The Dissertation Committee for Vahap Bülent Uysal
certifies that this is the approved version of the following dissertation:

Essays on Mergers and Acquisitions

Committee:

____

Sheridan Titman, Supervisor

____

Andres Almazan

____

Aydoğan Altı

____

Jay Hartzell

____

John Robinson

Essays on Mergers and Acquisitions

by

Vahap Bülent Uysal, B.S.; M.S.

Dissertation

Presented to the Faculty of the Graduate School of

the University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2005

Dedication

To my mom, dad and Nurcihan.

Acknowledgements

I am very grateful for the advice and counsel from my dissertation chair Professor Sheridan Titman, whose insights and encouragement were instrumental to my successful completion of this dissertation. In addition, I would like to thank my committee members, Andres Almazan, Aydoğan Altı, Jay Hartzell and John Robinson who have provided valuable comments. My special thanks go to James Lemieux, Musa Ayar, Randal Watson and Michael Yates for their suggestions.

Essays on Mergers and Acquisitions

Publication No. ___________

Vahap Bülent Uysal, Ph.D.
The University of Texas at Austin, 2005

Supervisor: Sheridan Titman

The question of whether M&A pays off has attracted considerable attention from researchers. I explore two important factors in M&A: bidder's excess debt capacity and asymmetric information. First, I examine how leverage affects bidding behavior. This is an issue that has generated considerable interest – my departure from the existing literature is that I consider how takeover activity is influenced by the acquiring firms' deviation from their target capital structures. I find that bidders which

are underleveraged relative to their target debt ratios pay higher premiums than other bidders, and are more likely to successfully acquire targets. Consistent with the free cash hypothesis, stock prices react more unfavorably to takeover announcements of underleveraged bidders. In addition, leverage deficit subsumes effects of leverage and excess cash reserves which have been shown to be important determinants of bidding behavior and stock price reactions.

Second, I empirically study the role of asymmetric information in takeover contests. A large body of work suggests that better informed bidders have advantages in takeover contests. However, testing these theories is quiet difficult, as the informational advantage of bidders is typically unobservable. The novel approach I take in this paper is to use geographical proximity between a bidder and a target. I find that (i) stock prices react more favorably to takeover announcements of local bidders; (ii) target shareholders of local bidders receive lower premiums; and (iii) locally merged firms show superior operating performance in the long run. These findings are consistent with the idea that there is less asymmetric information between geographically proximate bidders and targets.

Table of Contents

List of Tables

1. Introduction

Traditional theories of capital structure suggest that firms have target capital structures that are determined by balancing the costs and benefits of debt financing. However, as Myers (1977, 1984) and Myers and Majluf (1984) emphasize, because of problems relating to debt overhang and asymmetric information, firms deviate from their target capital structures. The deviation from the target debt ratio, which is defined as the leverage deficit, can potentially affect acquisition choices through two channels. First, information asymmetry between managers and investors makes excess debt capacity (i.e., financial slack) an important source of financing for positive NPV takeovers, especially if the firm is under-valued (Myers and Majluf 1984). Second, Jensen (1986) suggests that managers of underleveraged firms may make poor acquisition choices that benefit them personally.

Another factor which plays an important role in acquisition decisions is the informational advantage of bidders. Having private information gives bidders a substantial advantage in takeover contests. For example, Fishman (1988) concludes that since better-informed bidders deter other potential bidders, they are able to acquire targets with lower premiums. However, testing these theories is quite difficult, since the informational advantage of bidders is typically unobservable.

In this dissertation, I empirically characterize the effects of these two important factors in M&A: excess debt capacity and asymmetric information. Some articles use leverage as a proxy for excess debt capacity. For example, Maloney, McCormick and Mitchell (1993) use debt-equity ratio as a measure for excess debt capacity and document a positive relationship between higher leverage and better acquisition decisions. In particular, they examine abnormal returns to bidders whose leverage ratios increases substantially during the period. Stock price reactions to takeover announcements of these bidders are negative before restructuring, but positive afterward. Their findings suggest that debt reduces agency costs and aligns the interests of managers and shareholders. However, Moeller, Schlingemann and Stulz (2004) do not find significant effects of leverage on abnormal stock returns to bidders around takeover announcements. This finding indicates that the leverage ratio itself may not be a perfect proxy for free cash flow problems.

Leverage is not the only variable used to approximate free cash flow problems in the literature. For example, Lang, Stulz and Walkling (1991) use bidder's cash flow as a proxy for free cash flow troubles. They find that bidders with low growth opportunities (low q ratio) and high current cash flow exhibit negative abnormal returns around takeover announcements. However, they document that bidders with high growth opportunities and high cash flow do not suffer from free cash flow problems. In addition to taking the growth opportunities of bidders into account, Kim and Smith (1994) consider the growth opportunities of targets in their analysis. They find that mergers create value only when cash-rich bidders team with cash-poor targets. However, these studies do not take the firm-specific optimal level of cash reserves into account. One exception to these studies is Harford (1999), who uses a baseline model to identify acquisition differences across firms based on their excess cash reserves. He identifies a bidder as cash-rich if the bidder's cash holdings exceed the predicted value of the model plus 1.5 standard deviation of the bidder's cash reserve. He finds negative stock price reactions to takeover announcements of cash-rich bidders regardless of their growth opportunities. This result is not consistent with the findings of Lang et al. (1991). This could be driven by the view that excess cash reserves depend on firm-specific factors, which are not taken into account in Lang et al. (1991). However, cash measures may not fully capture the bidder's excess debt capacity. For example, Bruner (1988) examines the restructuring of bidders prior to acquisitions and concludes that bidders build up excess debt capacity rather than excess cash reserves. Furthermore, firms rely more on leverage than cash in all-cash acquisitions. Therefore, the approach of Harford (1999) may not completely capture the effect of free cash flow problems, although his model addresses the importance of firm-specific factors in determining excess cash reserves. Thus, a firm-specific leverage-based proxy might be a better proxy to capture the free cash flow problems in takeovers.

My departure from the existing literature is that I consider how takeover activity is influenced by the acquiring firms' deviation from their target capital structures. To empirically examine the effect of the leverage deficit on acquisition choices, I utilize a two-step estimation procedure similar to that of Hovakimian, Opler and Titman (2001). In the first step, I estimate the target leverage ratio by running a regression of leverage ratios on the main determinants of capital structure considered in the prior studies. For every year, firms with bottom quartile leverage deficits are defined as underleveraged. In the second stage regressions, I examine whether underleveraged bidders are significantly different from others in terms of the premiums they pay, their offer success and the stock price reactions to their takeover announcements.

I find that bidders which are underleveraged relative to their target debt ratios pay higher premiums and are more likely to successfully acquire their targets. Consistent with the free cash flow hypothesis, capital markets react unfavorably to their takeover announcements.

Some of the issues that Harford (1999) addresses are also addressed in this dissertation, but the two studies have major differences. Mainly, Harford (1999) focuses on excess cash reserves while this paper investigates the role of the deviation from target capital structure. As I show in the subsequent chapter, the effect of the leverage deficit variable subsumes the effect of Harford's cash-rich variable. In addition, I find that the effect of the leverage deficit also subsumes the effects of leverage and net leverage, which have been shown to be important determinants of bidding behavior and stock price reactions.

Another important topic explored in this dissertation is the effect of informational differences on takeover contests. The novel approach I take in this paper is to use geographical proximity between a bidder and a target as a proxy for the bidder's informational advantage. The premise of my tests is that since information transmission is facilitated by geographical proximity, bidders that are located closer to their targets are likely to be better informed. Within any given location, managers are likely to interact with each other through social, civic and business meetings. In addition, they may have common suppliers and customers and may read the same newspapers and watch the same television news. Hence, local bidders in a takeover contest have access to a great deal more information than distant bidders.

I attempt to characterize the effects of local information on takeover outcomes by examining the bidders' stock price reactions to takeover offers, the target premiums, and the long run operating performance of the merged firm. If geographical proximity is, in fact, a proxy for informational advantage, then local bidders will tend to deter other bidders, and this in turn is likely to result in lower premiums to target shareholders. As a result, local bidders are likely to receive more favorable stock price reactions to their takeover announcements and should outperform their distant counterparts in the long run.

My assumption that local bidders have an informational advantage is consistent with the recent investment literature on the role of geographical proximity in investments. For example, Coval and Moskowitz (1999, 2001) examine the role of geographical proximity in portfolio decisions of mutual funds. They show strong preference of mutual funds for locally headquartered firms. Furthermore, the performance of local mutual funds is better than that of distant funds. These findings suggest asymmetric information between local and distant professional investors.

Ivkovic and Weisbenner (2004) also find similar results at the individual investor level. They examine the portfolios of individual investors and document that local firms' stocks in individual investors' portfolios outperform distant firms stocks. In addition, Malloy (2004) reports that local equity analysts predict the future earnings of geographically proximate firms more accurately than their distant counterparts. All these papers indicate that geographical proximity facilitates information transmission. In contrast with these papers, the emphasis in the present research is on the information held by firms' managers, i.e., the active participants in takeover activity, rather than the information collected by investors.

This essay is also related to the literature on cross-border takeovers. For example, Dewenter (1995) compares target premiums in domestic and foreign acquisitions in the U.S. chemical and retail industries. She does not find conclusive evidence on the difference between the premiums offered to targets in cross-border and domestic takeovers. However, Eckbo and Thorburn (2000) find that Canadian bidding firms make better acquisitions than the U.S. bidders in Canada. The conflicting results in these papers can be interpreted in various ways. For example, in addition to information asymmetries, the results may be generated because of the cultural, legal and tax differences as well as varying currency and political risk across countries. In order to abstract away from these differences, DeLong (2001) studies the wealth effect of geographical proximity on domestic bank mergers and finds larger gains associated with mergers between banks that do business in the same region. While these results suggest that there may be more synergies in mergers with greater geographical proximity (at least within the banking industry), it does not address cross-industry takeovers, where these synergies are less likely to be important.

I find that i) stock prices react more favorably to takeover announcements of local bidders; ii) locally merged firms show superior operating performance in the long-run and iii)targets of local bidders receive lower premiums. These findings are consistent with the asymmetric information hypothesis, which predicts that better-informed bidders will deter other potential bidders from participating and will acquire targets by paying lower premiums.

An analysis of analyst coverage of target firms provides further empirical evidence that relates to the informational advantages of local bidders. Since there is likely to be more information asymmetry for targets that are not covered by analysts, the result should be stronger for this subsample. Consistent with this view, I find that local bidders realize larger gains when they acquire targets which are not covered by analysts.

A comparison of market reactions to cash versus stock offers further illustrates the informational role of geographical proximity. Myers and Majluf (1984) suggest that under-valued bidders are likely to shy away from stock offers and resort to cash acquisitions. As a result, the market interprets stock offers as signals of bidder over-valuation. Past studies have confirmed these predictions by documenting that the average bidder announcement effect is positive for cash offers but negative for stock offers (Travlos, 1987). Announcement effects for distant bidders in my sample exhibit the same pattern, pointing to asymmetric information problems between distant bidders and their targets. In contrast, I find no significant difference between the announcement effects of cash versus stock offers for the subsample of local bidders. This is consistent with the idea that local targets know (or at least know relatively more about) their bidders' intrinsic values. With well-informed targets, there is no need for an under-valued bidder to avoid a stock offer; hence, the method of payment does not convey information about the type of the bidder.

Although the focus of this research is on information issues, it is also possible that my results could be generated because there are greater synergies when the merged firms are closer. For example, firms in the same location can share common facilities and can easily transfer human capital. To test this I compare within-industry mergers to cross-industry mergers, reasoning that synergy gains in local cross-industry mergers are less likely to affect the stock price reaction. I find that local bidders appear in within and cross-industry mergers in approximately the same proportions, and the results for the cross-industry mergers are quite similar to the findings for the within-industry mergers. This evidence appears to be inconsistent with the hypothesis that high synergies in within-industry mergers explain the observed favorable stock price reaction to local bidders.

It is also the case that my evidence on target premiums does not support the high synergy gains hypothesis. If synergies play an important role in local mergers, then target shareholders should receive higher premiums, reflecting the synergy gains inherent in the merger. In contrast, I find that local bidders tend to pay lower target premiums, which is inconsistent with local mergers generating larger synergies. This evidence, however, is consistent with the asymmetric information hypothesis, which predicts that the required premium to deter potential bidders is likely to be lower when the bidder has better information.

Another alternative explanation for the favorable market reaction to local bidders is that geographical proximity might proxy for the size of a bidder. Previous empirical research documents a connection between small bidders and good acquisition choices (see Jarrell and Poulsen 1989; Loderer and Martin 1990; and Moeller, Schlingemann and Stulz 2004). Since local bidders are typically small, it could be the case that local-bidder status in my regressions proxies for bidder size. However, I find that the effect of geographical proximity remains significant even after controlling for bidder size. In fact, it is more pronounced for the subsample of the smallest bidders, which indicates that geographical proximity plays an important role that is independent of the size effect. Furthermore, since the proximity effect vanishes for larger firms, the evidence suggests that larger firms have better access to investment bankers and other information intermediaries, whereas small local bidders are more likely to rely on information gathered through geographical proximity.

Finally, I test whether locally merged firms show superior operating performance in the long run. I find that local mergers outperform their distant counterparts in the two years following the takeover. Specifically, the superior performance of local bidders is more pronounced for the subsample of small bidders. These results confirm the evidence from the stock price reactions and are consistent with the idea that local bidders enjoy informational advantages over their distant counterparts in acquisitions.

The remainder of the dissertation is organized as follows. Chapter 2 examines the role of deviation from the target capital structure in acquisitions. Chapter 3 studies asymmetric information in takeovers. Chapter 4 concludes.

2. Deviation from the Target Capital Structure and Acquisition Choices

2.1 Introduction

In this chapter, I empirically examine how the deviation from a firm's long-term target leverage ratio influences one of its major investment decisions: the acquisition or takeover of another company. I focus on takeover offers since there is detailed information about these investments, allowing an in-depth evaluation of the potential differences between the acquisition choices of underleveraged and overleveraged firms. Specifically, with a sample of 998 takeover attempts between 1986 and 2001, I examine whether a bidder's leverage deficit affects the premium paid by the bidder and how this, in turn, affects the likelihood of a successful offer. I also study the effect of leverage deficit on stock price reactions to takeover announcements.

2.2 Sample Selection and Descriptive Statistics

I use firm-level data from the Standard & Poor's COMPUSTAT Annual Files to estimate the target leverage ratio. The sample excludes financial firms (6000-6999) and regulated utilities (4900-4999). Furthermore, I exclude firms with book values of total assets less than 10 million in 1990 dollars in order to eliminate the noise created by small firms in target capital structure estimation. The sample has 67,214 firm-years covering the 1980-2001 period, and all nominal asset values are converted to real values in 1990 dollars.

The sample of completed and withdrawn takeover attempts is obtained from the Securities Data Company's (SDC) Mergers and Acquisitions Database for the period between January 1, 1986, and December 31, 2001. I include only those transaction announcements that meet the following criteria:

(i) Transaction is listed as completed or withdrawn with announcement and effective dates that fall within the sample period.

(ii) Transaction is identified by the SDC as a merger or an acquisition attempt to acquire majority interest.

(iii) Both bidder and target are non-financial and non-utility public firms in the U.S.

(iv) Bidder firm is found in the COMPUSTAT and the CRSP annual files.

(v) Bidder firm is identified as the first bidder.

(vi) Relative size of transaction to the market capitalization of the bidder is between 5% and 1000%.[1]

(vii) Transaction value is not less than 1 million dollars.

(viii) Stock price of the bidder is not less than 1 dollar.

[1] This restriction ensures that reverse mergers and the trivial impact of small targets are excluded from the analysis.

I combine the SDC Mergers and Acquisitions data with COMPUSTAT based on fiscal year information and announcement dates of takeover bids. Stock prices obtained from the CRSP tapes are then used to estimate the abnormal returns to bidder and target firms. The final sample consists of 998 takeover attempts. Of these takeover attempts, 78% of the takeover attempts in the sample are successful while 22% of them are withdrawn. Tender offers constitute 26% of the sample and the distribution of the method of payment over the sample period is fairly even: 31% all-cash, 35% all-stock and 34% mixed.

Table 1 shows the distribution of deal characteristics over the years between 1986 and 2001. Deal characteristics in the 1980s differ from those in the 1990s. For example, 85% of all offers in 2001, up from 68% in late 1980s, were successful. This increase was due in part to reduction in the rate of multiple bidders and to decrease in frequency of hostile offers during the sample period. These findings are also consistent with the second generation anti-takeover laws resulting in friendly offers in the 1990s.[2] Table 1 also shows that there is a significant change in the method of payment used by bidders during the period. For example, 17% of bids in 2001, down from 66% in 1986, were cash offers, and the rate of stock offers increased from 16% in 1986 to 30% in 2001.[3] Another change in takeovers is observed in the mode of acquisition. Bidders preferred mergers over

---

[2] See Holmstrom and Kaplan (2001) and Andrade, Mitchell and Stafford (2001) for a detailed discussion of differences between takeovers in the 1980s and the 1990s.

[3] Holmstrom and Kaplan (2001) assert that emergence of growth opportunities in new technologies and markets in 1990s contributed to extensive use of stocks as a means of takeover and to decrease in the percentage of cash offers in 1990s.

tender offers in the late 1990s, as the percentage of tender offers decreased from 52% in the late 1980s to 20% at the end of the period.

2.3 Target Leverage Ratio

2.3.1 Estimation Procedure

In order to estimate the deviation from the target capital structure, an explicit estimation of target leverage is required. However, the dependent variable, leverage ratio, takes values between zero and one. Thus, I use the Tobit cross-sectional regression which corrects for the censoring of the dependent variable.

I use book leverage, *Book Lev*$_i$, defined as total assets minus book equity divided by total assets, instead of market leverage in the target leverage regression for two reasons. First, there is a mechanical relationship between profitability and market leverage. Second, market-based leverage regressions are more likely to misidentify some firms as underleveraged due to steep run-ups of stock prices in the 1990s. Therefore, these firms may not have as high borrowing capacity as predicted. I find that the results are robust to market-based target leverage estimation, and these results are discussed in the robustness section at the end of the chapter.

$$Book\_Lev_i = \gamma' X_i + \varepsilon_{1i} \tag{1}$$

As given in equation (1), I regress *Book Lev*$_i$ over determinants of capital structure (X_i) used in previous studies. These determinants include proxies for profitability, size, growth opportunities and tangibility of assets. In order to control for industry effects, changes in tax rates and macroeconomic changes, dependent and independent variables in the Tobit regression are defined as differences from two-digit SIC industry means for a given year. The fitted value of this regression is defined as the target leverage ratio. From this variable, I construct a leverage deficit variable defined as actual debt minus the estimated target leverage from the first stage. The *Under_Leveraged* dummy takes the value of one if the firm falls in the bottom quartile of leverage deficits.

In the second stage, the *Under_Leveraged* variable is then used in an estimation of premiums received by target shareholders, *Target Premium*, as given in equation (2). Following Schwert (1996), *Target Premium* is defined as cumulative abnormal returns to target 40 days before and 40 days after the announcement day. In equation (3), I estimate the marginal effect of *Under_Leveraged* on the likelihood of offer success, *Pr (success=1)*. In addition, I test whether stock prices react more unfavorably to takeover announcements by underleveraged bidders in equation 4. Following the standard methodology, I use cumulative abnormal returns to bidders, *CAR*, which are calculated over a three-day event window (one day before and one day after the announcement date). The benchmark returns are the value-weighted index of returns including dividends for the combined New York Stock Exchange, American Stock Exchange and NASDAQ. The estimation window includes from 250 days to 50 days before the announcement date.

$$Target\ Premium_i = \alpha_0 + \alpha_1 \cdot Under\_Leveraged + \alpha_1 \cdot Z_i + \varepsilon_{2i} \qquad (2)$$

$$\Pr(success = 1) = \Phi(\beta_0 + \beta_1 \cdot Under\_Leveraged + \beta_1 \cdot Z_i) \qquad (3)$$

$$CAR_i = \theta_0 + \theta_1 \cdot Under\_Leveraged + \theta_1 \cdot Z_i + \varepsilon_{3i} \qquad (4)$$

One should note that the *Under_Leveraged* dummy is measured with error because it is constructed based on the first stage regression. The error in the *Under_Leveraged* dummy results in lower standard error. In order to correct the standard error, I use the methodology suggested by Heckman (1978).

2.3.2 Determinants of the Target Leverage Ratio

In this section, I examine the determinants of target leverage ratio and estimate the leverage deficit. Following the standard methodology in the target capital structure literature, the target leverage regression in equation (1) controls for profitability, size, growth opportunity and tangibility of assets.

Large firms are more diversified and have less volatile cash flows. This decreases financial distress cost and increases target leverage ratio (Rajan and Zingales 1995). Furthermore, they have easy access to capital markets. In order to capture this effect, I measure size as natural logarithm of net sales, *Sales*. In this chapter, profitability is measured as earnings before taxes, preferred dividends and interest payments over total assets, *ET_A*.

Growth opportunities of a firm also affect its target capital structure. As Myers (1977) indicates, debt overhang may prevent firms from investing in positive future NPV projects. In particular, this effect is costly for growth firms. Furthermore, Goyal et al. (2002) show that firms in the defense industry increase their leverage ratios as their growth opportunities shrink. This chapter uses two proxies for growth opportunities: market-to-book ratio, *M_B*, which is defined as sum of market value of equity and book value of total debt divided by total assets, and ratio of research and development (R&D) expenditures to sales, *RD/Sales*. The latter measure, *RD/Sales*, proxies for non-debt tax shield and product uniqueness, which might affect the target capital structure. For example, DeAngelo and Masulis (1980) argue that non-debt tax shield dilutes the benefits of leverage and decreases the target leverage ratio. Furthermore, Titman and Wessels (1988) indicate that product uniqueness increases financial distress cost and decreases target leverage ratio.

Another important determinant of target leverage ratio is tangibility of assets. Firms with liquid assets are more likely to borrow against their assets and have lower bankruptcy cost resulting in higher target leverage ratio (Titman and Wessels, 1988). This chapter uses ratio of tangible assets to the book value of total assets, *Tangrat*, as a proxy for tangibility of assets.

Table 2 summarizes estimates of the Tobit target leverage ratio regression. The Tobit regression takes the heteroskedasticity and clustering effect of firms into account in p-value calculations. Consistent with the findings in previous studies, the estimates of target capital structure yield a positive slope on *Sales* (p-value less than 0.001). Furthermore, *M_B* has a negative effect on the target leverage ratio (p-value less than 0.001). Moreover, there is negative relationship between profitability and the target leverage ratio. The coefficient estimate of *RD/Sales* is negative and significant. This finding is consistent with the view that R&D intensive firms have better growth opportunities. However, the coefficient estimate of *Tangrat* is positive, but not statistically significant at conventional levels.

2.4 The Second Stage Analysis

2.4.1 Descriptive Statistics of Bidders

Table 3 presents the descriptive statistics about the bidders in my sample. 22% of the bidders are identified as underleveraged. The median *Market Value* of the bidding firm, defined as market equity capitalization 60 days prior to announcement date, is 643 million dollars. The *Relative Size*, which is defined as transaction value to *Market Value* of the bidder, is between 5% and 904%, and the median *Relative Size* is 0.31. The median and mean *MB* of bidders are 1.58 and 2.01, respectively. These values are comparable with the previous studies on M&A.

2.4.2 The Second Stage Explanatory Variables

In the second stage analysis, the focus is the explanatory power of the *Under_Leveraged* dummy variable. If underleveraged firms use their leverage deficits in acquisitions, then I expect to find significant positive effect of *Under_Leveraged* on both *Target Premium* and the probability of successfully acquiring the target. However, the asymmetric information and the free cash flow hypotheses have different predictions on the signs of *Under_Leveraged* in the *CAR* regressions, where the latter hypothesis predicts negative coefficient estimates.

Consistent with the free cash flow hypothesis, Harford (1999) finds that excess cash reserves have negative effect on *CAR*. Hence, it could be the case that *Under_Leveraged* may proxy for excess cash reserves. That is, firms with high cash reserves may have low leverage deficits and, consequently, pay higher premiums. In order to disentangle the impact of leverage deficit from excess cash reserves, I include a *Cash_Rich* dummy variable as defined by Harford (1999).[4] The *Cash_Rich* dummy takes a value of 1 "if firm's cash holdings are more than 1.5 standard deviations above the value predicted by the fixed effect model" given by:

$$\begin{aligned} Cas\_Sal_{it} &= \beta_0 + \beta_1 \cdot NetCas\_Sal_{it} + \beta_2 \cdot Risk\,\mathrm{Pr}\,emium_{t+1} + \beta_3 \cdot \mathrm{Re}\,cession_t \\ &+ \beta_4 \cdot \Delta NetCas\_Sal_{i,t+1} + \beta_5 \cdot \Delta NetCas\_Sal_{i,t+1} + \beta_6 \cdot M\_B_{i,t-1} \\ &+ \beta_7 \cdot \mathrm{CFOVAR} + \beta_8 \cdot Size_{i,t-1} + \varepsilon \end{aligned}$$

where

Cas_Sal is cash/sales,

NetCas_Sal is operating cash flow net of investments[5],

Recession is a dummy variable for recession, which is identified by the National Bureau of Economic Research,

Risk Premium is the difference between AAA and junk bond yields,

M_B1 is the lag of market-to-book ratio,

Size is book value of assets,

---

[4] The analysis is also carried through adding Cash Holdings/Sales in regressions. The results are qualitatively the same.

[5] Definition of Operating cash flow is defined as in Dechow (1994). Operating cash flow = operating income before depreciation – interest – taxes – difference in non-cash working capital.

CFOVAR is coefficient of variation for the firm's cash flow.

The *Cash_Rich* dummy is not highly correlated with *Under_Leveraged*. This is also consistent with the empirical evidence presented by Moeller et al (2004), which shows that cash to assets ratios of small firms are low, although they have high leverage ratios. Therefore, the findings of this chapter are based on deviation from target leverage ratio and are not driven by excess cash reserves.

Previous literature on bidding behavior shows that unused debt capacity plays an important role in acquisitions. For example, Bruner (1988) finds that bidders with lower net debt ratio are more likely to be successful. Furthermore, he shows that mergers create value if these bidders acquire targets with high net debt ratio. In addition, Maloney et al. (1993) find that *CAR* increases with the bidder's leverage ratio. Bidder's leverage ratio does not only play an important role in *CAR*, but also affects the bidding behavior. Clayton and Ravid (2002) demonstrate that higher debt levels are associated with lower bids in FCC spectrum auctions. In order to control for this effect, I use Debt-Equity ratio, *D_E* in the second stage regressions.

The recent literature on mergers and acquisitions shows that characteristics of bidders may potentially affect the dependent variables in the second stage regressions (see Schwert 2000; Datta et al. 2001; Officer 2003; Moeller et al. 2004). For example, large firms are more diversified, and their cash flows are less volatile. They raise capital through capital markets better than small firms. These features allow them to bid more aggressively and increase their likelihood of success in takeover contests.[6] In addition, Moeller et al. (2004) show that the bidding behavior of large firms differ from that of small firms. Therefore, the second stage regressions control for bidder's financial measures.

Previous literature on mergers and acquisitions shows that characteristics of target firms may play important roles in takeover contests. For instance, Bruner (1988) finds that slack-rich bidders create value when they acquire slack-poor targets. Furthermore, Kim and Smith (1994) find that acquisitions create value if bidders with low growth opportunity and high liquidity pair with targets with high growth opportunity and low liquidity. Thus, I add *Target Firm M_B*, target firm's market-to-book ratio, in my analysis. Another important factor that may affect second stage regressions is target's Price/Earnings ratio, *Target Firm P_E*. Bidders may prefer targets with high Price/Earnings ratio in order to artificially inflate their stock prices. In addition, target firms with lower Debt/Equity ratios, *Target Firm D_E*, have low financial distress risk and are easier to manage after their acquisitions. Thus, bidders are expected to bid more aggressively for these targets.

Another factor that affects the dependent variables of second stage regressions is the mode of acquisition. For example, Rau and Vermaelen (1998) show that bidders in tender offers show better performance than bidders in mergers. In order to control for tender offers, I include a *Tender* dummy variable in the second stage regressions.

---

[6] The studies such as Lang et al. (1991) find that bidder returns are negatively related to cash flows for bidders with low Tobin's q ratios. I replicate the market reaction regression including market-to-book ratio, and results do not change. Furthermore, the analysis is repeated with bidder's financial performance measures such as sales growth and stock return, and the results are robust to the inclusion of these variables.

Means of payment is identified as an important determinant of market reaction to takeover announcements by studies such as, but not limited to, Travlos (1987), Fishman (1989) and Martin (1996). Capital markets react favorably to takeover announcements of bidders that make cash offers because these firms are not overvalued (Myers and Majluf 1984). In order to control for the means of payment, I use a dummy variable for all-cash offers, *Cash*, in the second stage regressions.

Other important factors that might affect the second stage regressions are changes in market and macroeconomic conditions. Furthermore, previous studies on takeovers, including Andrade et al. (2001) and Holmstrom and Kaplan (2001), show that the mergers in the 1980s differed from those in the 1990s. Thus, I include year dummies in the second stage regressions, but I do not report them in the interest of brevity.

2.4.3 Univariate Analysis

Table 4 shows that there are significant differences between underleveraged and other bidders in terms of variables of interest. For example, the two groups of bidders differ from each other in terms of target firms' stock price reactions to takeover announcements. *Target Premium* of underleveraged bidders is 0.10 higher than that of other bidders (t statistics of 3.04). This finding suggests that underleveraged bidders take their leverage deficit into account in their bids and use their excess debt capacities through paying higher premiums in acquisitions.

Table 4 presents that *CAR* of underleveraged bidders is –0.023 while that of other bidders is only -0.006 (t statistics of 3.01). Combined with the finding that underleveraged bidders pay higher premiums, this result indicates that underleveraged bidders make poor acquisition decisions.

Looking at the post-merger leverage ratio provides another way to identify the major factor of these results. If these findings are driven by excess debt capacity, then the increase in the post-merger leverage ratios of underleveraged bidders in all-cash offers should be higher than that of other bidders. Consistent with this prediction, there is a substantial difference between bidders in terms of *Book Leverage Difference*, which is defined as the difference between post-merger and pre-merger book leverage ratios of successful bidders in all-cash offers. Book leverage ratio of underleveraged bidders increases by 10% following the acquisition, while the impact of acquisition on leverage ratio is 2% for the rest of the sample (t statistics of 4.89). This finding suggests that underleveraged bidders finance their cash offers through debt issuance.[7] Thus, cash offers are debt-increasing, and firms rely on excess debt capacity rather than on excess cash reserves. Furthermore, anecdotal evidence also suggests that one of the major reasons for offer withdrawals is lack of financing, which is also related to firms' leverage deficits.

[7] Yook (2003) also confirms this finding.

2.4.4 Do Underleveraged Bidders Pay Higher Premiums?

In this section, I examine whether underleveraged bidders pay higher premiums. Table 5 provides the results of *Target Premium* regressions, controlling for bidder and target financial measures as well as deal characteristics. The regressions also include year dummies, which are not reported in the interest of brevity, to control for macroeconomic and seasonal changes. Models have R^2 of 11%, which is comparable to premium regressions in the literature. In order to correct for heteroskedasticity, p-values of coefficients are calculated with White's (1980) correction.

In all models, the estimates of *Under_Leveraged* are positive at conventional confidence levels. On average, targets of underleveraged bidders receive 13% higher premiums. Specifically in Model 1, underleveraged bidders pay 13.7% higher premiums (p-value of 0.019). The significance of the *Under_Leveraged* dummy persist even after controlling for the *Cash_Rich* dummy and *D_E* in Models 2 and 3, respectively. Furthermore, the significance of *Under_Leveraged* and insignificance of *Cash_Rich* suggest that the latter is not as important as the former in the *Target Premium* regressions. Furthermore, this finding is consistent with the increase in *Book Leverage Difference* in Table 3, indicating that underleveraged bidders use debt, rather than cash reserves, in acquisitions. In sum, the leverage deficit subsumes the effect of excess cash reserves on premiums.

The significant effect of *Under_Leveraged* is not necessarily driven by low leverage ratios, because the coefficient estimates of leverage ratio proxies do not have explanatory power in the regressions. In particular, *D_E* has a negative coefficient estimate at the conventional significance level (p value less than 0.001), but it lacks economic significance in Model 3. This evidence suggests that *Under_Leveraged* plays a more important role than leverage ratio.

In short, underleveraged bidders have aggressive bidding behavior in takeover contests, and this result is robust to model specifications. The next section will address the question of whether underleveraged bidders are more successful in their bids.

2.4.5 The Role of the Bidder's Leverage Deficit in Takeover Success

This section examines whether leverage deficit has a significant impact on the likelihood of the takeover success, defined as completion of takeover by the first bidder. Table 6 presents marginal effects of probit model of success since probit coefficient estimates are hard to interpret. Marginal effects of continuous variables are found at their means, while marginal effects of dummy variables are calculated through the difference in the cumulative distribution functions for discrete changes of dummy variables from 0 to 1. In order to test reliability of models, Wald statistics and p-values are computed. All p-values of Wald statistics are less than 0.001, indicating that all models are statistically reliable.

Chowdhry and Nanda (1994) argue that excess leverage can be used strategically as a commitment to bid aggressively. If this is the case, then overleveraged bidders are more likely to win takeover contests. On the other hand, if the leverage deficit of a bidder creates free cash for managers, then the bidding firm is more likely to complete the deal, and I should expect a positive sign for the *Under_Leveraged* dummy. Furthermore, the leverage deficit of a bidding firm can proxy for the survival of the firm: underleveraged firms are less likely to go bankrupt.[8] Consequently, the target management is more likely to resist the takeover attempt of a highly leveraged bidder if the benefits of the target management depend on the survival of the bidding firm. This implies a positive marginal effect of *Under_Leveraged*. Consistent with these predictions, marginal effects of *Under_Leveraged* are positive at conventional significance levels. For instance, underleveraged bidders are 6% more likely to succeed in Model 1 (p-value of 0.049).

Harford (1999) shows that cash-rich bidders are more successful in their takeover offers in a univariate setting. However, the probit analysis in Model 2 indicates that cash-rich bidders do not have significant success rates, while underleveraged bidders are 7% more likely to be successful (p-value of 0.028). This empirical finding is consistent with the anecdotal evidence that lack of financing is one of the major reasons for offer withdrawals.[9] However, a high success rate is not necessarily a consequence of a low leverage ratio. Specifically, *D_E* of a bidder does not affect the success probability of an offer although the marginal effect of *Under_Leveraged* is 6% (p-value of 0.055).

The evidence on the target premium and probability of success indicates that leverage deficit affects the bidding behavior and the outcome of a takeover offer.

[8] Zingales (1998) finds that highly leveraged trucking firms are less likely to survive after the deregulation in the trucking industry.

[9] For example, the deal synopsis reported by the SDC also indicates that lack of financing is one of the major reasons for offer withdrawals.

Furthermore, the *Under_Leveraged* dummy subsumes other effects which were found to be important determinants of bidding behavior. The next section examines whether underleveraged bidders use their excess debt capacity to increase shareholder value.

2.4.6 Capital Markets and Bidder's Leverage Deficit

Table 7 reports the coefficient estimates of regressions of *CAR* over *Under_Leveraged*, annual dummies and other explanatory variables detected in the literature. The models have R^2 of 7%, which are comparable to CAR regressions in previous studies. The p-values are calculated based on White's (1980) correction for heteroskedasticity.[10]

The primary result from Table 7 is that the coefficients of *Under_Leveraged* are negative and significant in all models. Consistent with the free cash flow hypothesis, this indicates that capital markets react unfavorably to takeover announcements of underleveraged bidders. Specifically, *Under_Leveraged* has a significant coefficient estimate of –1.7% in Model 1 (p-value of 0.002).

Another focus of interest is to detect the relative importance of excess cash reserves and leverage deficit in *CAR* regressions. Model 2 includes both *Under_Leveraged* and *Cash_Rich*. The effect of *Under_Leveraged* is significant (-1.7% at 1% confidence level) although *Cash_Rich* has an insignificant coefficient estimate.

[10] Another method of estimating the coefficients of CAR regression is the weighted least squares regression. The results are quantitatively the same if weighted least squares is used.

Contrary to Harford (1999), this evidence suggests that the major source of value destruction in acquisitions is leverage deficit, not excess cash reserves.[11]

Maloney et al. (1993) show that low bidder's leverage ratio is negatively associated with *CAR*. I investigate whether the negative relationship between *Under_Leveraged* and *CAR* is a consequence of a decrease in leverage per se or whether it is driven by deviation from target leverage ratio. Model 3 presents that *Under_Leveraged* subsumes the effect of *D_E*.

If leverage deficit plays an important role in takeover decisions, then the impact of *Under_Leveraged* on *CAR* should be directly proportional to the relative size of target. In order to test this hypothesis, Model 4 includes an interaction term of *Under_Leveraged*Relative Size*. Notably, the effect of *Under_Leveraged* on *CAR* increases with relative size of target to bidder (p-value of 0.002).

In short, capital markets recognize acquisitions of underleveraged firms and react unfavorably to takeover announcements of underleveraged bidders. That is, managers of bidders with low leverage deficits do not use company resources for shareholder benefits, but rather use them to diversify their human capital risk. Furthermore, these findings are driven neither by excess cash reserves nor by low leverage ratio.

[11] In particular, Yook (2003) shows that debt increases in cash offers, which is also documented in Table 4 in this chapter.

2.4.7 Leverage Deficit and Method of Payment

Firms deviate from their target capital structures through two channels. First, it could be the case that bidders have high earnings prior to their acquisitions, which may result in deviation from the target capital structure. Second, high stock prices of bidders may result in being underleveraged. The latter hypothesis implies that underleveraged bidders are more likely to use stock in their acquisitions.

In order to test this hypothesis, I employ an ordered probit analysis to estimate the likelihood of stock offers. Table 8 presents the coefficient estimates, where the dependent variable takes the value of (minus) one if the offer is an (all-cash) all-stock offer, and is zero, otherwise. The *Under_Leveraged* dummy is not significant. Therefore, I cannot conclude that a particular shock, such as high profitability or high stock price run-up, plays an important role in the bidding behavior. However, the other coefficient estimates shed light on the firm's choice of method of payment. For example, split and dividend adjusted annual stock return, *Stock Return*, results in high likelihood of using stock in acquisitions. This finding is consistent with Shleifer and Vishny (2003), which suggest that bidders use overvalued stocks in their acquisitions. In addition, bidders with better growth opportunities are more likely to use stock as means of payment. In fact, if target shareholders are aware of better growth opportunities of bidders, they are more likely to accept stock in takeovers. I expect that higher earnings increase the likelihood of cash offers. Consistent with this idea, the coefficient estimate of *ET_A* is negative, but is not statistically significant at conventional levels.

An analysis of the effect of interaction between method of payment and *Under_Leveraged* on stock price reaction may illustrate the role of deviation from target capital structure in takeovers. Table 9 reports the coefficient estimates of the interaction terms of *Under_Leveraged* and all-stock offers (*Stock*). The effect of *Under_Leveraged* is insignificant for all-stock offers, whereas it is significantly positive for other offers. This finding suggests that underleveraged bidders pay higher premiums when their offers have cash components. Furthermore, the effect of interaction terms is significant for all-stock and other offers, and the difference between the estimates of interaction terms is not significant at conventional levels. This finding indicates that the effect of *Under_Leveraged* is robust to the choice of method of payment.

One may argue that *Stock Percentage*, ratio of stock in the offer, might be a better proxy for the method of payment. However, this variable does not have a significant estimate in the *Target Premium* regression in Table 10. In addition, its marginal effect on probability of success and *CAR* is not economically significant. Moreover, inclusion of *Stock Percentage* does not affect the significance and magnitude of the *Under_Leveraged* dummy. In short, using continuous variable for method of payment does not change the findings.

2.5 Robustness

In this study, I focus on the announced takeovers. However, there are many other takeover bids, which are not observed since they fail at the initial stages of the takeover process. One may argue that this might result in a sample selection bias in the empirical findings of this chapter. In order to correct for this potential bias, I use the two-step Heckman procedure. In the first stage, I estimate a probit model for the likelihood of being a bidder and derive the *Mill's Ratio*, which corrects for the sample selection bias in the second stage regression. The explanatory variables in the probit model include *M_B, ET_A, Stock Return, Size, Tangrat* and annual dummies. Table 11 reports second stage regressions with *Mill's Ratio*. Adding *Mill's Ratio* into the analysis does not change the magnitude and statistical significance of *Under_Leveraged*. Hence, the selection bias does not affect the empirical findings in this chapter.

One may argue that market leverage ratio might be a better proxy if low-risk debt capacity depends on the market value of the firm. Table 12 reports regression results based on market leverage. All results with market leverage ratio are qualitatively the same as book leverage, except for likelihood of success. The marginal effect of *Under_Leveraged* is positive, but lacks statistical significance. Consistent with Shleifer and Vishny (2003), market value based underleveraged bidders are more likely to prefer stock if they believe that their companies are overvalued. Since this bidding behavior is anticipated by target firms, market leverage based underleveraged bidders may not be as successful as book leverage based underleveraged bidders.

Studies such as Holmstrom and Kaplan (2001) argue that takeovers in the 1990s differ from those in the 1980s. The differences may result in structural changes in capital markets' perception of acquisitions in the sample period. Thus, I decompose the effect of the *Under_Leveraged* dummy for the 1980s and 1990s in Table 13. The interaction terms of *Under_Leveraged* and time periods have significantly negative coefficients. Hence, the effect of *Under_Leveraged* on the stock price reaction is robust to the sample period. However, the effects of *Under_Leveraged* on *Target Premium* and probability of success are not significant for both periods. For instance, the interaction of *Under_Leveraged* and 1980s does not have a significant effect on *Target Premium* and probability of success, whereas the effect of *Under_Leveraged* dummy is significant for the 1990s. However, the difference is not statistically significant, indicating that this result might be a consequence of fewer observations in the 1980s than those in the 1990s.

A problem with the *CAR* variable, it may be argued, is that it does not take into account the market reaction to the joint value of bidding and target firms. In order to address this concern, I regress value-weighted *CAR* of bidder and target firms, *WCAR*, over the explanatory variables mentioned above. Table 14 reports that the results are qualitatively the same as in *CAR* regressions; *WCAR* of underleveraged bidders are 2.6% smaller (p-value of 0.007). Furthermore, inclusions of *D_E* and *Cash_Rich* dilute neither the magnitude nor the significance of *Under_Leveraged*.

Another point of interest is whether the explanatory power of the *Under_Leveraged* variable exists because of overleveraged bidders. In order to test this hypothesis, I carry out the second stage regressions for the subsample of non-overleveraged bidders. The coefficient estimates in Table 15 are similar with those found in the second stage regressions. This finding does not support the idea that the effect of *Under_Leveraged* is a consequence of difference between the unused borrowing powers of underleveraged and overleveraged bidders. On the contrary, underleveraged bidders show different bidding behavior than non-overleveraged bidders, and capital markets recognize this difference.

Another point of interest is the difference in bidding behavior of overleveraged and underleveraged bidders. Table 16 presents the effects of *Over_Leveraged* on the variables of interest. It appears that overleveraged bidders pay lower premiums than underleveraged bidders. Furthermore, the differences in the marginal effects of *Under_Leveraged* and *Over_Leveraged* are statistically significant in both probability of success and *CAR* analysis. Note that the effect of the *Over_Leveraged* dummy itself is insignificant in both analyses (p-value of 0.763 in probability of success and p-value of 0.725 in the *CAR* regression). These findings indicate significant differences between the bidding behavior of underleveraged and overleveraged bidders.

One may argue that borrowing debt capacity increases with cash reserves. Furthermore, Bruner (1988) argues that net leverage, leverage minus cash reserves, plays a more important role than leverage in the stock price reactions to takeover announcements. Therefore, deviation from the target net leverage might be a better proxy for borrowing debt capacity. In order to test this hypothesis, I estimate the target net leverage using the same procedure as in the first stage. Based on this measure, I construct the *Net_Under_Leveraged* dummy, which takes the value of one if the bidder falls in the lowest quartile of net leverage deficit. Consistent with Bruner (1988), Table 17 reports that stock prices react more unfavorably to takeover announcements by bidders in the *Net_Under_Leveraged* category. However, inclusion of the *Under_Leveraged* dummy subsumes the effect of *Net_Under_Leveraged*.

Another concern could be that the *Under_Leveraged* dummy picks up the non-linear effect of leverage. Therefore, the findings might be irrelevant to target capital structure. In order to disentangle the non-linear effect of leverage, I introduce the *Low_DE* dummy which takes the value of one if the bidder's leverage is in the bottom leverage quartile. In Model 3, the coefficient estimate for *Low_DE* is significantly negative (p-value of 0.002). Model 4 reports that this estimate is not statistically significant after adding the *Under_Leveraged* dummy into analysis.

Table 18 reports the correlation between the proxies for free cash flow hypothesis. All correlation coefficients are significant at 1 percent level. *Under_Leveraged* is not highly correlated with *Cash_Rich* indicating that findings are not driven by excess cash reserves. On the contrary, there is high correlation between *Under_Leveraged* and other leverage based proxies (*Low_DE* and *Net_Under_Leverage*). This is inevitable since these variables are constructed based on leverage ratio. Therefore, high correlation between *Under_Leveraged* and other leverage based proxies confirms the important role of leverage in my findings, but rejects the null hypothesis that there is trivial effect of leverage deficit.

Studies including Lang et al. (1991) and Bruner (1988) find that acquisitions create value if high-growth firms are acquired by bidders with financial slack. Therefore, underleveraged bidders might create value when they acquire high-growth targets. In order to test this hypothesis, I construct interaction variables of the *Under_Leveraged* dummy with the *Target Firm HMB* and *Target Firm HMB* dummies, where *Target Firm HMB* (*LMB*) is one if target firm has higher (lower) market to book ratio than the median in the sample. Table 19 reports that the interaction term of *Under_Leveraged* and *Target Firm HMB* is lower than that of *Under_Leveraged* and *Target Firm LMB*. This empirical finding does not support the idea that underleveraged bidders create value when they acquire targets with high growth opportunities. On the contrary, lower stock price reaction to acquisitions of targets with high market-to-book ratios may indicate that underleveraged bidders acquire overvalued targets.

In summary, this essay sheds light on the link between a firm's deviation from its target capital structure and its acquisition choices. I find that bidding firms that are underleveraged relative to their target debt ratios pay higher premiums and are more likely to successfully acquire their targets. Furthermore, consistent with the free cash flow hypothesis, capital markets react unfavorably to takeover announcements of underleveraged bidders. In addition, leverage deficit subsumes other effects of leverage and excess cash reserves which have been shown to be important determinants of bidding behavior and stock price reactions.

3. Does Geographical Proximity Matter in Takeover Contests?

3.1 Introduction

This chapter explores how informational differences affect takeover contests by examining the effect of geographical proximity on takeover outcomes. The premise of my tests is that since information transmission is facilitated by geographical proximity, bidders that are located closer to their targets are likely to be better informed. Within any given location, managers are likely to interact with each other through social, civic and business meetings. In addition, they may have common suppliers and customers and may read the same newspapers and watch the same television news. Hence local bidders in a takeover contest have access to a great deal more information than distant bidders. I characterize the effects of local information on takeover outcomes by examining the bidders' stock price reactions to takeover offers, target premiums, and the long run operating performance of the merged firm.

3.2 Sample Selection and Descriptive Statistics

3.2.1 Data

The sample used in this study consists of completed and withdrawn takeover attempts from the SDC Platinum Database for the period of January 1, 1986, to December 31, 2001. This database provides target and bidder names, zip codes, cities, states, announcement dates and status of the offer as well as deal characteristics such as the mode of acquisition and the method of payment. I calculate the physical distance between headquarters of bidders and targets in two steps. First, I find the longitudes and latitudes of targets and bidders from the U.S. Census Bureau's Gazetteer Place and Zip Codes Database. Second, I calculate the distance between bidder i and target j, *dist(i,j),* by the following formula:

$$dist(i,j) = \arccos\left\{\begin{array}{l} \cos(lat_i)\cdot\cos(long_i)\cdot\cos(lat_j)\cdot\cos(long_j) \\ +\cos(lat_i)\cdot\sin(long_i)\cdot\cos(lat_j)\cdot\sin(long_j) \\ +\sin(lat_i)\cdot\sin(lat_j) \end{array}\right\}\cdot 2\cdot\pi\cdot r/360,$$

where r is the radius of the earth (approximately 6,378 kilometers), lat is the latitude and long is the longitude.[12] Following Coval and Moskowitz (1999), I create a dummy variable *Dist100*, which takes the value of one if *dist(i,j)* is less than one hundred kilometers.[13] I use the *Dist100* dummy rather than a continuous distance variable,

[12] The formula is derived through the trigonometric latitudes and longitudes are measured in degrees.
[13] The results are qualitatively the same, if the cut-off value of 150 kilometers is used to define local bidders.

because the relationship between the variable of interest and distance is not necessarily linear and is difficult to explicitly specify in advance.

The sample consists of transaction announcements that meet the following criteria:

(i) Transactions that are listed as completed or withdrawn with announcement and effective dates falling within the sample period.

(ii) Transactions that are identified by the SDC as a merger or an attempt to acquire a majority interest.

(iii) Both bidder and target are non-financial and non-utility public firms in the U.S.

(iv) Bidder firms are found in the COMPUSTAT and the CRSP annual files.

(v) Bidder firms are identified as the first bidders.

(vi) Relative size of transaction to the market capitalization of the bidder is between 5% and 1000%.[14]

(vii) Transaction value is greater than 1 million dollars.

(viii) Stock prices of bidders are greater than 1 dollar.

(ix) Bidders (targets) in remote areas such as Hawaii and Alaska are excluded from the sample because they are more likely to choose distant targets and may dilute the effects of determinants of geographical proximity.[15]

[14] This restriction ensures that reverse mergers and trivially small targets are excluded from the analysis.
[15] The results remain qualitatively the same if this restriction is removed.

3.2.2 Descriptive Statistics

The final sample consists of 1,350 takeover attempts. Seventeen percent of targets in the sample are acquired by local bidders. Table 20 reports that the ratio of local bidders in takeover activities increased from 14% in 1986 to 25% in the early 1990s before declining somewhat to 20% in 2000. This indicates that decreases in transportation costs and developments in information transmission technology in the 1990s did not change the relative tendency of bidders to make offers to local targets.[16]

Another point of interest is the cross-sectional geographical distributions of bidders and targets. As Table 21 demonstrates, the major states where bidders are concentrated are California, which contains 18.6% of total bidders in the U.S. for the period, New York (10.6%), Texas (9%), Illinois (5.6%), Ohio (5.3%), New Jersey (4.9%), Pennsylvania (4.6%), and Massachusetts (4%). The targets are concentrated over similar states including California (22.4%), Texas (9.1%), New York (6.7%), Massachusetts (6.5%) and Florida (4.7%). The *local* bidders are also concentrated where bidders are the densest. For instance, the percentages of total local bidders are 19.6% and 19.7% in New York and Texas, respectively. This finding indicates that local bidders do not only emerge in remote areas but are also the major players in states where the acquisition activity is high.

[16] Malloy (2004) also finds that geographical proximity played a prominent role in the 1990s. He reports a significant increase in the number of analysts who covered geographically proximate firms in the 1990s.

In terms of deal characteristics, tender offers represent 25% of the 1,350 takeover attempts. Following Martin (1996), I categorize the method of payment into three groups: 100% cash offers (*Cash*), 100% stock offers (*Stock*), and mixed. *Cash* offers make up 34% of the bids, while 38% of the sample is *Stock* offers. However, these deal characteristics are not distributed uniformly across local and distant bidders. For example, Table 22 shows that distant bidders are more likely to use tender offers as modes of acquisition. Seventeen percent of local bidders choose tender offers as opposed to 26% of distant bidders (t statistics of 2.72). In terms of the payment method, the average for *Stock* in the local bidder subsample is 52% and 35% in the distant bidders subsample. However, the percentage of cash used in offers is not different across groups.

Another important characteristic of a deal is the hostility of the offer. Following Schwert (2000), I define an offer as *Hostile* if the target board identifies the initial bid as hostile. Only 3% of local bidders' offers are hostile, which is less than half the percentage of hostile offers from distant bidders. I also examine the distribution of local bidders among related and unrelated industry acquisitions. *Related Industry* takes a value of one if both bidder and target are categorized in the same two-digit SIC group. Averages of *Related Industry* are similar for local and distant bidders. Similarly, the ratio of local bidders in the *Related Industry* subsample is not different from that in the *Unrelated Industry* subsample.

Table 23 reports mean values for the financial measures of local and distant bidders. The average *Total Assets* of distant bidders, measured as the book value of bidder's total assets, is larger than that for local bidders. However, the transaction value normalized by market capitalization for distant bidders is not statistically different compared to those for local bidders. Local and distant bidders differ in terms of market-to-book ratio (*M_B*), which is defined as the book value of total assets minus the book value of equity plus market value of equity divided by the book value of total assets. The average *M_B* is 2.39 for distant bidders, compared to 2.73 for local bidders. The two groups are also statistically different with respect to book leverage (*Leverage*), measured as the ratio of total debt to book value of the bidder. The average *Leverage* is 0.506 for distant bidders, whereas it is 0.463 for local bidders. In relation to profitability, defined as earnings before interest (*ET_A*), there is no difference across local and distant bidder groups.

Table 23 presents mean values for the financial measures of targets, which reveal some further effects of spatial separation between firms. Targets of distant bidders differ firstly with respect to *Leverage* – the average book leverage ratio for distant targets is significantly greater than that for local targets (0.534 for the former versus 0.456 for the latter). The average *RD/Sales* ratio in distant bidders' targets is 0.096, whereas it is 0.153 for targets of local bidders (t statistics of -2.72). Other financial measures for the targets of distant and local bidders are statistically indistinguishable. For instance, the difference in market-to-book ratios between distant and local targets is negligible (average *Target Firm M_B* of 1.78 for distant bidders versus 1.79 for local bidders). Similarly, the ratio of price to earnings for targets (*Target Firm P/E*) of local bidders differs little from that for distant bidders.

3.3 Geographical Proximity and Market Reaction

In this section I examine whether financial markets take account of the geographical proximity between bidders and targets. Following the standard methodology, cumulative abnormal returns to bidders (*CAR*) over the three-day event window (-2,0) are calculated to measure the market reactions to takeover announcements. The benchmark returns are the value-weighted index of returns including dividends for the combined New York Stock Exchange, American Stock Exchange and NASDAQ. The estimation window includes from 300 to 60 days before the announcement date.

The average *CAR* of local bidders is greater than that for distant bidders. The mean *CAR* to local bidders is 0.005 while the average *CAR* of distant bidders is -0.010, and the difference in *CAR*'s is statistically significant at a 1% significance level. However, geographical proximity might be proxying here for particular features of a deal, or characteristics of local bidders, which in turn may result in favorable stock price reaction to bids for nearby firms. To address this concern, I run regressions of the following basic form:

$$\begin{aligned} CAR = \beta_0 &+ \beta_1 Dist100 + \beta_2 Cash + \beta_3 Stock + \beta_4 Hostile + \beta_5 Size + \beta_6 \, Relative\ Size \\ &+ \beta_7 M\_B + \varepsilon, \end{aligned} \tag{1}$$

where *Dist100* captures the geographical proximity effect and *Size* is the logarithm of bidder's market capitalization 60 days prior to the announcement date. The control variables include method of payment, hostility of the offer, year dummies and relative size of transaction to bidder's size as well as bidder's market-to-book ratio, which have been considered in previous studies.[17] Table 24 reports coefficient estimates and White (1980) heteroskedasticity corrected p-values. The regression has R^2 of 0.043 and F statistics of greater than 2.

The marginal effect of *Dist100* is statistically and economically significant. It has a positive coefficient estimate, which suggests that markets react favorably to the takeover announcements of local bidders. Controlling for bidder and deal characteristics, the *CAR*'s for local bidders are 0.016 greater than those for distant bidders (p value less than 0.01). This finding supports the idea that *Dist100* is not a proxy for deal and bidder characteristics. In view of the fact that this is a three-day return, its magnitude is quiet large. However, it is not unusual in the literature since other studies have found effects of similar sizes. For example, Moeller et. al (2004) find that the average *CAR* of small firms is 0.02 greater than that of large firms in a three-day period.

Consistent with the previous literature (e.g., Travlos 1987; Fishman 1989; and Martin 1996), I find that *Cash* has a positive significant coefficient estimate. Furthermore, the coefficient estimate for *Stock* is negative, but not statistically significant at conventional levels (p-value of 0.132). The coefficient estimate of *Size* is significantly negative. This is consistent with Moeller et al. (2004), who show that large firms make poor acquisitions.

In sum, the preceding evidence suggests that even after controlling for the other factors mentioned above, the geographical proximity of bidders and targets influences

[17] All bidder characteristics are the most recent prior to acquisition.

stock returns around merger announcements. In the subsequent analysis, I focus on the three possible explanations for this effect: 1) asymmetric information, 2) high synergy gains in local mergers, and 3) bidder size.

3.3.1 Asymmetric Information

There is a growing literature on the role of geographical proximity in information accumulation. For instance, Coval and Moskowitz (2001) show that local funds have better information about the value of local firms. Furthermore, Malloy (2004) finds that local analysts make more accurate forecasts of the prospects of local firms. These papers indicate that geographical proximity yields private information for professionals. In this regard, it is plausible to expect that corporate managers may also benefit from information transmitted through geographical proximity. Local managers interact with each other through social, civic and business meetings. They share suppliers and customers. These channels provide local managers with signals on the idiosyncrasies of targets' operations and on how these idiosyncrasies affect targets' future prospects.

If such informational advantages are a major factor in the favorable market reaction to takeover announcements of local bidders, then this effect should increase with the level of asymmetric information. Analyst reports are good source of updates and may eliminate most of the asymmetric information. Therefore I merge my sample with the IBES summary history database, which lists the firms covered by analysts. I use this database to introduce the *Covered* dummy, which takes the value of one if an analyst covers the target firm, and interact it with *Dist100*. Table 24 shows that the effect of *Dist100* is 0.018 (and significant at 1% level) for targets that are not covered by an analyst, whereas it is 0.005 (insignificant) for covered targets. This finding suggests that local bidders realize larger gains when there is more information asymmetry for local targets.

Looking at the effect of method of payment on the stock price reaction provides another way to identify the effects of asymmetric information.[18] Previous studies on takeovers argue that positive stock price reactions to *Cash* offers are a consequence of asymmetric information between bidders and targets (see Franks, Harris and Mayer 1988; Eckbo and Langohr 1989; Eckbo, Giammarino and Heinkel 1990). Thus, the impact of the payment method should depend on the level of information asymmetry between bidders and targets. If local targets and bidders are well informed about each other's stock prices, then local targets will not mind accepting stock offers. Therefore, the stock offers will not signal the overvaluation of bidders for the subsample of local bidders, and this behavior is incorporated into the expectations of capital markets. In sum, the effect of

[18] A potential avenue to test the implications of the asymmetric information hypothesis in acquisitions may be to examine the method of payment. Since stock offers provide option like payoffs for bidders and partially alleviate the asymmetric information problem, uninformed bidders may prefer *Stock* in their acquisitions. On the other hand, if targets and bidders are better-informed about their values, then these targets are more likely to accept stock offers. Furthermore, bidders are also more likely to prefer making stock offers for these targets because cash offers are mostly financed with debt, which increases the financial distress cost. In addition, other factors may be affecting firm's decision on the method of payment. For instance, in addition to signaling private information, the method of payment depends on factors such as bidder's size and the hostility of the offer. For these reasons, in this study the evidence related to the method of payment is interpreted with caution.

Cash should be insignificant in the stock price reactions of local bidders if geographical proximity initiates information transmission.

In order to test this hypothesis, I repeat the *CAR* regression for the subsamples of local and distant bidders, separately. Table 25 reports ordinary least squares estimates with White's (1980) heteroskedasticity corrected p-values. The coefficient estimate for *Cash* is significantly positive for distant bidders but is not statistically significant for local bidders. This finding supports the view that there is less asymmetric information in local mergers than in distant ones.

3.3.2 Synergy Gains

Synergy gains generated in local mergers are most likely to be driven by the sharing of high-cost facilities and human capital. These gains would be more pronounced in within-industry mergers, which were shown to be value increasing in previous studies. It is possible then that *Dist100* is proxying for industrial similarity between bidders and targets. However, in that case synergy gains should be less important for takeovers between unrelated industries. Table 26 indicates that the *CAR*'s for local bidders are significantly greater than for distant bidders whether or not the bidder and the target are in the same two-digit SIC industry category. This is consistent with evidence presented above, which showed that local bidders appear in *Related* and *Unrelated Industry* takeovers in approximately the same proportions. These findings suggest that favorable stock price reaction to local bidders is not merely a reflection of industrial similarity.

The regression results also support this view. Model 1 of Table 27 shows that the effect of geographical proximity remains significant even after controlling for industrial similarity (represented by the *Related Industry* dummy). Furthermore, Model 2 shows the marginal effect of the interaction of *Dist100* with the *Related Industry* dummy to be 0.015 (significant at the 7% level), and the estimate for the interaction *Dist100* with the *Unrelated Industry* dummy to be 0.018 (significant at the 6% level). The difference is not statistically significant, which suggests that the higher synergy gains in within-industry mergers are not sufficient to explain the positive stock price reactions to acquisition announcements by local bidders.

Another possibility is that higher *CAR*'s for local bidders occur because firms in the same industry tend to be geographically clustered. Since firms in clusters have access to a larger pool of specialized factors (e.g., labor and capital), firms' expansions can be facilitated more efficiently in clusters. To the extent that firms expand by merging with other firms, acquiring local targets may lead to positive bidders' stock price reactions around takeover announcements.[19]

To determine the effect of such industry clusters, I introduce *Ind_Cluster*, which takes the value one if a bidder makes a within industry takeover offer in a region where

[19] For instance, locating in Silicon Valley provides firms with the advantage of better access to highly qualified engineers, To the extent of this access, locally merged firms reduce adjustment costs (and raise expected profits) when a bidder enters an expansion phase by acquiring a nearby target in an industry cluster.

the number of COMPUSTAT firms with the same two-digit SIC group as the bidder within 100 kilometers is greater than 10. The difference between the *Ind_Cluster* and *Related Industry* dummies is that the latter one may not account for the positive externalities associated with relatively large groups of related nearby firms. When *Ind_Cluster* is included in the regression analysis, the results suggest that *Dist100* is not in fact proxying for such externalities. In Model 3 of Table 27 the coefficient estimate for *Ind_Cluster* is insignificant, whereas the effect for *Dist100* remains significant. In addition, Model 4 reports an insignificant estimate of the interaction of *Dist100* with the *Ind_Cluster* dummy (0.015 and insignificant) and a significant marginal effect for the interaction *Dist100* with the *Not Ind_Cluster* dummy (0.018 at the 3% significance level). The difference is not statistically significant, which suggests that the positive stock price reaction to acquisition announcements by local bidders cannot be explained through externalities associated with the industry clusters.

Synergy gains and the asymmetric information hypothesis have different predictions for wealth transfers to target shareholders. If local mergers exhibit higher synergy gains, then part of these gains should be reflected as higher target premiums (see Berkovitch and Narayanan 1990, Hirshleifer and Titman 1990). In contrast, the asymmetric information hypothesis predicts that better-informed bidders are able to acquire targets through paying lower premiums (see Milgrom 1981, Fishman 1988). In order to test these predictions, I follow Schwert (1996) and define *Target Premium*, as *CAR* of target 40 days before and 40 days after the announcement day. The mean *Target Premium* is 0.28 for local bidders and 0.36 for distant bidders. The difference is statistically significant at the 4% confidence level. To separate the effect of geographical proximity from other factors, Table 28 reports the coefficient estimates of an OLS regression of *Target Premium*. In Model 1, the estimated coefficient on *Dist100* is -0.089 (p value of 0.079), confirming that local bidders pay lower premiums than their distant counterparts. Furthermore, Model 2 shows that the effect is more prominent when local bidders acquire targets which are not covered by analysts. These findings are consistent with the asymmetric information explanation.

3.3.3 Does Geographical Proximity Proxy for Bidder Size?

Local bidders are typically small, and previous studies show that small bidders make good acquisitions on average (see Jarrell and Poulsen 1989; Loderer and Martin 1990; Moeller et. al 2004). Moeller et al. (2004) suggest that this bias toward good acquisitions for small firms is due to a managerial hubris problem in large firms. To address this concern, I create *Small* (*Large*) which takes the value of one if the bidder's size is (not) in the lowest size quartile of the sample and include *Small* in *CAR* regressions of Table 29.

Table 29 reports that the *Dist100* coefficient is significantly positive even after controlling for small bidders (0.016 at the 1% level), indicating that *Dist100* is not just proxying for small firms. Model 2 indicates that the effect of *Dist100* is in fact particularly strong for the subsample of the smallest bidders (0.035 at the 1.5% level), and disappears for the rest of the sample. This is consistent with the idea that geographical proximity is less important for larger firms that have better access to investment bankers and other information intermediaries.[20]

3.4 Long-run Operating Performance

This section examines whether the long-run operating performance of local bidders is consistent with the favorable stock price reaction to local mergers. To measure long-run performance, I use the ratio of earnings before interest and taxes to total assets (*ET_A*). In order to adjust for industry effects and pre-acquisition bidder and target characteristics, I construct a measure of the change over time in bidder's and target's deviations from a value-weighted average of performance in their respective industries in two years following an acquisition (Δ *ET_A*). That is, I take the difference of a) the deviation of the merged entity's post-acquisition *ET_A* from the value-weighted average performance of non-acquiring firms in the bidder's and target's industries and b) the average deviation of bidder's and target's pre-acquisition *ET_A* from their respective industry-wide means.[21] By controlling for both time-varying industry effects and time-constant firm-specific effects, this measure allows comparison of bidders in each group to their non-acquiring peers.

---

[20] Unreported *CAR* regressions for size-based quartiles also show that the effect of geographical proximity is significantly positive in the smallest bidders' quartile and vanishes as the size of the bidder increases.

[21] Specifically, the measure used is

$$\Delta ET\_A = ET\_A_{t+2}^{Bidder} - \left(wET\_A_{t+2}^{Bidder,Ind} + (1-w)ET\_A_{t+2}^{Tar,Ind}\right)$$
$$-\left[\left(wET\_A_{t-1}^{Bidder} + (1-w)ET\_A_{t-1}^{Tar}\right) - \left(wET\_A_{t-1}^{Bidder,Ind} + (1-w)ET\_A_{t-1}^{Tar,Ind}\right)\right]$$

where *w* represent the relative size, $ET\_A^{Bidder(Tar),\ Ind}$ is the average *ET_A* for the firms in the bidder's (target's) industry, and time t represents the effective date of the merger.

The local and distant bidders show significant differences in their post-acquisition performance. For example, the average change in the profitability of local bidders relative to their value-weighted industry benchmark is 0.011, and for distant bidders it is 0.001. The difference is statistically significant at the 5% level. Furthermore, the change in the operating performance for local bidders is more prominent for the subsample of small bidders. In the subsample of small bidders, the average Δ *ET_A* for local bidders is 0.025, although it is 0.002 for distant bidders (p-value of 0.03). This result is consistent with the finding that markets react more favorably to local bidders, particularly for the subsample of small bidders. Since asymmetric information will play a more important role for small bidders, the finding supports the asymmetric information hypothesis.

Next, I examine whether there is a systematic relationship between *Dist100* and post-acquisition operating performance in a multivariate setting. Table 30 reports the coefficient estimates of ordinary least square estimates for the whole sample as well as the subsamples of small and large bidders. It appears that the local bidders perform better than the distant bidders in the long-run (0.010 at the 4% level). This effect is more prominent for the subsample of small bidders (0.023 at the 4% level), and supports the finding of markets' favorable reactions to local bidders. Consistent with Healy et. al (1992), capital markets anticipate that local bidders make good acquisition choices, and eventually this expectation is realized in the post-acquisition performance of local bidders.

3.5 Robustness

My sample covers a period when there were drastic developments in information technology that could potentially reduce the advantages associated with geographical proximity. To test whether the advantages associated with proximity decline with time, Models 1 and 2 in Table 31 report coefficient estimates of *CAR* regressions for periods from 1986 to 1996 and from 1997 to 2001, respectively. *Dist100* have positive and significant estimates in both models. Specifically, the difference between *CAR*'s for local and distant bidders is 0.019 for the period from 1997 to 2001 (p value of 0.021), whereas it is 0.014 for the period from 1986 to 1996 (p value of 0.062). The difference in coefficient estimates of geographical proximity across the subsamples is insignificant. Thus, developments in information technology do not seem to have changed the importance of geographical proximity in takeovers.

Another concern could be the potential sample selection bias problem in my sample, which consists of announced takeover attempts. Some takeover attempts are not announced because they fail at the initial stages of the takeover process. Therefore, an analysis based on announced takeovers may result in bias estimates. In order to correct for this sample selection bias, I use the two-step Heckman procedure. The *Mill's Ratio* is calculated as in Chapter 2 and is then included as an explanatory variable in Model 3. The marginal effect of *Dist100* is 0.017 (p value of 0.004) indicating that the potential sample selection bias does not appear to have an effect on the empirical findings of this chapter.

Another explanation for the negative stock price reaction to takeover announcements by distant bidders might be that distant bidders are more likely to have free cash flow problems. However, the empirical evidence in this chapter does not support this hypothesis. For example, the average *Leverage* for distant bidders is in fact greater than that for local bidders. Furthermore, Table 32 reports that the effect of *Dist100* is significant even after controlling for the *Under_Leveraged* dummy.

In sum, this chapter explores the role of geographical proximity in takeovers and sheds light on the relationship between information and takeovers. The evidence suggests that informational advantage of local bidders result in better acquisition choices.

4. Conclusions and Discussions

This dissertation explores two important factors in M&A. First, I examine the role of deviation from the target capital structure in takeovers. In particular, I characterize the effects of leverage deficit in bidding behavior and the outcome of takeover contests. I find that bidders which are underleveraged relative to their target debt ratios pay higher premiums and are more likely to successfully acquire their targets. Consistent with the free cash flow hypothesis, capital markets react unfavorably to their takeover announcements. In addition, I find that the effect of deviation from the target leverage ratio subsumes other factors such as excess cash reserves and current debt, which have been shown to be important determinants of bidding behavior.

This essay also shows that bidders increase their leverage ratios following their acquisitions, suggesting that unused debt capacity is a more important factor than cash reserves. Consistent with this idea, I find that the effect of leverage deficit on acquisitions subsumes the effect of excess cash reserves, which Harford (1999) finds to be an important determinant of bidder behavior.

The findings of this essay are robust when I use different leverage proxies (book leverage vs. market leverage). In addition, potential sample selection bias problems do not affect the results. Furthermore, the effect of being underleveraged holds for the subsample of non-overleveraged bidders. This finding suggests that the effect is not a consequence of difference in bidding behaviors of underleveraged and overleveraged bidders.

This study provides further evidence of the usefulness of the target leverage concept. Hovakimian et al. (2001) show that deviation from the target capital structure affects the type of security issuance and that firms issue securities to move towards their target capital structures. This essay demonstrates that a deviation from the target capital structure also affects the acquisition choices and supports the free cash flow hypothesis.

Second, I explore the role of asymmetric information in takeovers. I find that i) stock prices react more favorably to takeover announcements of local bidders; ii) locally merged firms show superior operating performance in the long run and iii) targets of local bidders receive lower premiums. The asymmetric information hypothesis predicts that better informed bidders will deter potential bidders from bidding and will pay lower premiums in acquiring targets. Therefore, these findings are consistent with the asymmetric information hypothesis.

I find that local bidders realize lower gains when targets are covered by analysts. Since analyst reports eliminate most of the asymmetric information, this finding suggests that the effect of geographical proximity decreases with the availability of information on targets. Thus, the positive stock price reactions to local mergers reflect the informational advantages of local bidders.

Evidence on the effect of payment method on stock price reaction also supports the asymmetric information hypothesis. Previous studies indicate that positive market reaction to cash offers signals an informational advantage of bidders in an environment with bidders having heterogeneous information. Consistent with this idea, I find that for the subsample of distant bidders the stock price reactions to cash offers are more positive than for equity offers. In contrast, there is no significant effect of cash offers for the subsample of local bidders. This evidence is consistent with the idea that local targets and local bidders have better information on each other's intrinsic value and that they are therefore indifferent to the method of payment. Hence, the payment method does not signal informational advantage in the subsample of local bidders and does not affect the stock price reaction.

I also examine alternative explanations for the reported differences between local and distant bidders. More precisely, I find no evidence that supports a clear presence of synergy gains unrelated to information effects. Moreover, geographical proximity does not proxy for small bidders. In sum, the asymmetric information hypothesis dominates other alternative explanations.

Many authors in the popular press have suggested that recent developments in information technology have helped create a borderless economy, where spatial separation between agents is irrelevant in finance. However, evidence in this chapter suggests that geographical proximity between participants in takeovers yields better information for local bidders. Thus, it appears that geographical separation has important effects in takeovers, one of the major corporate activities. In this regard, exploring the further implications of geographical differences for other corporate decisions by firms constitutes a promising avenue for future research.

Tables

Table 1 Deal Characteristics between 1986 and 2001

This table shows the deal characteristics of takeover offers between 1986 and 2001. An offer is considered successful if a bidder takes over the target. *Tender* is a dummy variable for tender offers. *Cash* and Stock are dummy variables for all-cash and all-stock offers, respectively. *Hostile* is a dummy variable which takes the value of one if the board defines the initial offer as hostile.

Year	*Success*	*Tender*	*Cash*	*Stock*	*Hostile*
1986	0.68	0.52	0.66	0.16	0.16
1987	0.74	0.26	0.45	0.21	0.14
1988	0.65	0.46	0.67	0.11	0.20
1989	0.69	0.37	0.46	0.31	0.11
1990	0.82	0.29	0.43	0.29	0.00
1991	0.67	0.19	0.38	0.38	0.05
1992	0.83	0.22	0.26	0.43	0.13
1993	0.69	0.26	0.37	0.31	0.06
1994	0.67	0.23	0.27	0.52	0.19
1995	0.76	0.21	0.24	0.54	0.10
1996	0.79	0.24	0.26	0.44	0.15
1997	0.77	0.31	0.22	0.36	0.06
1998	0.83	0.15	0.20	0.37	0.04
1999	0.83	0.22	0.26	0.32	0.07
2000	0.81	0.25	0.24	0.41	0.04
2001	0.85	0.20	0.17	0.30	0.02

Table 2 Tobit Regression Estimates of the Target Leverage Ratio

This table presents the estimates of Tobit regression of target leverage ratio over key financial measures documented in the literature.

$$Book\_Lev_{it} = \beta_0 + \beta_1 \cdot RDD_{it-1} + \beta_2 \cdot RD\_Sal_{it-1} + \beta_3 \cdot Tangrat_{it-1} + \beta_4 \cdot Sales_{it-1}$$
$$+ \beta_5 \cdot M\_B_{it-1} + \beta_5 \cdot ET\_A_{it-1} + \varepsilon$$

Variables in Tobit regression are defined as differences from two-digit SIC industry means for a given year. *Book_Lev* is the ratio of book value of total debt to the sum of the book value of debt and market value of equity. *ET_A* is earnings before interest, taxes, depreciation and amortization divided by the book value of assets. *M_B* is the market-to-book ratio, which is defined as sum of market value of equity and book value of total debt divided by total assets. *Tangrat* is the ratio of plant, property and equipment to the book value of total assets. *Sales* is the natural logarithm of sales. *RD/Sales* is R&D expenses divided by sales. *RDD* is a dummy for missing values of R&D expenses.

Tobit Regression

	Book_Lev	
	Estimate	p-value
Intercept	-0.008	0.001
RDD	0.019	0.000
RD/Sales	-0.124	0.000
Tangrat	0.006	0.557
Sales	0.026	0.000
M_B	-0.024	0.000
ET_A	-0.393	0.000
N	67214	
W	2891	
p	0	

Table 3 Summary Statistics

Summary statistics of key financial measures for bidding firms are reported. *Market Value* is the sum of book value of debt and market value of equity. *Relative Size* is the ratio of transaction value to equity capitalization of the bidding firm 60 days prior to announcement date. *M_B* is the market-to-book ratio of the bidder. Leverage deficit is actual leverage minus predicted leverage. Any given year, *Under_Leveraged* takes the value of one if the bidder falls in the lowest leverage deficit quartile.

	N	Mean	Median	Min	Max
Market Value (Mil $)	998	4,030	643	4	239,000
Relative Size (%)	998	0.630	0.310	0.050	9.040
M_B	998	2.001	1.580	0.540	8.718
Under_Leveraged	998	0.22	0	0	1

Table 4 Univariate Analysis

This table reports the descriptive statistics for underleveraged and other bidders for 1986-2001. The firms in the bottom quartile of leverage deficit for each year are identified as *Under_Leveraged*. The estimation window includes from 250 to 60 days before the announcement date (day 0). *CAR* is cumulative abnormal returns to bidder calculated from one day before the announcement date to one day after the announcement [-1,1] *Target Premium*, is defined as the *CAR*'s to target shareholders 40 days before and 40 days after the announcement date. *Book Leverage Difference* is the difference between post-merger and pre-merger book leverage ratios of bidders in all-cash offers.

	Underleveraged Bidders	*Other Bidders*	*t stat.*
Target Premium	0.394	0.296	2.12
CAR	-0.023	-0.008	-3.01
Book Leverage Difference	0.101	0.026	4.89

Table 5 Target Premium Estimation

This table presents robust OLS estimates of premium regressions. The dependent variable is *Target Premium*, is defined as the *CAR*'s to target shareholders 40 days before and 40 days after the announcement date. *Under_Leveraged* is a dummy for underleveraged bidders, which are in the lowest quartile of leverage deficit prior to announcement date. *Size* of the bidder is defined as natural logarithm of equity capitalization of the bidding firm 60 days prior to announcement date. *D_E* is the debt-equity ratio of the bidder. *Hostile* takes the value of one if the offer is considered as hostile by the target management. *Target Firm M_B* is the market to book ratio of the target firm. *Tender* is the dummy variable for a tender offer. Cash is the dummy variable for an all-cash offer. *Target Firm P_E* is the target's year-end stock price to earnings per share for the prior fiscal year. *Target Firm D_E* is target firm's debt-equity ratio. *Cash_Rich* is a dummy variable, which takes value of 1 if firm's cash holdings exceed the level predicted by the model in Harford (1999). *Relative Size* is the ratio of transaction value to equity capitalization of the bidding firm 60 days prior to announcement date. The p-values are calculated based on White's (1980) correction for heteroskedasticity.

Dependent Variable: *Target Premium*

	Model 1		Model 2		Model 3	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Under_Leveraged	0.137	0.019	0.133	0.020	0.123	0.036
Relative Size	-0.051	0.059	-0.052	0.058	-0.045	0.097
Size	-0.004	0.763	-0.004	0.784	-0.005	0.716
Cash	-0.071	0.184	-0.073	0.165	-0.068	0.202
Tender	0.158	0.002	0.158	0.002	0.148	0.004
Hostile	0.045	0.391	0.042	0.427	0.050	0.344
Target Firm M_B	-0.071	0.001	-0.072	0.000	-0.072	0.000
Target Firm D_E	-0.009	0.107	-0.009	0.108	-0.009	0.128
Target Firm P_E	0.000	0.064	0.000	0.058	0.000	0.055
Cash_Rich			0.048	0.559		
D_E					-0.017	0.000
N	541		541		541	
R2	11		12		11	

Table 6 Probit Estimates of Success

A probit model predicts whether takeover bids for US public target firms between 1986 and 2001 are completed and marginal effects are reported in this table. The dependent variable is a dummy variable, which either takes the value of one if the bidder takes over the target firm within the announcement and effective dates of the first bidder, or takes the value of zero in other cases. Heteroskedasticity corrected p-values are also reported. Other variables are defined as in previous tables.

Dependent Variable: P(success=1)

	Model 1		Model 2		Model 3	
	dF/dX	p-value	dF/dX	p-value	dF/dX	p-value
Under_Leveraged	0.061	0.049	0.068	0.028	0.060	0.055
Relative Size	-0.045	0.002	-0.045	0.002	-0.045	0.002
Size	0.036	0.000	0.036	0.000	0.035	0.000
Cash	-0.148	0.000	-0.148	0.000	-0.149	0.000
Tender	0.203	0.000	0.204	0.000	0.204	0.000
Hostile	-0.552	0.000	-0.553	0.000	-0.551	0.000
Cash_Rich			-0.070	0.135		
D_E					-0.002	0.588
N	998		998		998	
W	154		158		155	
p	0		0		0	

Table 7 CAR Estimation

The table reports robust OLS estimates of bidder's stock price reactions to takeover announcements. The dependent variable is CAR[-1,1], which is cumulative abnormal returns to bidder one day before, and one day after the announcement date. *Under_Leveraged* is a dummy for underleveraged bidders, which are in the lowest quartile of leverage deficit prior to announcement date. *Size* of the firm is defined as natural logarithm of equity capitalization of the bidding firm 60 days prior to announcement date. Sales Growth is the bidder's sales growth rate. The p-values are calculated based on White's (1980) correction for heteroskedasticity. Other variables are defined as in previous tables.

Dependent Variable: *CAR*

	Model 1		Model 2		Model 3		Model 4	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p
Under_Leveraged	-0.017	0.002	-0.017	0.001	-0.016	0.002		
Relative Size	-0.002	0.341	-0.002	0.340	-0.002	0.333	0.000	0.860
Size	-0.005	0.000	-0.005	0.000	-0.005	0.000	-0.005	0.000
Cash	0.019	0.000	0.019	0.000	0.020	0.000	0.019	0.000
Tender	0.001	0.804	0.001	0.815	0.001	0.889	0.001	0.734
Hostile	-0.002	0.733	-0.002	0.731	-0.002	0.737	-0.001	0.780
Cash_Rich			0.006	0.450				
D_E					0.000	0.569		
*Under_Leveraged*Relative*							-0.019	0.002
N	998		998		998		998	
R2	7		7		7		7	

Table 8. Ordered Probit Model

This table reports the ordered probit model of payment method. The dependent variable takes the value of (minus) one if the offer is an (all-cash) all-stock offer, and is zero, otherwise. Stock Return is dividend and split-adjusted annual stock return. Heteroskedasticity corrected p-values are reported. Other variables are defined as in previous tables.

Ordered Probit(=-1 for cash, 0 for mixed, 1 for stock)

	Model 1		Model 2		Model 3	
	coef	p-value	coef	p-value	coef	p-value
Under_Leveraged	-0.070	0.461			-0.073	0.444
Relative Size	0.066	0.055	0.067	0.047	0.064	0.060
Size	-0.050	0.021	-0.034	0.117	-0.038	0.091
M_B	0.331	0.000	0.292	0.000	0.299	0.000
Stock Return			0.157	0.006	0.157	0.006
ET_A			-0.217	0.118	-0.222	0.110
N	998		998		998	
W	136		129		132	
p	0		0		0	

Table 9 Robustness (Method of Payment)

This table reports estimates of interaction of underleveraged bidders and all-stock offers. The p-values are calculated based on White's (1980) correction for heteroskedasticity. Other variables are defined as in previous tables.

	Target Premium		Pr(success=1)		*CAR*	
	Estimate	p	dF/dX	p	Estimate	p
*Under_Leveraged * Stock*	0.097	0.204	0.059	0.218	-0.020	0.054
*Under_Leveraged * Non-stock*	0.159	0.046	0.061	0.124	-0.014	0.010
Relative Size	-0.039	0.143	-0.034	0.013	-0.004	0.136
Size	0.000	0.998	0.040	0.000	-0.006	0.000
Stock	0.081	0.107	0.045	0.162	-0.020	0.000
Tender	0.148	0.001	0.176	0.000	0.001	0.902
Hostile	0.044	0.414	-0.562	0.000	-0.001	0.804
Target Firm M_B	-0.076	0.000				
Target Firm D_E	-0.009	0.126				
Target Firm P_E	0.000	0.042				
N	539		998		998	
R2	11				7	
W			156			
p			0			

Table 10 Robustness (Stock Percentage)

This table reports estimates when percentage of stock in the offer is included. Other variables are defined as in previous tables.

	Target Premium		Pr(success=1)		*CAR*	
	Estimate	p-value	dF/dX	p-value	Estimate	p-value
Under_Leveraged	0.139	0.019	0.060	0.056	-0.016	0.002
Relative Size	-0.040	0.130	-0.040	0.005	-0.002	0.312
Size	0.001	0.934	0.038	0.000	-0.005	0.000
Stock Percentage	0.000	0.653	0.001	0.001	0.000	0.000
Tender	0.108	0.048	0.200	0.000	-0.008	0.086
Hostile	0.033	0.529	-0.547	0.000	-0.005	0.372
Target Firm M_B	-0.069	0.001				
Target Firm D_E	-0.008	0.145				
Target Firm P_E	0.000	0.054				
N	539		998		998	
R2	11				9	
W			160			
p			0			

Table 11 Robustness (Mill's Ratio)

This table reports estimates when Mill's Ratio is included in analysis. *Mill's Ratio* is computed by the ratio of density function to cumulative distribution function of being a bidder which is estimated by maximum likelihood of being a bidder between 1980 and 2001. Other variables are defined as in previous tables.

	Target Premium		Pr(success=1)		*CAR*	
	Estimate	p-value	dF/dX	p-value	Estimate	p-value
Under_Leveraged	0.118	0.043	0.054	0.078	-0.016	0.003
Relative Size	-0.053	0.049	-0.042	0.004	-0.002	0.446
Size	-0.007	0.633	0.035	0.000	-0.005	0.000
Cash	-0.076	0.159	-0.140	0.000	0.019	0.000
Tender	0.156	0.002	0.187	0.000	0.001	0.880
Hostile	0.051	0.340	-0.554	0.000	-0.002	0.683
Target Firm M_B	-0.085	0.000				
Target Firm D_E	-0.009	0.137				
Target Firm P_E	0.000	0.080				
Mill's Ratio	0.668	0.168	-0.289	0.291	-0.039	0.341
N	533		998		980	
R2	11				7	
W			152			
p			0			

Table 12 Robustness (Market Leverage Deficit)

This table reports replicates of the previous analysis when leverage deficit is calculated through market leverage in Tobit regression. *Tobit_Market_Under_Leveraged* is a dummy variable, which takes the value of one if bidder is in the lowest quartile of leverage deficit estimated by the market based leverage regression. Other variables are defined as in previous tables.

	Target Premium		Pr(success=1)		*CAR*	
	Estimate	p	dF/dX	p	Estimate	p
Market_Under_Leveraged	0.135	0.007	0.026	0.383	-0.017	0.000
Relative Size	-0.054	0.049	-0.045	0.002	-0.002	0.340
Size	-0.012	0.375	0.034	0.000	-0.004	0.001
Cash	-0.069	0.195	-0.144	0.000	0.019	0.000
Tender	0.162	0.001	0.200	0.000	0.000	0.915
Hostile	0.054	0.305	-0.553	0.000	-0.002	0.708
Target Firm M_B	-0.077	0.000				
Target Firm D_E	-0.009	0.105				
Target Firm P_E	0.000	0.099				
N	541		998		998	
R2	11				7	
W			156			
p			0			

Table 13 Robustness (Acquisitions in the 1980s and 1990s)

This table decomposes the effect of Under_Leveraged for 1980s and 1990s. Y1980s (Y1990s) takes the value of one if the offer is announced in the 1980s (1990s). Other variables are defined as in previous tables.

	Target Premium		Pr(success=1)		*CAR*	
	Coef	p	dF/dX	p	Coef	p
*Under_Leveraged * Y1980s*	0.144	0.286	0.051	0.498	-0.019	0.005
*Under_Leveraged * Y1990s*	0.135	0.038	0.061	0.069	-0.016	0.010
Relative Size	-0.050	0.070	-0.044	0.003	-0.002	0.336
Size	-0.004	0.775	0.036	0.000	-0.005	0.000
Cash	-0.070	0.183	-0.145	0.000	0.019	0.000
Tender	0.157	0.003	0.200	0.000	0.001	0.790
Hostile	0.044	0.408	-0.552	0.000	-0.002	0.729
Target Firm M_B	-0.071	0.000				
Target Firm D_E	-0.009	0.107				
Target Firm P_E	0.000	0.064				
N	539		998		998	
R2	11				7	
W			156			
p			0			

Table 14 Robustness (WCAR Estimation)

The dependent variable is WCAR[-1,1], which is the value weighted cumulative abnormal returns to bidder and target one day before, and one day after the announcement date. The p-values are calculated based on White's (1980) correction for heteroskedasticity. Other variables are defined as in previous tables.

Dependent Variable: *WCAR*

	Model 1		Model 2		Model 3	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Under_Leveraged	-0.026	0.007	-0.025	0.008	-0.026	0.007
Relative Size	0.008	0.224	0.008	0.223	0.008	0.215
Size	-0.010	0.000	-0.010	0.000	-0.010	0.000
Cash	0.004	0.618	0.004	0.613	0.003	0.658
Tender	0.037	0.000	0.037	0.000	0.037	0.000
Hostile	-0.002	0.843	-0.002	0.850	-0.002	0.855
Cash_Rich			-0.003	0.803		
D_E					-0.001	0.516
N	597		597		596	
R2	11		11		11	

Table 15 Robustness (Non-overleveraged Bidders Subsample)

This table presents second stage regression estimates for the subsample of non-overleveraged bidders. Any given year, overleveraged is defined as bidders in the highest leverage deficit quartile. Other variables are defined as in previous tables. The p-values are calculated based on White's (1980) correction for heteroskedasticity.

	Target Premium		Pr(success=1)		*CAR*	
	Estimate	p-value	dF/dX	p-value	Estimate	p-value
Under_Leveraged	0.1080	0.0640	0.0585	0.0630	-0.0166	0.0020
Relative Size	-0.0214	0.2730	-0.0352	0.0360	-0.0021	0.4860
Size	-0.0146	0.2480	0.0368	0.0000	-0.0050	0.0010
Cash	-0.0801	0.2040	-0.1236	0.0010	0.0188	0.0000
Tender	0.1470	0.0140	0.1846	0.0000	0.0031	0.5060
Hostile	-0.0115	0.8340	-0.5922	0.0000	-0.0026	0.6750
Target Firm M_B	-0.0784	0.0000				
Target Firm D_E	-0.0074	0.3530				
Target Firm P_E	0.0002	0.0970				
N	439		806		806	
R2	12				7	
W			123			
p			0			

Table 16 Robustness (Under and Over-Leveraged Bidders)

This table presents second stage regression estimates of under- and over-leveraged bidders. Any given year, overleveraged is defined as bidders in the highest leverage deficit quartile. Other variables are defined as in previous tables. The p-values are calculated based on White's (1980) correction for heteroskedasticity.

	Target Premium		Pr(success=1)		*CAR*	
	Estimate	p-value	dF/dX	p-value	Estimate	p-value
Under_Leveraged	0.113	0.055	0.057	0.078	-0.017	0.002
Over_Leveraged	-0.101	0.059	-0.010	0.763	-0.002	0.725
Relative Size	-0.046	0.083	-0.043	0.003	-0.002	0.357
Size	-0.007	0.623	0.036	0.000	-0.005	0.000
Cash	-0.071	0.180	-0.145	0.000	0.019	0.000
Tender	0.146	0.004	0.200	0.000	0.001	0.826
Hostile	0.052	0.336	-0.553	0.000	-0.002	0.724
Target Firm M_B	-0.071	0.001				
Target Firm D_E	-0.008	0.129				
Target Firm P_E	0.000	0.059				
N	541		998		998	
R2	12				7	
W			156			
p			0			

Table 17 Robustness (Net Leverage and Non Linear Leverage Effect)

This table presents the effects of *Net_Under_Leverage* and *Low_DE*. Net leverage is book leverage minus cash reserves. Net leverage deficit is net leverage minus the predicted net leverage. *Net_Under_Leveraged* dummy takes the value of one if the bidder falls in the lowest quartile of net leverage deficit. *Low_DE* dummy takes the value of one if the bidder's leverage is in the bottom leverage quartile. Other variables are defined as in previous tables. The p-values are calculated based on White's (1980) correction for heteroskedasticity.

Dependent Variable: *CAR*

	Model 1		Model 2		Model 3		Model 4	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p
Net_Under_Leverage	-0.013	0.007	-0.005	0.394				
Low_DE					-0.015	0.002	-0.009	0.138
Under_Leveraged			-0.013	0.032			-0.011	0.089
Relative Size	-0.002	0.437	-0.002	0.347	-0.002	0.330	-0.002	0.301
Size	-0.005	0.000	-0.005	0.000	-0.005	0.000	-0.005	0.000
Cash	0.019	0.000	0.019	0.000	0.020	0.000	0.019	0.000
Tender	0.001	0.728	0.001	0.793	0.001	0.846	0.001	0.851
Hostile	-0.002	0.696	-0.002	0.706	-0.002	0.643	-0.002	0.664
N	998		998		998		998	
R2	6		7		7		7	

Table 18 Correlations between Proxies for Free Cash Flow

This table reports the correlations between proxies for free cash flow. These proxies include *Under_Leveraged, Cash_Rich, Low_DE and Net_Under_Leverage*. These variables are defined as described in previous tables. All correlations are significant at 1%.

	Under_Leveraged	*Cash_Rich*	*Net_Under_Leverage*	*Low_DE*
Under_Leveraged	1.000			
Cash_Rich	0.133	1.000		
Net_Under_Leverage	0.661	0.305	1.000	
Low_DE	0.654	0.149	0.568	1.000

Table 19 Robustness (Target Growth Opportunity)

This table decomposes the effect of *Under_Leveraged* based on target growth opportunity. *Target Firm HMB* (*LMB*) is one if the target firm has higher (lower) market to book ratio than the median in the sample. Other variables are defined as in previous tables. The p-values are calculated based on White's (1980) correction for heteroskedasticity.

Dependent Variable: *CAR*

	CAR	
	Estimate	p-value
*Under_Leveraged * Target Firm HMB*	-0.039	0.003
*Under_Leveraged * Target Firm LMB*	-0.017	0.025
Relative Size	-0.003	0.482
Size	-0.005	0.008
Cash	0.023	0.000
Tender	0.002	0.710
Hostile	-0.002	0.718
N	649	
R2	9	

Table 20 Distribution of Local Bidders over Time, 1986-2001

The table reports the percentage of local bidders in the sample across years. The sample consists of transaction announcements that meet the following criteria:

i) Transactions that are listed as completed or withdrawn with announcement and effective dates falling within the period from 1986 to 2001; ii)Transactions that are identified by the SDC as a merger or an attempt to acquire a majority interest; iii) Both bidder and target are non-financial and non-utility public firms in the U.S.; iv) Bidder firms are found in the COMPUSTAT and the CRSP annual files; v) Bidder firm is identified as the first bidder; vi) Relative size of transaction to the market capitalization of the bidder is between 0.05 and 10. vii) Transaction value is not less than 1 million dollars; viii) Stock prices of bidders are not less than 1 dollar. ix) Bidders (targets) do not have headquarters in remote areas such as Hawaii and Alaska. Local bidders are defined as bidders, which are less than 100 kilometers from their targets (*Dist100*=1).

Year	***N***	***Local Bidders***
1986	51	14%
1987	52	19%
1988	67	7%
1989	44	25%
1990	38	24%
1991	31	26%
1992	31	29%
1993	39	18%
1994	65	17%
1995	94	17%
1996	104	14%
1997	131	20%
1998	170	16%
1999	158	11%
2000	153	20%
2001	122	16%

Table 21 Bidder and Target Distribution over States, 1986-2001

The table reports the geographical distribution of local bidders. Local bidders are defined as bidders, which are less than 100 kilometers from their targets (*Dist100*=1). *N* is the number of bidders (targets) in the state, and percentage of bidder (target) is the ratio of bidders (targets) in the state to total number of bidders in the sample. Percentage of local bidders is the ratio of local bidders to total number of bidders in the state.

	Bidder			*Target*	
States	***N***	***Bidders (%)***	***Local Bidders (%)***	***N***	***Targets (%)***
Alabama	5	0.37	0.00	8	0.59
Arizona	10	0.74	0.00	19	1.41
Arkansas	6	0.44	0.00	1	0.07
California	251	18.59	31.08	303	22.44
Colorado	26	1.93	19.23	41	3.04
Connecticut	37	2.74	10.81	41	3.04
District of Columbia	11	0.81	9.09	1	0.07
Delaware	3	0.22	33.33	2	0.15
Florida	53	3.93	15.09	55	4.07
Georgia	42	3.11	11.90	33	2.44
Idaho	5	0.37	20.00	2	0.15
Illinois	75	5.56	8.00	52	3.85
Indiana	13	0.96	7.69	14	1.04
Iowa	2	0.15	0.00	3	0.22
Kansas	3	0.22	0.00	7	0.52
Kentucky	6	0.44	16.67	3	0.22
Louisiana	11	0.81	9.09	4	0.3
Maine	1	0.07	0.00	1	0.07
Maryland	18	1.33	5.56	26	1.93
Massachusetts	54	4.00	20.37	88	6.52
Michigan	29	2.15	3.45	22	1.63
Minnesota	46	3.41	21.74	51	3.78
Mississippi	2	0.15	0.00	3	0.22
Missouri	27	2.00	7.41	16	1.19
Montana			0.00	3	0.22
Nebraska	8	0.59	0.00	4	0.3
Nevada	11	0.81	36.36	12	0.89
New Hampshire	5	0.37	20.00	8	0.59
New Jersey	66	4.89	16.67	46	3.41
New Mexico	6	0.44	0.00	3	0.22
New York	143	10.59	19.58	91	6.74
North Carolina	22	1.63	18.18	25	1.85
North Dakota			0.00	1	0.07
Ohio	72	5.33	6.94	48	3.56
Oklahoma	14	1.04	21.43	17	1.26
Oregon	14	1.04	0.00	17	1.26
Pennsylvania	63	4.67	6.35	41	3.04
Rhode Island	10	0.74	0.00	4	0.3
South Carolina	3	0.22	33.33	9	0.67
South Dakota			0.00	1	0.07
Tennessee	16	1.19	6.25	14	1.04
Texas	122	9.04	19.67	123	9.11
Utah	6	0.44	0.00	12	0.89
Vermont			0.00	1	0.07
Virginia	20	1.48	15.00	36	2.67
Washington	8	0.59	12.50	24	1.78
Wisconsin	5	0.37	40.00	14	1.04

Table 22 Deal Characteristics of Local and Distant Bidders

The table reports the deal characteristics across the distant and local distant bidders groups. Local bidders are defined as bidders, which are less than 100 kilometers from their targets (*Dist100*=1). *Cash (Stock)* is a dummy variable for 100% cash (stock) offers. *Cash Percentage* is the percentage of cash payment in transaction value. *Tender* is a dummy for tender offer. *Hostile* is a dummy variable which takes the value of one if the board defines the initial offer as hostile. *Related Industry* takes the value of one if both target and bidder are categorized in the same two-digit SIC.

	Distant Bidders	*Local Bidders*	*t- statistics*
Cash	36%	24%	3.4885
Stock	35%	52%	-4.6068
Cash Percentage	83%	79%	1.2414
Related Industry	33%	34%	-0.4099
Tender	26%	17%	2.7274
Hostile	7%	3%	2.3281
N	1121	229	

Table 23 Summary Statistics for Bidders and Targets

The table reports the summary statistics for local and distant bidders groups. Local bidders are defined as bidders, which are less than 100 kilometers from their targets (*Dist100*=1). *Total Assets* is the book value of bidder's total assets. (*Target Firm*) *M_B* is the market-to-book ratio of the bidder (target) defined as book value of assets minus book value of equity plus market value of equity divided by book value of total assets. *ET_A* is earnings before interest and taxes divided by book value of assets. (*Target Firm*) *Leverage* is ratio of total debt to book value of the bidder (target). *Target RD/Sales* is the ratio of R&D expenses to sales of the bidder (target). *Relative Size* is the ratio of transaction value to equity market capitalization of bidder 60 days prior to takeover announcement. *Target Firm P/E* is the price-earnings ratio of target.

	Distant Bidders	*Local Bidders*	*t- statistics*
Total Assets ($ million)	4,651	2,962	2.003
M_B	2.386	2.736	-2.506
ET_A	0.144	0.136	0.672
Leverage	0.506	0.463	2.502
RD/Sales	0.09	0.175	-1.925
Relative Size	0.597	0.521	0.577
Target Firm M_B	1.781	1.789	-0.062
Target Firm Leverage	0.534	0.456	2.627
Target Firm P/E	11.533	12.314	0.555
Target Firm RD/Sales	0.096	0.153	-2.72

Table 24 OLS Regression Predicting CAR

This table reports White (1980) corrected OLS regression estimates. Following the standard methodology, cumulative abnormal returns to bidders (*CAR*) over the three-day event window (-2,0) are calculated to measure the market reactions to takeover announcements. The benchmark returns are the value-weighted index of returns including dividends for the combined New York Stock Exchange, American Stock Exchange and NASDAQ. The estimation window includes from 300 to 60 days before the announcement date. *Dist100* takes the value of one if the distance between a bidder and its target is less than one hundred kilometers. *Cash* (*Stock*) is a dummy for an all-cash (all-stock) offer. *Tender* is a dummy for a tender offer. *Size* is the natural logarithm of equity market capitalization of bidder 60 days prior to takeover announcement. *Covered (Not Covered)* takes the value of one if the target is (not) covered by analysts. *Relative Size* is the ratio of transaction value to equity market capitalization of bidder 60 days prior to takeover announcement. *M_B* is market-to-book ratio of the bidder, defined as the book value of assets minus book value of equity plus market value of equity divided by book value of total assets. The regressions include year dummies but are not reported due to brevity. Other variables are defined as in previous tables.

Dependent Variable: CAR

	Model 1		Model 2	
	Estimate	p-value	Estimate	p-value
Intercept	0.068	0.034	0.066	0.038
Dist100	0.016	0.007		
*Dist100*Covered*			0.005	0.676
Dist100 Not Covered*			0.018	0.006
Cash	0.011	0.035	0.011	0.036
Stock	-0.009	0.132	-0.009	0.133
Hostile	-0.002	0.799	-0.002	0.806
Size	-0.004	0.023	-0.004	0.027
Relative Size	-0.001	0.370	-0.001	0.373
M_B	0.001	0.470	0.001	0.489
N	1350		1350	
F	2.42		2.34	
R2	0.043		0.044	

Table 25 OLS Regressions Predicting *CAR* for the Subsamples of Local and Distant Bidders

This table reports White (1980) corrected OLS regression estimates for the local and distant bidders subsamples. Dependent variable is *CAR*. Local bidders are defined as bidders, which are less than 100 kilometers from their targets (*Dist100*=1). The regressions include year dummies but are not reported due to brevity. Other variables are defined as in previous tables.

Dependent Variable: *CAR*

	Distant Bidders		*Local Bidders*	
	Estimate	p-value	Estimate	p-value
Intercept	0.035	0.311	0.194	0.023
Cash	0.020	0.000	-0.007	0.635
Hostile	-0.002	0.769	0.016	0.514
Size	-0.002	0.197	-0.010	0.029
Relative Size	-0.001	0.532	-0.004	0.626
M_B	0.001	0.722	0.001	0.736
N	1121		229	
R2	0.037		0.103	

Table 26 *CAR* for Local and Distant Bidders across Related and Unrelated Industry Mergers

The table reports the average *CAR* for local and distant bidders groups. Local bidders are defined as bidders, which are less than 100 kilometers from their targets. *Related Industry* takes the value of one if both target and bidder are categorized in the same two-digit SIC.

	Distant Bidders		*Local Bidders*		*t statistics*
	N	*CAR*	*N*	*CAR*	
Related Industry	639	-0.010	124	0.002	-1.733
Unrelated Industry	482	-0.009	105	0.008	-1.911

Table 27 OLS Regressions Predicting CAR for Various Groups

This table reports White (1980) corrected OLS regression of estimates for interaction of *Dist100* with the *Related* and *Unrelated Industry* as well as *Ind_Cluster* and *Not Ind_Cluster*. *Related Industry* takes the value of one if both target and bidder are categorized in the same two-digit SIC. *Ind_Cluster* takes the value one if a bidder makes a within industry takeover offer in a region where the number of COMPUSTAT firms with the same two-digit SIC group as the bidder within 100 kilometers is greater than 10 Dependent Variable is *CAR.*. The regressions include year dummies but are not reported due to brevity. Other variables are as defined in previous tables.

Dependent Variable : *CAR*

	Model 1		Model 2		Model 3		Model 4	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p
Intercept	0.068	0.041	0.067	0.043	0.066	0.046	0.066	0.05
Dist100	0.016	0.007			0.017	0.006		
*Dist100*Related Industry*			0.015	0.067				
Dist100 Unrelated Industry*			0.018	0.053				
*Dist100*Ind_Cluster*							0.015	0.117
Dist100 Not Ind_Cluster*							0.018	0.027
Cash	0.011	0.037	0.011	0.036	0.011	0.035	0.011	0.035
Stock	-0.009	0.133	-0.009	0.138	-0.008	0.158	-0.008	0.161
Hostile	-0.002	0.799	-0.002	0.796	-0.002	0.779	-0.002	0.782
Size	-0.004	0.025	-0.004	0.025	-0.004	0.026	-0.004	0.028
Relative Size	-0.001	0.366	-0.001	0.368	-0.001	0.365	-0.001	0.367
M_B	0.001	0.471	0.001	0.476	0.001	0.449	0.001	0.456
Related industry	0	0.952	0	0.984	0.002	0.756	0.002	0.742
Ind_Cluster					-0.004	0.475	-0.003	0.545
N	1350		1350		1350		1350	
F	2.32		2.22		2.22		2.13	
R2	0.043		0.043		0.043		0.043	

Table 28 OLS Regressions Predicting Target Premium

This table reports White (1980) corrected OLS regression estimates for *Target Premium*, which is defined as the *CAR*'s to target shareholders 40 days before and 40 days after the announcement date. Local bidders are defined as bidders, which are less than 100 kilometers from their targets (*Dist100*=1). *Relative Size* is the ratio of transaction value of target to market capitalization of bidder sixty days prior to announcement date. *Target Firm M_B* is market-to-book ratio of the target firm. *Target Firm Leverage* is book leverage of the target firm. *Target Firm P/E* is the price-earnings ratio of the target firm. *Cash* is a dummy variable for 100% cash offers. *Hostile* is a dummy variable which takes the value of one if the board defines the initial offer as hostile. (*Not*) *Covered* is one if the target firm is (not) covered by an analyst. The regressions include year dummies but are not reported due to brevity.

Dependent Variable: Target Premium

	Model 1		Model 2	
	Estimate	p-value	Estimate	p-value
Intercept	0.03	0.879	0.020	0.912
Dist100	-0.089	0.079		
*Dist100*Covered*			-0.021	0.815
*Dist100*Not Covered*			-0.108	0.061
Size	0.021	0.023	0.025	0.004
Relative Size	0.002	0.759	0.002	0.623
Target Firm Leverage	-0.174	0.005	-0.167	0.008
Target Firm P/E	0.000	0.017	0.000	0.042
Target Firm M_B	-0.053	0.000	-0.059	0.000
Hostile	0.005	0.926	-0.011	0.832
Cash	0.06	0.091	0.048	0.172
N	744		744	
F	3.1		4.140	
R2	0.086		0.055	

Table 29 OLS Regressions Predicting CAR

This table reports White (1980) corrected OLS regression estimates for size-based Quartiles. The dependent variable is *CAR*. *Small* (*Large*) takes the value of one if bidder is (not) in the lowest size quartile. Other variables are as defined in previous tables.

Dependent Variable: CAR

	Model 1		Model 2	
	Estimate	p-value	Estimate	p-value
Intercept	0.010	0.823	0.011	0.807
Dist100	0.016	0.007		
*Dist100*Small*			0.035	0.015
*Dist100*Large*			0.009	0.166
Cash	0.011	0.042	0.011	0.036
Stock	-0.009	0.119	-0.009	0.132
Hostile	-0.001	0.848	-0.001	0.907
Size	-0.001	0.609	-0.001	0.609
Relative Size	-0.001	0.306	-0.001	0.334
M_B	0.001	0.580	0.001	0.582
Related Industry	0.000	0.996	0.000	0.974
Small	0.018	0.015	0.013	0.087
N	1350		1350	
R2	0.047		0.050	
F	2.340		2.310	

Table 30 OLS Regression Predicting Long-Run Operating Performance

This table reports OLS regression estimates of the long-run performance. *ET_A* is the ratio earnings before interest and taxes to total assets. The dependent variable is the value-weighted adjusted operating measure of bidder and target from the year before through two years after the acquisition (Δ *ET_A)*, which is defined as *ET_A* minus the average *ET_A* of the group within the two-digit SIC. *Relative Size* is the ratio of transaction to market capitalization of the bidder. Large (Small) bidders are defined as the bidders if bidder's size is larger (smaller) than the median of the sample.

Dependent Variable: Δ *ET_A*

	Whole Sample		Large Bidders		Small Bidders	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.000	0.839	0.002	0.052	0.000	0.897
Dist100	0.010	0.037	0.000	0.944	0.023	0.032
Relative Size	0.002	0.388	-0.007	0.003	0.002	0.580
N	437		257		180	
Adjusted R2	0.01		0.03		0.03	

Table 31 Robustness

The table reports OLS regression estimates of *CAR*. Model 1 is the subsample from 1986 to 1996 and Model 2 is the subsample from 1997 to 2001. *Mill's Ratio* is computed by the ratio of density function to cumulative distribution function of being a bidder which is estimated by maximum likelihood of being a bidder between 1980 and 2001. The other variables are defined as in previous tables.

Dependent Variable: *CAR*

	Model 1		Model 2		Model 3	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.135	0.000	0.038	0.240	0.065	0.007
Dist100	0.014	0.062	0.019	0.021	0.017	0.004
Cash	0.012	0.125	0.008	0.331	0.011	0.044
Stock	-0.005	0.563	-0.012	0.091	-0.007	0.191
Hostile	-0.006	0.565	0.001	0.952	-0.002	0.816
Size	-0.007	0.000	-0.003	0.076	-0.003	0.001
Relative Size	0.001	0.482	-0.012	0.000	-0.001	0.405
Related Industry	0.001	0.916	0.001	0.879	0.000	0.989
Mill's Ratio					0.091	0.736
N	616		734		1349	
F	2.29		3.42		2.58	
R2	0.06		0.05		0.04	

Table 32 Geographical Proximity and Free Cash Flow

This table presents estimates of *Under_Leveraged* and *Dist100*. Heteroskedasticity corrected p-values are reported. Other variables are defined as in previous tables.

	CAR	
	Estimate	p-value
Under_Leveraged	-0.017	0.003
Dist100	0.020	0.004
Relative Size	-0.001	0.684
Size	-0.006	0.000
Cash	0.022	0.000
Tender	0.001	0.868
Hostile	-0.002	0.798
N	840	
R2	8	

References

Almazan, A., A. de Motta, and S. Titman, 2003, Firm location and the creation and utilization of human capital, NBER Working Paper 10106.

Andrade, G., M. Mitchell and E. Stafford, 2001, New evidence and perspectives on mergers, *Journal of Economic Perspectives*, 15, 103-120.

Barber, B. and J. Lyon, 1996, Detecting abnormal performance: The empirical power and specification of test statistics, *Journal of Financial Economics*, 11, 359-400

Berkovitch, E. and M.P. Narayanan, 1990, Competition and the medium of exchange in takeovers, *Review of Financial Studies* 3, 153-174.

Boone, A.L. and H.J. Mulherin, Corporate restructuring and corporate auction, Unpublished Working Paper, Claremont College, Claremont, CA

Bradley, M., G.A. Jarrell, and E.H. Kim, 1984, On the existence of an optimal capital structure: Theory and evidence, *Journal of Finance*, 39, 857-78

Bruner, R. F., 1988, The use of excess cash and debt capacity as a motive for merger, *Journal of Financial and Quantitative Analysis*, 23, 199-217

Carroll, C. and J.M. Griffith, 1999, Hostile vs. white knights, *Managerial and Decision Economics*, 20, 163-171

Chowdhry, B. and V. Nanda, 1993, The strategic role of debt in takeover contests, *Journal of Finance*, 48, 731-45

Clayton, M.J. and S. A. Ravid, 2002, The effect of leverage on bidding behavior: Theory and evidence from the FCC auctions, *Review of Financial Studies*, 15, 723-750.

Cleary, S., 1999, The relationship between firm investment and financial status, *Journal of Finance*, 54, 673-692

Comment, R. and G.W. Schwert, 1995, Poison or placebo? Evidence on the deterrence and wealth effects of modern anti-takeover measures, *Journal of Financial Economics*, 39 (1995), 3-43

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045-2073

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811-841

Datta, S., M. Datta, and K. Raman, 2001, Executive compensation and corporate acquisition decisions, *Journal of Finance*, 56, 2299-2336.

DeAngelo, H. and R.W. Masulis, 1980, Optimal capital structure under corporate and personal taxation, *Journal of Financial Economics*, 8, 3-29

Dechow, P., 1994, Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals, *Journal of Accounting and Economics*, 18, 3-42

DeLong, G. L., 2001, Stockholder gains from focusing versus diversifying bank mergers, *Journal of Financial Economics*, 59, 221-52

Dewenter, K. L., 1995, Does the market react differently to domestic and foreign takeover announcements? Evidence from the U.S. chemical and retail industries, *Journal of Financial Economics*, 37, 421-441

Dickerson, A.P., A.P. Gibson, and E. Tsakalotos, 1997, The impact of acquisitions on company performance: Evidence from a large panel of UK firms, *Oxford Economic Paper*, 49, 344-61

Eckbo, B. E. and H. Langohr, 1989, Information disclosure, method of payment, and takeover premiums, *Journal of Financial Economics*, 24, 363-403

Eckbo, B. E., R. M. Giammarino, and R. L. Heinkel, 1990, Asymmetric information and the medium of exchange in takeovers: Theory and tests, *Review of Financial Studies*, 3, 651-675

Eckbo, B. E., and K. S. Thorburn, 2000, Gains to bidder firms revisited: Domestic and foreign acquisitions in Canada, *Journal of Financial and Quantitative Analysis*, 35, 1-25

Fama, E.F. and K.R. French, 2002, Testing trade-off and pecking order predictions about dividends and debt, *Review of Financial Studies*, 15, 1-33

Fazzari, S.M., R.G. Hubbard, and B.C. Petersen, 1988, Financing constraints and corporate investment, Brookings Papers on Economic Activity, 141-195

Fishman, M.J., 1988, A theory of preemptive takeover bidding, *RAND Journal of Economics*, 19, 88-101

Fishman, M.J., 1989, Preemptive bidding and the role of the medium of exchange in

Acquisitions, *Journal of Finance*, 44, 41-57

Franks, J. R., R. S. Harris, and C. Mayer, 1988, Means of payment in takeovers: Results for the U.K. and the U.S., in A. Auerback (editor), *Corporate Takeovers: Causes and Consequences*, NBER, University of Chicago Press, Chicago

Frank, M. Z. and V. K. Goyal, 2003, Testing the pecking order theory of capital structure, *Journal of Financial Economics*, 67, 217-248

Gillan, S. and L. Starks, 2000, Corporate governance proposals and shareholder activism: The role of institutional investors, *Journal of Financial Economics*, 57, 275-305

Goyal, V.K., K. Lehn, and S. Racic, 2002, Growth opportunities and corporate debt policy: The case of the U.S. defense industry, *Journal of Financial Economics*, 64, 35-59

Heckman, J.J., 1978, Dummy endogenous variables in a simultaneous equation system, *Econometrica*, 46, 931-959

Harford, J., 1999, Corporate cash reserves and acquisitions, *Journal of Finance*, 54, 1969-1997

Healy, P., K. Palepu, and R. Ruback, 1992, Does corporate performance improve after mergers?, *Journal of Financial Economics*, 31, 135-75

Hirshleifer, David and Sheridan Titman, 1990, Share tendering strategies and the success of hostile takeover bids, *Journal of Political Economy*, 98, 295-324

Holmstrom, B. and S.N. Kaplan, 2001, Corporate governance and merger activity in the United States: Making sense of the 1980s and 1990s, *Journal of Economic Perspectives*, 15, 121-144.

Hovakimian, A., G. Hovakimian, and H. Tehranian, 2004, Determinants of target capital structure: The case of dual debt and equity issues, *Journal of Financial Economics*, 71, 517-540

Hovakimian, A., T. Opler, and S. Titman, 2001, The debt-equity choice, *Journal of Financial and Quantitative Analysis*, 36, 1-24

Huang, Y. and R.A. Walkling, 1987, Target abnormal returns associated with acquisition announcements: Payment, acquisition form, and managerial resistance, *Journal of Financial Economics*, 19, 329-49

Ivkovic, Zoran and Scott Weisbenner, 2004, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance forthcoming*

Jalilvand, A. and R.S. Harris, 1984, Corporate behavior in adjusting to capital structure and dividend targets: An econometric study, *Journal of Finance*, 39, 127-145.

Jarrell, G. A. and A. B. Poulsen, 1989, The returns to acquiring firms in tender offers: Evidence from three decades, *Financial Management*, 18, 12-19

Jensen, M.C., 1986, Agency costs of free cash flow, corporate finance and takeovers, *American Economic Review*, 76, 323-329

Jensen, M.C. and W.H. Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics*, 3, 305-60

Kaplan, S.N. and L. Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints, *Quarterly Journal of Economics*, 112, 169-215

Kim, J. and R.L. Smith, 1994, The combined effects of free cash flow and financial slack on bidder and target stock returns, *Journal of Business*, 67, 281-310

Lamont, O., 1997, Cash flow and investment: Evidence from internal capital markets, *Journal of Finance*, 52, 83-109.

Lang, L.H.P., R.M. Stulz, and R.A. Walkling, 1991, A test of free cash flow hypothesis: The case of bidder returns, *Journal of Financial Economics*, 29, 315-336

Loderer, C. and K. Martin, 1990, Corporate acquisitions by listed firms: The evidence of a comprehensive sample, *Financial Management* 19, 17-33

Malloy, C. J., 2004, The geography of equity analysts, *Journal of Finance forthcoming*

Maloney, M.T., R.E. McCormick, and M.L. Mitchell, 1993, Managerial decision making and capital structure, *Journal of Business*, 66, 189-217

Martin, K., 1996, The method of payment in corporate acquisitions, investment opportunities, and management ownership, *Journal of Finance*, 51, 1227-1246

Milgrom, P. R., 1981, Rational expectations, information acquisition and competitive bidding, *Econometrica*, 49, 921-943

Moeller, S.B., F. P. Schlingemann, and R. Stulz, 2004, Firm size and the gains from acquisitions, *Journal of Financial Economics*, 73, 201-228

Myers, S.C., 1977, Determinants of corporate borrowing, *Journal of Financial Economics*, 5, 147-175

Myers, S.C., 1984, The capital structure puzzle, *Journal of Finance*, 34, 575-592

Myers, S.C. and N.S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics*, 13, 187-221

Officer, M., 2003, Termination fees in mergers and acquisitions, *Journal of Financial Economics*, 69, 431-67

Perry, T. and M. Zenner, 2001, Pay for performance? Government regulation and the structure of compensation contracts, *Journal of Financial Economics*, 62, 453-88

Pulvino, T. C., 1998, Do asset fire sales exist? An empirical investigation of commercial aircraft transactions, *Journal of Finance*, 53, 939-78

Rajan, R.G. and L. Zingales, 1995, What do we know about capital structure? Some evidence from international data, *Journal of Finance*, 50, 1421-60.

Rau, P.R. and T. Vermaelen, 1998, Glamour, value and the post-acquisition performance of acquiring firms, *Journal of Financial Economics*, 49, 223-53

Schwert, G. W., 1996, Markup pricing in mergers and acquisitions, *Journal of Financial Economics*, 41, 153-192

Schwert, G.W., 2000, Hostility in takeovers: In the eyes of the beholder?, *Journal of Finance*, 55, 2599-2640

Shleifer, A. and R. W. Vishny, 2003, Stock market driven acquisitions, *Journal of Financial Economics*, 70, 295-311

Shyam-Sunder, L. and S.C. Myers, 1999, Testing static tradeoff against pecking order models of capital structure, *Journal of Financial Economics*, 51, 219-244

Titman, S. and R. Wessels, 1988, The determinants of capital structure choice, *Journal of Finance*, 43, 1-19

Travlos, N., 1987, Corporate takeover bids, methods of payments and bidding firms' stock returns, *Journal of Finance*, 42, 943-963

White, H., 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica*, 48, 817-38

Yook, K., 2003, Larger return to cash acquisitions: Signaling effect or leverage effect, *Journal of Business*, 76, 477-98

Zingales, L., 1998, Survival of the fittest or the fattest? Exit and financing in the trucking Industry, *Journal of Finance*, 53, 905-38

Vita

Vahap Bülent Uysal was born in Akyazı, Turkey on July 14, 1974, the son of Sabire Uysal and Mehmet Uysal. He entered Bilkent University in 1992, and received a Bachelor of Science degree in Mathematics in 1996. Upon graduation, Vahap entered the graduate program in economics at the Middle East Technical University, where he received a Masters of Science degree in 1998. In August 1998, he joined the doctoral degree program in economics at the University of Texas, Austin. Upon receiving Master of Science, Vahap entered the doctoral program in finance at the McCombs School of Business at the University of Texas, Austin.

Permanent Address: 7201 Wood Hollow Dr #427 Austin, TX 78731

This dissertation was typed by the author.