with the liquidity discount shown in Officer (2006). All of these results are consistent with prior studies (Fuller, Netter, and Stegemoller, 2002; Moeller, Schlingemann, and Stulz, 2004).

Moeller, Schlingemann, and Stulz (2004) hypothesize that the size effect reported in their paper and here is likely due to agency problems of larger firms, though they provide no formal tests. I test this hypothesis directly by including measures of internal monitoring and managerial entrenchment/antitakeover provisions in the regressions. As a measure of internal monitoring I use the number of non-officer directors that are blockholders in the firm. These data on 1,913 firms over 1996-2001 come from the Blockholders database maintained by Wharton Research Data Services (WRDS) and described in Dlugosz, Fahlenbrach, Gompers, and Metrick (2006). Entrenchment is measured using the Gompers-Ishii-Metrick (GIM) governance index of the data in the Investor Responsibility Research Center's (IRRC) Governance database. This dataset provides data on 24 antitakeover provisions such as staggered boards, poison pills, and others, for a sample of predominately large firms for selected years starting in 1990. For further information see Gompers, Ishii, and Metrick (2003). I hypothesize that more non-officer director blockholders will be associated with higher returns and more antitakeover provisions will be associated with lower returns. Since internal monitoring and the market for corporate control may be substitutes, I also look at the interaction between the two.

When these variables are included in the regression in column two of Table 8, the outside director blockholder is significant and positive as hypothesized, the entrenchment index is negative, but not significant, and the interaction term is significantly negative. The negative sign of the interaction term indicates that the benefit of internal monitoring is eroded with more entrenchment provisions. Also of note is that the size effect has been reduced considerably in magnitude and is not significant, implying that the size effect is explained by governance issues. Also, the coefficient for public targets is relatively unchanged after including the governance variables, but the interaction term between stock payment and private and public targets has become positive (0.0636 and 0.0478, respectively). Since the all stock dummy has a coefficient of -0.0819, this implies that negative returns associated with using all equity are mitigated most by buying a private firm, then a public firm, though they are always expected to be negative. This supports the findings of Chang (1998), who finds that equity purchases of private firms generate new blockholders in the acquiring firm.

To further investigate hubris and agency, I look at premiums paid and characteristics of the target. The relation between premiums and CARs is not well defined. The learning model of Aktas, de Bodt, and Roll (2005) states that higher premiums drive down abnormal returns from acquisitions made by rational CEOs. Decreasing premiums lead to increasing returns for hubris-infected CEOs. However, in contrast to this theory, it is possible that high premiums may indicate the possibility of high synergies between bidder and target, which could lead to higher abnormal returns. I test this relation by restricting my sample to acquisitions of public targets for which premiums can be calculated. The results in column three of Table 8 suggest that there is no relationship between premiums and CARs. However, target size has a significant negative relation to acquirer CARs, though target Tobin's q has a positive relation. Also, when these variables are included, the acquirer size effect becomes insignificant.

Finally, to test the diminishing opportunity set theory, I would like to be able to measure the number and quality of remaining targets for a given acquirer. However, I am unaware of any direct measure of these factors. Instead, I include acquirer book-to-market, Tobin's q, and prior year returns in the regression model. These variables have been used in other studies to measure growth options, and I assume that a component of these growth options measures include acquisition options (Billett, King, and Mauer, 2006).

I also include target Tobin's q in the third regression of public targets. The target q-ratio is positive and significant implying that targets with greater growth options provide higher bidder returns. However, none of the acquirer opportunity set measures are statistically significant.

6.2. Do the Cross-Sectional Determinants Vary by Deal Number?

The above results indicate that deal number is not related to abnormal returns, but rather that changing firm and deal characteristics explain the pattern of declining returns. Governance issues, relative size of target, public targets, and the use of equity explain cross-sectional variation in abnormal returns. If these variables are changing consistently over deal sequences, they will also explain the pattern of declining CARs reported in Table 2. To determine which of these variables are consistently changing over deal number, I calculate means and medians of firm and deal characteristics by deal number for all firms in the sample as well as slope coefficients for both a linear and squared term similar to the procedure in Aktas, de Bodt, and Roll (2006). These results are presented in Table 9.

Agency problems do not appear to have any relation to acquisition returns. First, though the number of outside director blockholders is significantly related to CARs, they are unchanging over deal sequence, a surprising result considering the large increase in the average acquirer size. This directly contradicts the agency prediction that large firms will have less managerial oversight than smaller firms. Second, though managers are significantly more entrenched in later deals than in earlier deals in a statistical sense, the actual change in the average number of antitakeover provisions over the first ten deals is very small. Next, though premiums are increasing significantly over deal sequences, I find above that they have no relation to acquirer returns. Finally, the only significant growth option variable in the cross-section, the target q-ratio, is constant over the first ten deals. These results contradict agency, hubris, and opportunity set explanations of the pattern of repeat acquirer returns.

6.3. Cost Minimization Hypothesis

As an alternative, to the above theories I posit that the pattern of declining returns is due to acquirers' attempts to minimize the search and integration costs of M&As. Balancing these costs leads to an optimal relative size of target to acquirer. In my sample, average acquirer size continues to grow over subsequent acquisitions, but the relative size of the target is a stable 10% on average (3% at the median) for fifth and later deals. Thus later deals are dominated by acquisitions of large targets which are more likely public, though of a small relative size. Since public firms have been shown to command a liquidity premium (Officer, 2006) and because relatively smaller targets create smaller abnormal returns, acquirer returns are decreasing. Future research may test this hypothesis by examining M&A costs directly and by identifying the determinants of relative size of target to acquirer, controlling for cost variables.

7. Conclusions

This paper investigates the determinants of the pattern of declining event returns to repeat acquirers. Two theories unique to repeat acquirers are directly tested, market anticipation and organizational learning. I find no evidence to support the predictions of market anticipation. In particular, announcement returns reflect only the estimated value change from the current acquisition, not future acquisitions, and the informativeness of this signal does not diminish as acquirers gain more acquisition experience. This implies that announcement returns are deal-specific.

I next test the theory of organizational learning by examining whether current acquisition decisions are influenced by past returns. I find that firms choose target organizational status and payment method based in part on the shareholder wealth created in prior deals, consistent with learning, though I find evidence against learning in the choice of bidder-target relatedness. Furthermore, firms are sophisticated in the way that prior returns influence current decisions. Both average returns over an entire acquisition history and statistically controlled returns influence current decisions, whereas the sole returns to the immediately prior deal do not. Finally, I find that those firms that make current M&A decisions consistent with prior market returns have higher acquisition returns overall.

Given that the results on learning and market anticipation are contrary to the pattern of declining performance over deal sequences, I further investigate the determinants of abnormal returns. First, controlling for deal number, more managerial monitoring and a smaller target size increase returns, though public targets decrease returns. Increasing relative value of target to bidder magnifies returns. Comparing these factors in earlier to later deals, monitoring is unchanging, though targets are getting larger, more likely public, and of smaller relative sizes. I reject agency or hubris explanations for declining returns, as I show that premiums do not affect abnormal returns, and managerial monitoring and entrenchment measures do not change substantially over deal sequences.

Instead, I hypothesize that declining returns are explained by firms' desires to balance post-completion costs of integration and pre-completion costs of search and transaction. This leads firms to set an optimal relative target size needed to overcome the fixed component of search costs while reducing integration costs. Acquirer growth over deal sequences implies targets get larger and hence more likely public, though relative sizes decrease to a stable level, all reducing returns. This hypothesis suggests that more research on the costs of acquisitions may be warranted as they may help explain M&A decisions. In particular my hypothesis, as well as the theoretical models of Jovanovic and Rousseau (2002) and Yang (2006), assume M&A activity incurs a substantial fixed cost to the acquirer which affects their decision-making process.

The evidence supporting organizational learning also warrants further research. Here, firms learn from their own acquisition histories. However, since all the data are publicly available, firms may also learn from competitors' acquisition histories. In addition, firms may learn from other M&A activities, such as divestitures, in order to increase acquisition performance. Finally, it would be important to know why some firms are more responsive to market signals than are other firms. Does managerial oversight have an effect, or are there costs to learning that vary across firms?

Appendix: Variable Definitions

Variable	Description
$\text{CAR}_{(-2,+2)}$	Cumulative abnormal return over event days (-2,+2) computed by summing over five days the difference between the CRSP equal-weighted index from the firm return for each day.
Deal number	The ordered acquisition number for a firm in a series of acquisitions.
Days since last	The number of trading days since the last acquisition announcement or the listing date if the acquisition is the first.
Days since listing	The number of trading days from first listing on CRSP
Debt/Equity	Long term debt (Compustat item 9)/Common Equity (item 60)
Entrenchment index	The Gompers-Ishii-Metrick index of 24 antitakeover provisions recorded in the Investor Responsibility Research Center (IRRC) database of primarily large firms. Higher values indicate more antitakeover provisions. Data is recorded in 1990, 1993, 1995, 1998, 2000, 2002, and 2004. Following (Gompers, Ishii, and Metrick, 2003), I fill each missing year with the most recent governance provisions available. Also firms with dual class common stock are omitted.
Free cash flow	[Operating income before depreciation (Compustat item 13) - interest income (item 15) - income taxes (item 16) - capital expenditures (item 128)]/[Total assets (item 6)]
$\frac{\text{Internal}}{\text{Total investment}}$	[Capital Expenditures (Compustat item 128) - Sale of Property, Plant, & Equipment (PPE) (item 107)]/[Capital Expenditures - Sale of PPE + Acquisitions (item 129)]
Leverage	[Debt in current liabilities (Compustat item 34) + Long term debt (item 9)]/[Total assets (item 6) - Common equity (item 60) + Market equity (item 24 × 25)]
Net Payout Yield	[Dividends (Compustat item 21) + Common Stock purchases (item 115) - Common Stock sales (item 108)]/Market Equity (item 24 × item 25)
NYSE B/M	NYSE vigintile of book-to-market (B/M). B/M is calculated for each firm for each year as accounting book value over market value where book value is total assets (Compustat item 6) - liabilities (item 181) + balance sheet deferred taxes and investment credits (item 35) - preferred stock liquidating value (item 10) or preferred stock redemption value (item 56) or carrying value (item 35), in this order. Market equity is price times shares outstanding at the end of December. If the fiscal year-end of a company is between January and May, the book equity from the prior year is matched against the market equity of December.
NYSE Prior Returns	NYSE vigintile of the buy and hold return over the prior 12 months.
NYSE Size	Market equity vigintile of NYSE market equities. Market equity is price times shares outstanding. Vigintiles are 1/20ths of unity.
Outside director blockholders	The number of non-officer director blockholders (5% stock ownership). These data comes from the WRDS Blockholder database with observations from 1996 to 2001. For observations past 2001, I use 2001 values. See Dlugosz, Fahlenbrach, Gompers, and Metrick (2006).
Premium	Transaction value recorded by SDC divided by the market value of the target 50 trading days before the announcement. Premiums are restricted to range between 0 and 3. Only available for public firms.
Prior industry deals	Total number of completed acquisitions above $1 million in the acquirer's Fama-French 49 Industry classification
Private	=1 if the target firm is private as recorded on SDC, 0 otherwise.
Public	=1 if the target firm is public as recorded on SDC, 0 otherwise.
Relative value	The transaction value as recorded by SDC, divided by the acquirer market equity
Same Industry	=1 if the target and bidder are in the same Fama French 49 industry classification
Subsidiary	=1 if the target firm is a subsidiary as recorded on SDC, 0 otherwise.
Tobin's q	Total assets (Compustat item 6) - common equity(item 60) + market equity (item 25)× (item 24)/ Total assets (item 6)
Toehold	The percentage of the target firm held by the bidder prior to the announcement as reported in SDC.
Transaction value	The value of all consideration paid in a deal minus the costs and fees as reported by SDC. Values are reported in $2005 adjusted millions.
Wave dummy	=1 if the deal is classified as an industry merger wave, 0 otherwise. Industry merger waves are identified using the technique of Harford (2005), with the only exception that I restrict to $1 million deals or greater and I only count industry deals based on acquirer industry, rather than a combination of bidder and target as in Harford.

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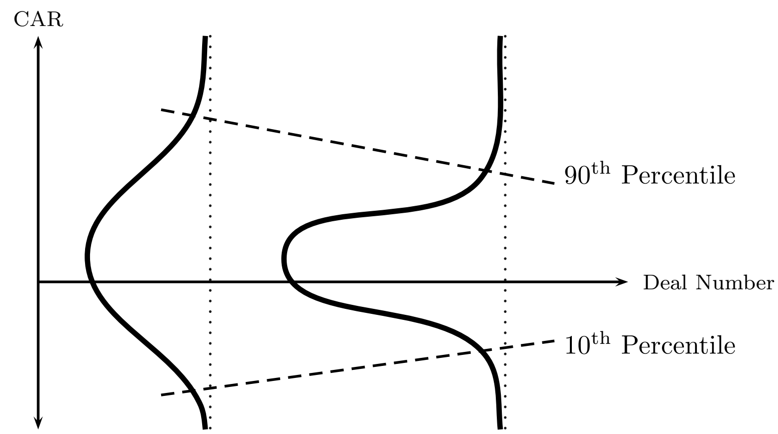

Figure 1
Anticipation Theory
This figure represents a stylized representation of the anticipation theory. The dark curves represent the distribution of CARs conditional on deal number. The anticipation theory posits that the distribution of CARs becomes less dispersed at higher deal numbers. The dashed lines represent the conditional percentiles of the distributions, for the 90th and 10th percentiles. These fitted lines correspond to the quantile regression estimates of CAR on deal number at each percentile.

Table 1

Summary of Acquisitions by Year

'Series Starts' reports first-time acquisition announcements in a given year. 'Mean Series Length' reports the mean number of deals of all acquisition series begun in a given year. 'Total Deals in Year' lists all recorded acquisitions for a given year. 'Median Transaction Value' is the median transaction value for all deals announced in a given year. 'Total Transaction Value' is the aggregate transaction value for a given year. Transaction value is defined by the SDC database to be the total value of consideration paid excluding fees and expenses. Values are reported in millions of 2005 adjusted dollars.

Year	Series Starts	Mean Series Length	Total Deals In Year	Median Transaction Value	Total Transaction Value
1981	1	2.00	1	$10.81	$11
1982	16	1.94	19	16.36	642
1983	48	3.65	61	16.03	3,789
1984	75	3.45	101	15.50	4,726
1985	40	4.13	54	71.26	16,388
1986	56	3.46	93	50.14	13,395
1987	75	3.41	111	38.04	14,457
1988	102	3.32	139	33.88	16,315
1989	141	3.67	231	17.52	22,669
1990	128	2.92	228	12.53	13,671
1991	159	3.75	263	12.55	17,306
1992	205	3.40	398	12.81	21,022
1993	276	3.09	582	15.20	55,004
1994	398	3.22	800	15.37	64,832
1995	361	2.84	887	18.68	73,584
1996	402	3.01	1,096	24.18	175,711
1997	501	2.53	1,437	24.22	227,085
1998	442	2.27	1,418	29.34	513,396
1999	378	2.29	1,118	33.00	370,423
2000	321	2.02	980	39.13	615,382
2001	257	1.89	770	33.56	153,839
2002	173	1.72	713	24.54	88,193
2003	170	1.35	686	37.49	153,685
2004	154	1.10	756	37.31	151,526
All	4,879	2.65	12,942	$25.38	$2,787,050

Table 2

Announcement Returns by Number of Acquisitions, Acquisition Order, and Target Organizational Status.

Cumulative abnormal returns (-2,+2) in percent terms computed using a equally-weighted market-adjusted model. Numbers in parentheses indicate sample sizes. Statistical significance is tested with the sign test. Sample is over 1981 to 2004. Total sample size is 12,942.

Number of Deals in Series	Acquisition Number in Series: 1st	2nd	3rd	4th	5th	>5th	All Deals
Panel A: All Targets							
1	3.39***						3.39***
	(2,212)						(2,212)
2	2.97***	1.49**					2.23***
	(1,060)	(1,060)					(2,120)
3	2.38*	2.52***	1.74***				2.21***
	(558)	(558)	(558)				(1,674)
4	3.58***	2.12***	1.34	1.51			2.14***
	(343)	(343)	(343)	(343)			(1,372)
5	2.73	3.11***	0.82	0.99	−0.09		1.51**
	(203)	(203)	(203)	(203)	(203)		(1,015)
> 5	3.55***	2.48***	1.72**	1.75***	1.22	−0.11	1.14***
	(503)	(503)	(503)	(503)	(503)	(2,034)	(4,549)
All	3.19***	2.10***	1.53***	1.52***	0.84	−0.11	1.98***
	(4,879)	(2,667)	(1,607)	(1,049)	(706)	(2,034)	(12,942)
Panel B: Public Targets							
1	1.13						1.13
	(378)						(378)
2	−0.66	−1.08					−0.88
	(157)	(171)					(328)
3	−2.02	−1.68	1.43				−0.62
	(79)	(74)	(93)				(246)
4	1.24	−0.60	−0.54	−2.34			−0.58
	(53)	(61)	(61)	(56)			(231)
5	2.73	0.68	−4.53	−4.08**	−3.01		−1.55
	(33)	(38)	(26)	(36)	(39)		(172)
> 5	0.81	−0.65	−3.13**	−0.19	−1.30	−2.06***	−1.67***
	(66)	(86)	(84)	(92)	(102)	(504)	(934)
All	0.35	−0.88	−1.06	−1.61*	−1.78	−2.06***	−0.86***
	(766)	(430)	(264)	(184)	(141)	(504)	(2,289)

continued on next page

Table 2 - *Continued*

Number of Deals in Series	Acquisition Number in Series: 1st	2nd	3rd	4th	5th	>5th	All Deals
Panel C: Private Targets							
1	3.43 (1,165)						3.43 (1,165)
2	3.36*** (594)	0.88 (586)					2.13*** (1,180)
3	3.37*** (315)	1.74** (314)	1.24* (301)				2.13*** (930)
4	3.38*** (205)	3.31*** (178)	1.52 (196)	2.28 (170)			2.63*** (749)
5	3.20 (109)	3.67*** (103)	1.13 (118)	2.14 (97)	1.44 (86)		2.32** (513)
> 5	3.37*** (290)	3.03*** (272)	2.26** (276)	2.38*** (256)	1.70 (255)	0.72** (980)	1.79*** (2,329)
All	3.39*** (2,678)	1.96*** (1,453)	1.60*** (891)	2.30*** (523)	1.63 (341)	0.72** (980)	2.30*** (6,866)
Panel D: Subsidiary Targets							
1	4.59*** (669)						4.59*** (669)
2	4.06*** (309)	4.12*** (303)					4.09*** (612)
3	2.62 (164)	5.78*** (170)	2.83* (164)				3.77*** (498)
4	5.53*** (85)	1.67 (104)	2.27 (86)	2.24 (117)			2.81** (392)
5	1.88 (61)	3.67 (62)	2.56* (59)	2.01 (70)	−0.31 (78)		1.85* (330)
> 5	5.88*** (147)	3.32*** (145)	3.51*** (143)	1.87*** (155)	2.13** (146)	0.19 (550)	1.98*** (1,286)
All	4.32*** (1,435)	3.97*** (784)	2.90*** (452)	2.02*** (342)	1.28** (224)	0.19 (550)	3.09*** (3,787)

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 3
Cross-Sectional Returns of First Acquisitions by Single, Repeat, and Frequent Acquirers
This table compares deal characteristics of the 'Single' subsample ($n = 662$) of active firms with only one acquisition over the sample period, the first deal for the 'Repeat' subsample ($n = 2,667$) of acquirers with more than one acquisitions in the sample period, and the 'Frequent' subsample ($n = 503$) of acquirers with more than five acquisitions in the sample period. All variable definitions are in the appendix. Sample is over 1981 to 2004. Statistical significance in columns two and three refer to a $t-$test assuming unequal variances between the 'Single' subsample and the 'Repeat' and 'Frequent' subsamples, respectively. Statistical significance of the regression coefficients is determined by a heteroskedasticity-robust $t-$test where observations are assumed independent across industry classification, but not necessarily within; $p-$values are reported in parentheses.

	Mean Values			Regression Coefficients	
	Single Acquirers	Repeat Acquirers	Frequent Acquirers	(1)	(2)
Acquirer Characteristics					
$CAR_{(-2,+2)}$	0.034	0.030	0.036		
		(0.436)	(0.828)		
2–5 Deals Dummy				0.0077	
				(0.217)	
> 5 Deals Dummy				0.0164**	
				(0.026)	
Total Deals					0.0014***
					(0.005)
NYSE Size	19.781	26.980***	30.477***	−0.0007***	−0.0007***
		(0.000)	(0.000)	(0.001)	(0.001)
NYSE Prior Returns	57.810	67.493***	73.489***	−0.0004***	−0.0004***
		(0.000)	(0.000)	(0.000)	(0.000)
NYSE B/M	38.834	33.604***	29.479***	0.0002	0.0002
		(0.000)	(0.000)	(0.197)	(0.203)
Days since listing	1130.361	927.435***	812.408***	0.0000	0.0000
		(0.000)	(0.000)	(0.299)	(0.312)
Tobin's q	2.733	3.256***	3.089	0.0001	0.0001
		(0.000)	(0.169)	(0.789)	(0.824)
Prior industry deals	62.227	63.238	59.688	−0.0001	−0.0001
		(0.587)	(0.396)	(0.435)	(0.408)
Wave dummy	0.271	0.281	0.239	0.0051	0.0051
		(0.434)	(0.130)	(0.534)	(0.526)

continued on next page

Table 3 - *Continued*

	Mean Values			Regression Coefficients	
	Single Acquirers	Repeat Acquirers	Frequent Acquirers	(1)	(2)
Target Characteristics					
Public	0.171	0.145**	0.131**	−0.0645***	−0.0645***
		(0.016)	(0.020)	(0.000)	(0.000)
Private	0.527	0.567***	0.577**	−0.0137**	−0.0135**
		(0.005)	(0.042)	(0.018)	(0.020)
Subsidiary	0.302	0.287	0.292		
		(0.246)	(0.651)		
Same Industry	0.599	0.606	0.660***	−0.0029	−0.0030
		(0.604)	(0.010)	(0.567)	(0.552)
NYSE Size	14.841	17.607*	21.389**		
		(0.084)	(0.038)		
NYSE Prior Returns	44.329	49.637*	55.185**		
		(0.072)	(0.040)		
NYSE B/M	49.030	43.115*	34.348**		
		(0.077)	(0.044)		
Tobin's q	1.502	2.006***	2.391***		
		(0.000)	(0.007)		
Deal Characteristics					
Relative Value	0.38	0.24***	0.25***	0.0213**	0.0213**
		(0.000)	(0.005)	(0.042)	(0.042)
Transaction Value	88.71	109.51	94.70	0.0000	0.0000
		(0.136)	(0.683)	(0.285)	(0.285)
Toehold	0.20	0.09*	0.02***	0.0010	0.0009
		(0.056)	(0.001)	(0.500)	(0.518)
Tender Offer	0.02	0.02	0.02	0.0463***	0.0463***
		(0.996)	(0.529)	(0.002)	(0.002)
All Stock	0.25	0.27*	0.30**	0.0217***	0.0216***
		(0.062)	(0.043)	(0.006)	(0.007)
All Cash	0.39	0.39	0.41	−0.0037	−0.0036
		(0.711)	(0.318)	(0.420)	(0.438)
Constant				0.0354*	0.0412**
				(0.086)	(0.017)
Year dummies				Yes	Yes
Industry dummies				Yes	Yes
n				3,499	3,499
R^2				0.0673	0.0669

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 4
Fixed Effects Simultaneous Equations Model Estimates
Results in columns 1–2 are from equation-by-equation first-differenced GMM estimations of a simultaneous equations model. Observations are over 1981-2004. Robust $p-$values are reported in parentheses. Variable definitions are in the appendix.

	Pr(Future Deal)	$\text{CAR}_{(-2,+2)}$
Endogenous Variables		
$\text{CAR}_{(-2,+2)}$	-0.1258	
	(0.611)	
Pr(Future Deal)		0.0803
		(0.501)
Acquirer Characteristics		
NYSE Market Equity	0.0027***	-0.0019***
	(0.006)	(0.001)
NYSE Prior Returns		-0.0002**
		(0.046)
NYSE B/M	-0.0007*	0.0003
	(0.080)	(0.128)
Deal Number	-0.1633***	0.0113
	(0.000)	(0.569)
Deals/Year	0.0798**	-0.0195
	(0.015)	(0.224)
Days Since Last	0.0000*	0.0000
	(0.078)	(0.186)
Tobin's q	-0.0016	0.0020
	(0.615)	(0.270)
Industry deals prior year		-0.0002
		(0.430)
Wave Dummy	0.0241	0.0002
	(0.186)	(0.977)
Net Payout Yield	-0.0990*	
	(0.078)	
Internal/(Total investment)	0.0719***	
	(0.003)	

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Table 4 - *Continued*

	Pr(Future Deal)	$CAR_{(-2,+2)}$
Target Characteristics		
Public		−0.0255***
		(0.006)
Private		−0.0016
		(0.750)
Relative value	−0.0152	0.0131
	(0.341)	(0.144)
Transaction value		0.0000
		(0.828)
Toehold		−0.0002
		(0.798)
Same industry	0.0081	0.0039
	(0.539)	(0.495)
Deal Characteristics		
Tender offer	−0.0279	0.0103
	(0.438)	(0.484)
All equity	−0.0221	0.0107
	(0.174)	(0.598)
All cash	−0.0015	−0.0020
	(0.911)	(0.722)
All equity × Private		0.0096
		(0.627)
All equity × Public		−0.0557**
		(0.014)
1981–1991	0.1167**	−0.0184
	(0.016)	(0.446)
1992–1999	0.0982***	0.0027
	(0.003)	(0.880)
Firms	1,055	1,055
Observations	2,709	2,709
R^2	0.1843	0.0331

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 5
Quantile Regression Estimates
This table reports quantile regression coefficients with the five day CAR as the dependent variable. Observations are taken from the first six deals of the 'Frequent' subsample of acquirers who make more than five acquisitions. Sample is over 1981 to 2004. The F statistic from a Wald test of equality of coefficients is reported in the last three columns where the null hypothesis is equality. Numbers in parentheses represent $p-$values.

	Quantiles					Wald Test - F Statistic		
	0.10	0.25	0.50	0.75	0.90	All Equal	.25=.75	.10=.90
Panel A								
Deal Number	−0.004**	−0.003**	−0.003***	−0.007***	−0.010***	2.92**	6.87***	4.19**
	(0.019)	(0.014)	(0.001)	(0.000)	(0.000)	(0.020)	(0.009)	(0.041)
Constant	−0.061***	−0.021***	0.018***	0.082***	0.154***	120.670***	351.230***	357.060***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,018	3,018	3,018	3,018	3,018			
Pseudo R^2	0.0031	0.002	0.002	0.006	0.012			
Panel B								
Acquirer Characteristics								
Deal Number	−0.004*	−0.002	−0.001	−0.005**	−0.007***	1.550	0.890	1.330
	(0.097)	(0.146)	(0.390)	(0.011)	(0.004)	(0.187)	(0.346)	(0.248)
NYSE Market Equity	0.000	0.000	0.000*	0.000***	−0.001***	6.260***	8.670***	18.060***
	(0.933)	(0.347)	(0.077)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
NYSE Prior Returns	0.000	0.000**	0.000**	0.000**	0.000	0.380	0.010	0.000
	(0.421)	(0.032)	(0.011)	(0.036)	(0.477)	(0.820)	(0.923)	(0.961)
NYSE B/M	0.000	0.000	0.000***	0.000	0.000	0.410	0.030	0.030
	(0.196)	(0.167)	(0.008)	(0.242)	(0.455)	(0.805)	(0.852)	(0.867)
Deals/Year	−0.002	−0.004	−0.008**	−0.002	0.000	0.900	0.110	0.050
	(0.749)	(0.322)	(0.012)	(0.578)	(0.960)	(0.464)	(0.743)	(0.819)
Days Since Last	0.000	0.000	0.000	0.000	0.000	0.340	0.010	0.250
	(0.446)	(0.737)	(0.709)	(0.874)	(0.356)	(0.854)	(0.939)	(0.614)
Tobin's q	0.001	0.002	0.002*	0.003*	0.004***	1.300	0.690	3.190*
	(0.392)	(0.107)	(0.058)	(0.027)	(0.001)	(0.269)	(0.407)	(0.074)
Industry Deals Prior Year	0.000*	0.000	0.000	0.000	0.000	1.920	1.490	2.690
	(0.055)	(0.977)	(0.317)	(0.171)	(0.602)	(0.105)	(0.222)	(0.101)
Wave dummy	−0.001	0.002	−0.001	0.002	0.013	0.700	0.000	1.060
	(0.922)	(0.696)	(0.808)	(0.733)	(0.190)	(0.591)	(0.974)	(0.303)
Target Characteristics								
Public	−0.035**	−0.021**	−0.024***	−0.012	−0.010	0.440	0.430	1.070
	(0.039)	(0.038)	(0.008)	(0.323)	(0.556)	(0.779)	(0.513)	(0.301)
Private	−0.004	−0.005	−0.008*	0.002	−0.003	1.280	1.290	0.010
	(0.576)	(0.307)	(0.089)	(0.679)	(0.700)	(0.275)	(0.256)	(0.909)
Relative value	−0.015	−0.005	0.018*	0.034***	0.032*	3.460***	9.560***	5.030**
	(0.172)	(0.633)	(0.074)	(0.000)	(0.055)	(0.008)	(0.002)	(0.025)
Transaction Value	0.000***	0.000	0.000	0.000	0.000	1.160	0.170	4.000*
	(0.098)	(0.885)	(0.448)	(0.725)	(0.257)	(0.328)	(0.681)	(0.046)
Toehold	0.000	0.000	−0.001	0.000	0.000	0.390	0.010	0.110
	(0.689)	(0.998)	(0.459)	(0.919)	(0.932)	(0.815)	(0.924)	(0.745)

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Table 5 - *Continued*

	Quantiles					Wald Test - F Statistic		
	0.10	0.25	0.50	0.75	0.90	All Equal	.25=.75	.10=.90
Same industry	−0.001	0.002	0.002	0.009	0.000	1.050	1.630	0.010
	(0.878)	(0.718)	(0.588)	(0.113)	(0.977)	(0.378)	(0.202)	(0.930)
Deal Characteristics								
Tender offer	0.036**	0.012	0.007	−0.014	−0.036	1.930	2.750*	6.350**
	(0.024)	(0.337)	(0.570)	(0.338)	(0.167)	(0.103)	(0.097)	(0.012)
All equity	−0.033	0.006	0.017	0.039*	0.034	0.650	1.570	2.030
	(0.427)	(0.746)	(0.345)	(0.095)	(0.197)	(0.625)	(0.211)	(0.154)
All cash	0.001	0.001	0.001	−0.008	−0.009	0.560	1.650	0.650
	(0.860)	(0.808)	(0.917)	(0.257)	(0.343)	(0.692)	(0.199)	(0.421)
All equity × Private	0.035	−0.001	−0.007*	−0.042	−0.029	1.010	2.690	1.960
	(0.397)	(0.979)	(0.725)	(0.076)	(0.248)	(0.402)	(0.101)	(0.162)
All equity × Public	0.005	−0.018	−0.035	−0.066**	−0.061**	0.830	2.650	1.700
	(0.903)	(0.387)	(0.141)	(0.013)	(0.028)	(0.507)	(0.104)	(0.192)
Constant	−0.078	−0.011	−0.017	0.048	0.159			
	(0.037)	(0.751)	(0.703)	(0.436)	(0.029)			
Year Dummies	Yes	Yes	Yes	Yes	Yes			
Industry Dummies	Yes	Yes	Yes	Yes	Yes			
Observations	2,470	2,470	2,470	2,470	2,470			
Pseudo R^2	0.111	0.053	0.040	0.083	0.118			

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 6
Dynamic Acquisition Choices
Dynamic panel data results are found using the first-differenced GMM procedure of Arellano and Bond (1991) implemented in Stata with the command xtabond2 (Roodman, 2003). Significance is reported as $p-$values in the parentheses where idiosyncratic errors are assumed homoskedastic. Observations include 5th and later deals in a firm's sequence. Each column presents the results of a regression of a current (deal t) dummy choice variable on lagged (indicated $t-1$) and current values (no subscript). $\text{Public}_t = 1$ if the target of the deal at t is a public firm. Private and subsidiary are defined analogously. Public (Private, Subsidiary) $\overline{\text{CAR}}_{t-1}$ is the average CAR over deals 1 through $t-1$ for Public (Private, Subsidiary) targets. Cash $\overline{\text{CAR}}_{t-1}$ and others are defined analogously. Public (Private) t-stat_{t-1} is the t-statistic on the dummy variable Public (Private) in the following OLS regression,

$$CAR = \beta_0 + \beta_1 Size + \beta_2 RelVal + \beta_3 Pub. + \beta_4 Priv. + \beta_5 Cash + \beta_6 Stock + \beta_7 SameInd. + \varepsilon$$

where observations include the time series of a firm's prior deals. Thus, for firm i at deal t, observations included firm i's deals $1,\ldots,t-1$. The t-statistic is not robust to heteroskedasticity. Cash, Stock, and Same Industry t-statistics are found analogously. All t-statistics are winsorized to 0.5% and 99.5% to eliminate outliers. Cash (stock) is a dummy variables = 1 if the majority of the transaction was made with cash (stock). Other variable definitions may be found in the appendix. Hansen's J and AR tests are reported as $p-$values. The AR tests are conducted as in Arellano and Bond (1991). Observations are over 1981-2004.

	Public_t	Private_t	Cash_t	Stock_t	Same Industry_t
Lagged and Dynamic Variables					
Public_{t-1}	-0.0147 (0.623)				
$\text{Public}_{t-1}\times\text{CAR}_{t-1}$	0.2410 (0.433)				
Private_{t-1}		0.0000 (1.000)			
$\text{Private}_{t-1}\times\text{CAR}_{t-1}$		-0.0073 (0.979)			
Public $\overline{\text{CAR}}_{t-1}$	3.1053** (0.033)	-2.1460 (0.165)			
Private $\overline{\text{CAR}}_{t-1}$	0.7726 (0.139)	-0.1177 (0.884)			
Subsidiary $\overline{\text{CAR}}_{t-1}$	1.6058 (0.156)	-1.0534 (0.460)			
Public t-stat_{t-1}	0.0232* (0.056)	-0.0189 (0.241)			
Private t-stat_{t-1}	-0.0516 (0.244)	0.0627 (0.188)			
Cash_{t-1}			0.0582* (0.061)		
$\text{Cash}_{t-1}\times\text{CAR}_{t-1}$			-0.2795 (0.316)		

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Table 6 - *Continued*

	Public_t	Private_t	Cash_t	Stock_t	Same Industry_t
Stock_{t-1}				0.0501 (0.121)	
$\text{Stock}_{t-1} \times \text{CAR}_{t-1}$				−0.2162 (0.371)	
Cash $\overline{\text{CAR}}_{t-1}$			1.6892* (0.059)	−1.7490** (0.027)	
Stock $\overline{\text{CAR}}_{t-1}$			1.6117 (0.192)	−0.8261 (0.476)	
Other $\overline{\text{CAR}}_{t-1}$			−0.9039 (0.853)	4.2946 (0.547)	
Cash t-stat_{t-1}			0.0945 (0.559)	−0.1717 (0.420)	
Stock t-stat_{t-1}			−0.1571 (0.308)	0.2385 (0.247)	
Same Industry_{t-1}					−0.0291 (0.386)
Same $\text{Ind}_{t-1} \times \text{CAR}_{t-1}$					−0.2373 (0.381)
Same Industry $\overline{\text{CAR}}_{t-1}$					1.1067 (0.125)
Diversify $\overline{\text{CAR}}_{t-1}$					−1.0706 (0.258)
Same Ind. t-stat_{t-1}					−0.0707*** (0.008)
CAR_{t-1}	−0.0444 (0.637)	−0.0470 (0.834)	−0.1148 (0.514)	0.3043* (0.092)	0.0231 (0.917)
Acquirer Characteristics at Current Deal					
Deal Number	0.0212*** (0.006)	−0.0249** (0.030)	0.0103 (0.386)	−0.0103 (0.393)	−0.0010 (0.915)
NYSE Size	−0.0015 (0.260)	0.0017 (0.305)	−0.0048** (0.011)	0.0048*** (0.009)	−0.0009 (0.583)
NYSE Prior Returns	−0.0004 (0.185)	0.0001 (0.823)	−0.0007 (0.132)	0.0007* (0.089)	−0.0004 (0.329)
NYSE B/M	0.0004 (0.437)	−0.0001 (0.924)	0.0008 (0.359)	−0.0008 (0.351)	−0.0004 (0.634)
Free Cash Flow			0.1633 (0.392)	−0.2596 (0.219)	
Leverage			−0.0724 (0.720)	0.1296 (0.476)	−0.2927* (0.079)
Debt/Equity			−0.0003 (0.954)	−0.0029 (0.165)	−0.0008 (0.581)

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Table 6 - *Continued*

	Public_t	Private_t	Cash_t	Stock_t	Same Industry_t
Target Characteristics at Current Deal					
Public			−0.5596***	0.5391***	0.0557
			(0.000)	(0.000)	(0.114)
Private			−0.2050***	0.1772***	−0.0102
			(0.000)	(0.000)	(0.705)
Same Industry	0.0267	−0.0316			
	(0.122)	(0.261)			
Relative Value	0.2261***	−0.2423***	−0.0993**	0.0734*	0.0155
	(0.000)	(0.000)	(0.028)	(0.067)	(0.585)
Transaction Value	0.0000*	0.0000**	0.0000	0.0000**	0.0000
	(0.097)	(0.027)	(0.117)	(0.032)	(0.604)
Deal Characteristics at Current Deal					
Majority Cash	−0.0808*	−0.1126**			0.0773*
	(0.053)	(0.044)			(0.084)
Majority Stock	0.2146***	−0.0785			0.0669
	(0.000)	(0.188)			(0.176)
LBO	−1.0534***	0.0378	−0.6613***	0.6328***	−0.9252***
	(0.000)	(0.496)	(0.000)	(0.000)	(0.000)
Tender Offer	0.6915***	−0.3768***	0.3724***	−0.3798***	−0.0624
	(0.000)	(0.000)	(0.000)	(0.000)	(0.336)
Year Effects	Yes	Yes	Yes	Yes	Yes
Hansen's J	0.880	0.989	0.381	0.411	0.414
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.727	0.876	0.836	0.876	0.335
Firms	616	616	547	547	598
Observations	2,341	2,341	1,993	1,993	2,258

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 7
Abnormal Returns and Firm Responsiveness
This table presents the results from a pooled OLS regression where the dependent variable is the five day CAR. High Responsiveness Dummy variables equal 1 if the acquisition is made by a firm that has an above-median percentage of responsive deals over all deals starting with its second. Responsive deals are those where the acquirer chose the payment, public target status, and target industry consistent with the choice that has generated the highest average CARs in its deal sequence at deal t. High Responsiveness Proportion is the percentage of deals a firm made that are considered responsive to prior average returns. Other variable definitions are reported in the appendix. Significance is reported as heteroskedasticity robust $p-$values in parentheses. Observations are over 1981-2004.

Firm Responsiveness Variables		
High Responsiveness Dummy - Payment	0.0160***	
	(0.000)	
High Responsiveness Dummy - Public	0.0089***	
	(0.001)	
High Responsiveness Dummy - Industry	0.0073***	
	(0.005)	
Firm Responsiveness Proportion - Payment		0.0231***
		(0.000)
Firm Responsiveness Proportion - Public		0.0198***
		(0.000)
Firm Responsiveness Proportion - Industry		0.0079**
		(0.032)
Acquirer Characteristics		
NYSE Size	−0.0004***	−0.0004***
	(0.000)	(0.000)
NYSE Prior Returns	−0.0002***	−0.0001***
	(0.001)	(0.001)
NYSE B/M	0.0001*	0.0001*
	(0.068)	(0.058)
Deal Number	−0.0004	−0.0001
	(0.324)	(0.691)
Deals/Year	−0.0082***	−0.0085***
	(0.000)	(0.000)
Days Since Last	0.0000***	0.0000***
	(0.001)	(0.001)
Tobin's q	0.0007*	0.0007*
	(0.062)	(0.068)
Industry deals prior year	−0.0001	−0.0001
	(0.100)	(0.103)
Wave Dummy	0.0042	0.0043
	(0.239)	(0.226)

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Table 7 - *Continued*

Target Characteristics		
Public	−0.0491***	−0.0482***
	(0.000)	(0.000)
Private	−0.0105***	−0.0115***
	(0.001)	(0.000)
Relative value	0.0200**	0.0199**
	(0.012)	(0.012)
Transaction value	0.0000	0.0000
	(0.413)	(0.383)
Toehold	0.0004	0.0004
	(0.197)	(0.225)
Same industry	−0.0019	−0.0018
	(0.514)	(0.530)
Deal Characteristics		
Tender offer	0.0298***	0.0300***
	(0.000)	(0.000)
Majority Stock	−0.0041	−0.0053
	(0.416)	(0.291)
Majority Cash	0.0102*	0.0096
	(0.094)	(0.117)
Year Effects	Yes	Yes
Industry Effects	Yes	Yes
Firms	4,008	4,008
Observations	10,420	10,420
R^2	0.058	0.061

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 8
Abnormal Returns, Governance, and Public Targets
Columns 1 and 2 present results from a first-differenced OLS regression. Column 3 presents results from a firm fixed-effect (mean deviation) regression. The dependent variable in all regressions is the five day market adjusted CAR using the equally-weighted CRSP index as the market. Observations are over 1981-2004. Robust $p-$values are reported in parentheses. All variable definitions are in the appendix.

	Unrestricted	Governance Data	Public Targets
Acquirer Characteristics			
NYSE Market equity	−0.0012***	−0.0003	−0.0002
	(0.000)	(0.667)	(0.746)
NYSE Prior returns	0.0000	−0.0001	−0.0001
	(0.505)	(0.564)	(0.491)
NYSE B/M	0.0001	−0.0003	0.0003
	(0.447)	(0.332)	(0.386)
Deal number	−0.0026	0.0004	0.0047
	(0.171)	(0.921)	(0.108)
Deals/Year	−0.0135*	−0.0260	−0.0336
	(0.071)	(0.649)	(0.309)
Days since last	0.0000***	0.0000	0.0000*
	(0.008)	(0.466)	(0.063)
Tobin's q	−0.0007	0.0005	−0.0004
	(0.430)	(0.681)	(0.845)
Industry deals prior year	−0.0002	−0.0002	0.0000
	(0.155)	(0.235)	(0.739)
Wave dummy	0.0049	0.0028	−0.0092
	(0.351)	(0.773)	(0.381)
Outside director blockholders		0.1911*	
		(0.010)	
Entrenchment index		−0.0062	
		(0.204)	
Directors × Entrenchment		−0.0150*	
		(0.065)	
Target Characteristics			
Public	−0.0318***	−0.0195**	
	(0.000)	(0.056)	
Private	−0.0042	0.0006	
	(0.237)	(0.937)	
Relative value	0.0061	−0.0508**	−0.0259*
	(0.104)	(0.044)	(0.068)
Transaction value	0.0000	0.0000	0.0000
	(0.175)	(0.771)	(0.817)
Premium			0.0069
			(0.425)
NYSE Market equity			−0.0006*
			(0.091)
NYSE Prior returns			0.0001
			(0.486)

continued on next page

Table 8 - *Continued*

	Unrestricted	Governance	Public Targets
Tobin's q			0.0057**
			(0.012)
Toehold	0.0003	0.0006	0.0011*
	(0.362)	(0.499)	(0.053)
Same industry	0.0044	0.0064	0.0324**
	(0.297)	(0.348)	(0.017)
Deal Characteristics			
Tender offer	0.0135	0.0017	0.0272**
	(0.149)	(0.908)	(0.029)
All stock	−0.0027	−0.0819***	0.0070
	(0.835)	(0.008)	(0.625)
All cash	−0.0044	−0.0100	0.0149
	(0.259)	(0.214)	(0.329)
All stock × Private	0.0155	0.0636*	
	(0.238)	(0.053)	
All stock × Public	−0.0257*	0.0478	
	(0.078)	(0.143)	
1981–1991	−0.0146		0.1117***
	(0.260)		(0.002)
1992–1999	0.0088	0.0191	0.0682***
	(0.213)	(0.130)	(0.000)
Firms	2,187	320	217
Observations	6,420	982	601
R^2	0.040	0.070	0.146

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Table 9

Mean and Median Characteristics by Deal Number

For each characteristic the mean and median values of all available observations for a particular deal number for all firms are presented, with the mean above the median. The last two columns indicate the coefficients in the model, Variable = $\beta_0 + \beta_1$Deal Number + β_2(Deal Number)^2, where observations are not restricted to the first ten deals. The first row of each variable presents the OLS estimate, and the second row presents the Least Absolute Deviation estimate. Abnormal \$ returns are the abnormal changes (from the market adjusted returns) in market equity from two days before to two days after the deal announcement. Significance is tested with a robust t−statistic, not reported.

	Deal Number											
	1	2	3	4	5	6	7	8	9	10	β_1	β_2
Acquirer Characteristics												
CAR	0.032	0.021	0.015	0.015	0.008	0.000	−0.004	−0.002	0.004	−0.005	-0.005^{***}	0.000^{***}
	0.010	0.009	0.006	0.004	0.004	−0.001	0.000	−0.003	0.004	−0.004	-0.002^{***}	0.000^{**}
Abnormal \$ Returns (millions)	−0.451	−5.371	−7.010	20.245	39.170	−31.325	38.584	29.332	41.838	−316.900	13.045	−2.278
	0.484	0.666	0.569	0.572	0.764	−0.754	−1.031	−2.694	0.991	−4.32	1.260^{***}	-0.179^{***}
NYSE Size	23.716	29.617	34.372	39.299	44.108	47.455	49.986	53.507	55.049	59.071	4.839^{***}	-0.717^{***}
	15.000	20.000	30.000	35.000	45.000	45.000	50.000	50.000	55.000	60.000	6.173^{***}	-0.100^{***}
NYSE Prior Returns	63.103	62.532	62.495	62.998	62.755	64.851	64.620	63.153	62.913	62.500	−0.153	0.010^{*}
	75.000	70.000	70.000	70.000	70.000	75.000	70.000	70.000	70.000	70.000	0.058	−0.008
NYSE B/M	36.057	35.137	34.485	33.634	32.813	34.392	33.464	32.543	33.164	29.275	-0.587^{***}	0.001
	25.000	25.000	25.000	25.000	25.000	30.000	25.000	30.000	30.000	25.000	0.062^{***}	-0.008^{***}
Deals/Year	0.603	0.722	0.791	0.863	0.973	1.026	1.121	1.180	1.191	1.294	0.079^{***}	-0.000^{**}
	0.381	0.474	0.544	0.623	0.718	0.756	0.853	0.905	0.944	1.045	0.070^{***}	−0.000
Days since last	1019.436	475.703	370.887	323.063	251.666	247.159	194.022	208.041	220.864	198.397	-124.993^{***}	3.084^{***}
	657.000	277.000	215.000	202.000	139.500	134.000	116.000	125.000	122.500	106.000	-72.911^{***}	2.478^{***}
Tobin's q	3.019	3.042	2.849	2.653	2.738	2.943	2.858	2.728	2.783	2.996	−0.069	0.004^{***}
	1.736	1.749	1.715	1.734	1.751	1.760	1.679	1.724	1.629	1.769	0.019^{***}	-0.002^{***}
Wave dummy	0.276	0.315	0.323	0.329	0.348	0.346	0.329	0.343	0.335	0.327	0.011^{***}	-0.000^{***}
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outside director blockholders	0.092	0.114	0.104	0.129	0.099	0.133	0.091	0.080	0.089	0.098	0.002	−0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Entrenchment index	8.354	8.223	8.368	8.235	8.332	8.205	8.450	8.465	8.354	8.253	0.086^{**}	-0.004^{***}
	8.000	8.000	8.000	8.000	8.000	8.000	8.000	8.000	8.000	8.000	0.031^{***}	-0.002^{***}
Target Characteristics												
Public	0.157	0.161	0.164	0.175	0.200	0.185	0.207	0.276	0.243	0.276	0.017^{***}	-0.000^{***}
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Private	0.549	0.545	0.554	0.499	0.483	0.499	0.505	0.485	0.500	0.481	-0.016^{***}	0.001^{***}
	1.000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.500	0.000	0.000	0.000
Subsidiary	0.294	0.294	0.281	0.326	0.317	0.316	0.288	0.239	0.257	0.244	0.000	-0.000^{**}
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Same Industry	0.603	0.612	0.638	0.648	0.647	0.676	0.674	0.672	0.680	0.667	0.015^{***}	-0.001^{***}
	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.000
NYSE Size	16.271	18.138	21.214	21.164	23.198	23.176	29.737	26.769	29.778	30.610	1.572^{***}	-0.030^{**}
	5.000	10.000	15.000	15.000	10.000	15.000	20.000	15.000	20.000	20.000	1.525^{***}	-0.038^{***}
NYSE Prior Returns	47.073	49.760	55.850	54.281	57.432	56.757	48.596	49.154	55.222	57.805	1.011^{**}	−0.011
	45.000	50.000	55.000	55.000	65.000	62.500	50.000	45.000	55.000	65.000	1.397^{**}	−0.003
NYSE B/M	45.920	43.825	45.146	43.272	47.315	45.556	42.556	38.906	33.571	35.500	-1.177^{***}	0.033^{**}
	40.000	40.000	40.000	35.000	42.500	45.000	40.000	25.000	35.000	32.500	-1.694^{**}	0.056^{**}
Tobin's q	1.756	1.999	2.343	1.839	2.283	2.006	2.299	2.100	2.033	1.907	0.033	−0.001
	1.208	1.321	1.305	1.194	1.240	1.364	1.381	1.266	1.221	1.247	0.011	−0.000
Relative Value	0.304	0.192	0.205	0.143	0.116	0.102	0.124	0.127	0.140	0.088	-0.030^{***}	0.001^{***}
	0.090	0.071	0.058	0.049	0.034	0.030	0.032	0.027	0.025	0.026	-0.009^{***}	0.000^{***}
Transaction Value (millions)	100.080	134.111	168.178	178.161	292.225	335.558	594.251	589.392	821.305	686.571	82.030^{***}	-1.600^{***}
	17.696	22.174	28.807	33.051	33.637	41.000	41.944	47.773	42.315	70.319	5.467^{***}	-0.040^{***}
Toehold	0.143	0.214	0.136	0.204	0.257	0.129	0.217	0.118	0.019	0.000	-0.020^{**}	0.002^{***}
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Deal Characteristics												
Tender Offer	0.020	0.022	0.019	0.018	0.020	0.016	0.033	0.041	0.049	0.026	0.002^{**}	-0.000^{***}
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
All Stock	0.264	0.257	0.241	0.237	0.256	0.262	0.242	0.276	0.301	0.308	0.001	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
All Cash	0.392	0.427	0.430	0.450	0.497	0.515	0.511	0.463	0.481	0.455	0.015^{***}	-0.000^{***}
	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	-0.001^{***}	0.000^{***}
Premium	0.562	0.638	0.715	0.744	0.706	0.769	0.829	0.829	0.797	0.598	0.024^{***}	-0.001^{*}
	0.467	0.510	0.624	0.590	0.590	0.553	0.674	0.660	0.621	0.566	0.015^{**}	−0.000

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.