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"The Effects of Credit Ratings in Mergers and Acquisitions"

by

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Abstract

This thesis studies the effects of the credit ratings in mergers and acquisitions (M&As). The first chapter establishes that credit ratings affect the choice of payment method in mergers and acquisitions. I find that bidders holding a high rating level are more likely to use cash financing in a takeover. I attribute this finding to lower financial constraints and enhanced capability of highly rated firms to access public debt markets as implied by their higher credit quality. The second chapter investigates the effect of the proximity to credit rating changes on the acquisition decisions of the bidding firms. I apply different measures to proxy for a potential credit rating change and I find a non linear association between firms' real credit rating levels (credit quality) and acquisition decisions. Furthermore, I show that all my proxies for future credit rating upgrades (downgrades) are positively (negatively) associated with acquisition decisions. Overall the findings in this chapter support my hypotheses and specifically, document the real impact of CRAs' ratings and opinions on firms' takeover policies. The third chapter re-examines the shareholder wealth effects around the announcements of mergers between bidders and targets that complement each other on the levels of debt capacity and growth opportunities, when high degrees of information asymmetry prevail. In sum I find that this type of merger transactions creates value for the combined firms as also for the bidding firms. Regarding the target firms there is some evidence of value destruction which nonetheless, comes at the benefit of the combined and bidding firms as the latter firms avoid overpayment. Additionally, the significant effect of the complementary fit on synergy, bidding and target firm returns is mainly driven by the group of target firms that operate under a high information asymmetry environment.

Declaration of Originality

"I hereby declare that this document has been composed by myself and has not been presented or accepted in any previous application for a degree. The work, of which this is a record, has been carried out by myself unless otherwise stated and where the work is mine, it reflects personal views and values. All quotations have been distinguished by quotation marks and all sources of information have been acknowledged by means of references including those of the Internet. As of submission date, a paper based on Chapter 2 of this thesis has been under review in The Journal of Corporate Finance as an article entitled "Credit Ratings and Choice of Payment Method in Mergers and Acquisitions" co-authored with Dimitris Petmezas and Nickolaos G. Travlos."

Nikolaos Karampatsas, 2 October 2013

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Any shortcomings of this work are my sole responsibility.

Abbreviations and Glossary

2SLS – Two Stage Least Squares

AMEX – American Stock Exchange

CAR – Cumulative Abnormal Return

CRAs – Credit Rating Agencies

CRSP – Center for Research in Security Prices (University of Chicago)

EEVs – Endogenous Explanatory Variables

GLM – Generalized Linear Model

IVs – Instrumental Variables

LDV – Limited Dependent Variable

LIML – Limited Information Maximum Likelihood

LPM – Linear Probability Model

M&A – Mergers and Acquisitions

MLE – Maximum Likelihood Estimator

NASDAQ – National Association of Securities Dealers Automated Quotations

NRSROs – Nationally Recognized Statistical Rating Organizations

NPV – Net Present Value

NYSE – New York Stock Exchange

OLS – Ordinary Least Squares

PSM – Propensity Score Matching

QMLE – Quasi-Maximum Likelihood Estimator

SDC – Securities Data Corporation (Thomson Financial)

SEC – Securities and Exchange Commission

SIC – Standard Industrial Classification

S&P – Standard & Poor's

VIF – Variance Inflation Factor

WH – Wu-Hausman

"Your criterion should be not whether or not you can reject or accept the hypothesis, but what you can learn from the data. The best thing you can do is use the data to enhance your description of the world." .

Eugene Fama

Nobel Laureate in Economic Sciences 2013

Chapter 1

Introduction

Credit Rating Agencies (CRAs) produce and disseminate qualitative information about the creditworthiness of corporate entities and their financial obligations. In order to accomplish that, CRAs analyze information related with the issuer, its market and its economic state of affairs. In the majority of the cases the final outcome derived from this analysis materializes to a single credit rating. This rating is a letter grade measuring the creditworthiness of a firm and can be translated as the opinion of rating agencies regarding the likelihood that the issuer will be able to meet its contractual and financial debt obligations, when they become due. The use of credit ratings has expanded in recent years mostly due to the globalization of financial markets, the growing complexity of financial products, and a sheer increase in the usage of ratings in financial regulation and contracting (Kisgen (2006, 2009), and Frost (2007)). The function and effectiveness of CRAs in capital markets has continuously been brought into the public's and regulators' attention, especially after major incidents like the East Asian Financial Crisis (1997), and the bankruptcies of Enron (2001), and Worldcom (2002) however, it has never been so pronounced as during the recent financial crisis.

The purpose of this thesis is to examine the impact of CRAs' actions and decisions on a set of different Mergers and Acquisitions (M&As) outcomes, and bring together two very generic strands of literature. Few economic phenomena receive so much attention and empirical research, as the numerous forms of transactions in what Manne (1965) named "the market for corporate control". Corporate takeovers are among the largest investments that a company will ever undertake thus, providing a particular research setup into the value implications of managerial decisions, incentives, bid strategies, and set of complex contractual devices that have evolved to enable the deals to go through (Betton, Eckbo and Thorburn (2011)). In the presence of information asymmetries the supply of credit and ultimately the access to public debt markets as it is certified by the credit ratings, can influence the firms' financing and investment decisions. Specifically, in the context of M&As the relevance of debt capacity and credit quality (credit rating levels) can be crucial, since some of the most important M&As' aspects like the choice of payment method, the decision to acquire another firm, and the value creation for the shareholders are intrinsically tied to the ability of firms to raise debt capital. In particular, it is very likely that bidding firms' choice between cash and stock for the consummation of the deal, or the decision to takeover another firm, are related with their capability of using debt capital as, in the former case it is known from the existing literature that cash acquisitions are to a great extent funded by debt. In the latter, since the Myers (1984) Pecking Order Theory it is widely known that when firms decide the source of funds that will use in order undertake any investment project (i.e., acquisitions), a higher priority is given to debt over stock capital and consequently, firms primarily try to access the debt markets. Furthermore, the ability of the combined firms to finance any Net Present Value (NPV) project due to their high debt capacity in the post-merger period should be reflected on the short run window of the acquisition announcement. From the above preliminary remarks and the scarce relevant literature up to date it seems that a thorough examination of the credit ratings impact on M&As is particularly interesting. In that respect, this thesis examines three different aspects of the M&A process. The bidding firm's decision regarding the choice of payment method used to consummate the deal, the acquirer firms' managerial incentives and decisions to undertake a takeover of another firm, and the short-term shareholder wealth creation related with the announcements of acquisitions.

In more detail, the decision to examine the association between credit ratings and the method of payment in M&As, is motivated by the importance which the cost of debt and financial constraints hold for firms who decide to pay by cash in the acquisition deals. In general, firms with higher credit ratings (high credit quality) are able to borrow capital at lower interest rates than firms with lower credit ratings (low credit quality), and as a consequence high rating firms are more likely to choose cash as the payment method in M&As. In the case of firms' decisions to acquire another firm, current and "expected" credit ratings concerns should also have a considerable impact. Anecdotal evidence from a survey study (Graham and Harvey (2001)), documents that credit ratings are considered as one of the most important factors influencing firms' corporate decisions. Thus, it is very likely that considerations related with the credit rating levels in the post-merger period, should affect bidder firms' management decisions to acquire another company. Finally, following the theoretical model of Myers and Majluf (1984), mergers between bidders and targets that complement each other on the levels of debt capacity and growth opportunities, should promote shareholder wealth creation around the acquisition announcements. By measuring firms' debt capacity with the availability and level of credit ratings, I am able to examine this theoretical proposition on an empirical level.

The literature on CRAs argues that credit ratings affect firms' access to the credit markets and ultimately, to the supply of credit, a fact with major implications for firms' capital structure and investment policies. According to the classical finance literature this result is counterintuitive, as in perfect frictionless capital markets firms' investment and capital structure policies should be based only on firms' investment opportunities and their demand for capital hence, rendering the source of financing irrelevant for these policies (Modigliani and Miller (1958)). This is due to the fact that companies can shift freely between equity and debt, when deciding their source of capital. However, in the presence of information asymmetries the type of financing plays an important role on corporate policies (Stiglitz and Weiss (1981), Greenwald, Stiglitz and Weiss (1984), Myers and Majluf (1984), and Myers (1984)), and therefore, the impact of credit supply along with that of credit ratings gain a paramount significance for corporate policies.

The study of the effects of credit ratings on the choice of payment method in M&As, is motivated by the lack of any detailed examination of this topic in the hitherto literature; the same is true for the impact of "expected" credit rating changes on the outcome of acquisition decisions, whereas the investigation of shareholder wealth effects around the announcement of complementary acquisitions, is motivated by the need to re-validate the previous theoretical and empirical evidence, while using credit ratings as a proxy for debt capacity.

Chapter 2 investigates the impact of credit ratings existence, and levels on the likelihood of using cash as the payment method in M&As. The existing literature demonstrates that firms which hold a (highly) rated public debt by a CRA, and consequently have access to the public credit markets, face lower levels of financial constraints and exhibit higher debt capacity (Bolton and Freixas (2000), Diamond (1991), Fazzari, Hubbard, Petersen, Blinder and Poterba (1988), and Whited (1992)). On the other hand, a growing body of M&As literature documents that cash-acquisitions are to a great extend funded by debt (Bharadwaj and Shivdasani (2003), and Harford, Klasa and Walcott (2009)). By combining these two strands of literature, I attempt to examine how firms' increased debt capacity, as it is implied by the existence of a high credit rating (high credit quality), affects the likelihood of paying by cash in merger deals. Additionally the unused debt capacity from the bidders' or the targets' side, might lead firms to pay by cash in acquisitions since, the unused debt capacity in one of the two merging parties will lead bidders to use cash for the consummation of the deal, as any increase in leverage associated with cash payments will be absorbed by the unused debt capacity of the combined firm.

These hypotheses were tested on a sample of US public and private acquisitions over the period 1998-2009. It is found that bidding firms with a high credit rating on their debt (high credit quality), are more likely to use cash financing in a takeover. I attribute this finding to the lower financial constraints, and enhanced capability of highly rated firms to access public debt markets, as it implied by their higher credit quality. In economic terms one point rise in bidder rating level increases the likelihood of cash means of financing used in an M&A transaction by 6.52% over the sample average. Moreover, unused debt capacity, measured with the relative credit rating level of bidder to target, also appears to be a determinant of cash financing in M&As, corroborating the view that credit ratings are related with the choice of payment method in acquisitions. Finally, my results appear to be robust even after I control for the potential endogeneity bias of the existence and level of credit ratings, suggesting that the findings are not an artifact of a specification error in my variables.

Chapter 3 addresses the influence which "expected" credit rating changes exert on bidder firms' management decisions to acquire another company. While the importance of credit rating changes has been documented in the context of capital structure (Kisgen (2006, 2009), and earnings management decisions (Jung, Soderstrom and Yang (2012), and Alissa, Bonsall Iv, Koharki and Penn Jr (2013)), the literature still remains relatively silent when it comes to firms' investment decisions, and particular M&As. The traditional finance logic posits that the relationship between cost of capital and investment is a linear one, as under market conditions firms that face low cost of debt are able to borrow at any point in time, and undertake every positive NPV project when the investment opportunity arises. Nevertheless, the previous literature on credit ratings documented that due to a number of business, regulatory and contractual purposes (Cantor and Packer (1997), Kisgen (2006), and Chernenko and Sunderam (2012)) credit ratings entail discrete benefits and costs for firms. Due to this fact, very often firms' management takes into account the firms' past and future credit ratings when deciding their corporate policies; a circumstance resulting into the presence of an atypical investment/financial behavior.

The effect of the proximity to a credit rating change on firms' acquisition decisions is examined using a sample of US public and private acquisitions over the period 1996-2009. In order to measure the imminence of a credit rating change I apply three different measures. Credit rating outlook reports, the lagged credit rating changes, and the deviation of firms' real rating from an "expected" empirically modeled credit rating. It is found for a first time in the literature, a non linear association between firms' real credit rating levels (credit quality) and acquisition decisions. Furthermore, positive (negative) rating outlooks are positively (negatively) associated with acquisition decisions. Regarding past upgrades (downgrades) there seems to hold a positive (negative) relationship with acquisition decisions. Additionally, the association between the estimated deviation from an "expected" credit rating and takeover decisions is a positive. My results are statistically and economically significant, even after controlling for variables related with the likelihood of undertaking a takeover, and after controlling for the endogeneity of credit ratings. Overall my findings support the hypotheses and specifically, document the real impact of CRAs' ratings and opinions on firms' takeover policies.

Chapter 4 investigates the shareholder wealth effects around the announcements of mergers between bidders and targets that complement each other on the levels of debt capacity and growth opportunities, when high degrees of information asymmetry prevail. Theoretical literature explains that information asymmetry problems might lead to the distortion of "optimal" investment thus, leading to "underinvestment" (Myers and Majluf (1984)). The same literature suggests that one way to resolve "underinvestment" is through the conduction of a complementary acquisition. In particular, a complementary fit between a high debt capacity bidder facing limited investment opportunities and a low debt capacity target facing high investment opportunities, along with high information asymmetry can create value through the undertaking of the positive NPV projects by the financially unconstrained bidder, which the financially constrained target, might pass up. The importance of this theoretical proposition for the amelioration of information asymmetry, and the creation of shareholder wealth is of a great magnitude however, the empirical literature on the topic is still scarce and sporadic. The study tries to shed more light on this issue by using a new data set, and a different research design from the one which has been used so far.

In order to re-examine this topic the study uses a sample of US public acquisitions over the period 1996-2009. One of my innovations is the use of bidders' and targets' credit ratings to proxy for debt capacity, and the relative creditworthiness between the firms. In sum I find that synergy gains are positively associated with the magnitude of complementarity in debt capacity and growth opportunities between the bidder and the target. The bidder returns are positively related with the degree of complementary fit between the bidder and the target. When it comes to target returns there exist a negative relationship with the amount of complementarity, as it appears that bidders avoid overpayment. Additionally, the significant effect of the complementary fit on synergy, bidding and target firm returns is mainly driven by the group of target firms that operate under a high information asymmetry environment. Finally the main results remain robust after testing for endogeneity bias in credit ratings.

Overall, the results of all three studies broadly support the existence of a material impact of CRAs actions and decisions on the outcomes of M&As.

The thesis is organized as follows: Chapter 2 investigates the impact of credit ratings on the method of payment in M&As. Chapter 3 examines the effect of "expected" credit ratings changes on the likelihood of acquisitions. Chapter 4 re-investigates the shareholder wealth creation from complementary acquisitions. Each study is presented in a self-contained way. Final remarks and conclusions are given in the closing section.

Chapter 2

Credit Ratings and the Choice of Payment Method in Mergers and Acquisitions

2.1 Introduction

Credit Rating Agencies (CRAs) have an important role in the finance world by evaluating the creditworthiness of a particular firm, security or obligation (see Securities and Exchange Commision (2003)) and assigning a rating. CRAs disclose and publicize this information (see Healy and Palepu (2001)) to the market, reducing information asymmetry and, as consequence, lowering the firm's cost of capital. Additionally, previous literature gives evidence on how a firm's capability to access public debt markets, implied either by the existence of firm credit rating (see Cantillo and Wright (2000), Faulkender and Petersen (2006), Lemmon and Zender (2010), Mittoo and Zhang (2008), and Harford and Uysal (2012)) or rating level (see Bolton and Freixas (2000), Denis and Mihov (2003), Diamond (1991), Rauh and Sufi (2010), and Radhakrishnan, Song and Yerramilli (2013)) can affect capital structure or investment decisions. In this respect, Kisgen (2006, 2009) documents that firms regularly target either specific rating levels or seek to preserve a certain threshold (for instance, investment grade); specifically, in order to secure the rating, firms adjust their capital structure policies by issuing equity, buying back debt or through assets sales and dividend cuts. Similarly, Koziol and Lawrenz (2010) argue that due to the presence of rating-triggered events, as step-up bonds, loss of access to the commercial paper market and strategic benefits in bidding for contracts, credit ratings have an impact on firm capital structure decisions.

In turn, the capital structure decision has been demonstrated to have a high importance in the corporate financing decision of merger and acquisition (M&As) investments. Bidding firms consummate M&As by using either cash or stock as the sole consideration in the transaction, while some transactions apply a mixture of cash and stock means of payment.[1] A developing body of prior M&A studies has indicated that cash-financed acquisitions are to a great magnitude funded by debt (see Bharadwaj and Shivdasani (2003), Faccio and Masulis (2005), Harford et al. (2009), and Uysal (2011)). Additionally, in the literature which associates investment decisions with financial constraints, Fazzari et al. (1988) argue that information asymmetry influences firm investment decisions since, it forms financial constraints in the credit markets. Along these lines, Almeida, Campello and Weisbach (2004), Gilchrist and Himmelberg (1995), Whited (1992), and Campello and Chen (2010) use credit ratings as a proxy of firm financial constraints in the credit markets and propose that the existence of credit ratings mitigates information asymmetry about firm value, thus reducing financial constraints. This allows firms with rated public debt to issue funds in a short notice according to their investment needs. However, one could argue that the simple existence of a credit rating does not prove *ex-ante* that a rated firm possess a higher capability to borrow funds. To illustrate this, assume we have two firms A and B. Firm A has high growth opportunities and a strong financial structure, but is deprived of public debt and credit rating. On the other hand, firm B has lower growth opportunities and a very low credit rating, as it faces a high debt burden and large default costs. Apparently, in this case the unrated firm A has a higher debt capacity than firm B, instead of the fact that it does not carry a credit rating. The above argument raises two interesting questions in relation to the association between bidders' credit ratings, as implied by their capability to access public debt markets, and the choice of method of payment. Does the mere existence of the bidding firms' credit ratings - regardless of the level - affect the financing decision in M&As? What is the impact of a rating level on the choice of the acquisitions' mode of exchange?

[1] The use of cash as a method of payment in corporate takeovers was prevalent during the 80's, followed by a decline during the 90's, and it became popular again over the first decade of the new century (see Andrade, Mitchell and Stafford (2001), and Martynova and Renneboog (2008)).

Motivated by the low financial constraints of (highly) rated firms due to their relatively higher debt capacity and credit quality, I focus on these questions and investigate the role of credit ratings in the choice of payment method in mergers and acquisitions. Regarding to debt capacity, various prior studies (see Cantillo and Wright (2000), Faulkender and Petersen (2006), and Lemmon and Zender (2010)) apply credit rating existence as a measure of debt capacity. There are two main interpretations proposed for the relationship between debt capacity and credit ratings: 1) the demand and supply factors of debt capacity,[2] and 2) the pecking order theory. By stating that debt capacity is driven by demand and supply factors, these studies document that firms with credit ratings have relatively more tangible assets and fewer growth opportunities (demand side), lower levels of information asymmetry and less external frictions of debt in the form of credit rationing and reorganization costs (supply side) hence, being more leveraged (see Cantillo and Wright (2000), and Faulkender and Petersen (2006)). Specifically, Faulkender and Petersen (2006)) empirically demonstrate that firms holding credit ratings are, in general, more leveraged; in particular, they employ 35% more debt in their capital structure implying relatively higher debt capacity. Secondly, Lemmon and Zender (2010) show that in the group of firms having a credit rating, the pecking order theory of capital structure is a good first-order explanation of their financing policy. That is, firms first select to use internally generated cash; however, when it comes to the choice of debt versus equity, financially unconstrained firms use firstly debt and lastly equity. Specifically, they face favorable borrowing costs up to the point where they do not surpass their debt capacity and consequently the use of extra debt does not comprise a burden in their value (see Myers (1977)).

[2] On the demand side, firms with stable cash flows, higher proportions of fixed assets and low growth opportunities have higher debt capacity and therefore higher demand for debt financing (see Myers (1977)). On the supply side, asymmetric information between firm management and investors (see Stiglitz and Weiss (1981)) and debt market frictions (see Faulkender and Petersen (2006)) can impede firms' capability to issue more debt, mainly due to credit rationing from the lenders and imperfect access to public debt markets.

Accordingly, Billett, Hribar and Liu (2011) state that firms with higher credit ratings face lower cost of debt, which, *ceteris paribus,* prompts an enhanced debt capacity. Regarding credit quality, Liu and Malatesta (2005), and Frank and Goyal (2009) argue that the higher the level of credit ratings, the lower the information asymmetry and the adverse selection problem confronted by firms. In a different framework, theoretical studies that investigate firms' debt composition suggest that as credit quality improves, it is more probable for firms to choose "arms length" than bank-debt funding (Boot and Thakor (1997), Chemmanur and Fulghieri (1994), Diamond (1991), Holmstrom and Tirole (1997), and Bolton and Freixas (2000)). Specifically, firms face a choice between bank- and public-debt. On the one hand, banks are more efficient in minimizing the cost of financial distress through their monitoring function; nevertheless, they bear intermediation costs that are passed out to the borrowers creating bank debt more expensive than public debt. On the other hand, bonds carry lower interest rates however; public borrowers incur higher costs if they become distressed. The final corollary of the proposed models is that firms with high credit quality borrow from public bond markets, while it pays off for firms with low levels of credit quality to turn into bank (monitored) financing. Along the same lines, Rauh and Sufi (2010) document empirically that low credit quality firms seem to depend more often on costly types of debt financing that include secured bank-debt with tight covenants for liquidity, and subordinated public-debt relative to high credit quality firms.

Furthermore, Radhakrishnan et al. (2013) demonstrate that firms with high credit ratings face a lower exposure to rollover-risk and their bonds trade at lower yield spreads than firms with low credit ratings. Similarly, evidence from studies that investigate in particular the impact of credit rating levels on bond yield spreads (see Ederington, Yawitz and Roberts (1987), Liu and Thakor (1984), West (1973), Ziebart and Reiter (1992), and Chen, Lesmond and Wei (2007)) document a strong negative relationship. Finally, several regulations of financial institutions and other intermediaries are directly fixed to credit ratings issued by "Nationally Recognized Statistical Rating Organizations" (NRSROs) (see Kisgen (2007)). Specifically, a high number of institutional investors are prohibited from investing in low credit rating firms or below a certain threshold (investment grade) due to considerations associated with investors' wealth conservation. Hence, firms with high levels of credit ratings avoid these regulatory constraints and face a larger "investor base" when seeking to borrow capital for the financing of their investment projects.

In this study, I use a sample of US acquisitions of publicly traded bidders over the period 1998-2009 in order to investigate my main hypotheses which are outlined as follows: 1) bidders holding a credit rating should have better access to public debt markets. Thus, this lack of financial constraints makes them less hesitant to use their cash in the present as it will be relatively easier for them to borrow "fresh cash" in the future whenever it is required.[3] However, this hypothesis does not capture the full dimensions of a firms' debt capacity status as discussed above. In fact, the simple existence of bidder firms' credit rating does not necessarily implies higher debt capacity than unrated firms and hence, does not entail *ceteris paribus* a positive relation with the use of cash financing in M&As. Therefore, the sign and magnitude of the association between rating existence and cash mode of exchange is a matter of empirical investigation; 2) bidders with a higher credit rating level (i.e., better credit quality) have relatively better opportunities to borrow as they incur lower cost debt and higher demand for their debt securities. Hence, it is expected a positive relationship between rating level and cash method of payment in M&As.

However, previous literature, which investigated the determinants of the method of payment in acquisitions, documents that this choice is driven either by other variables used to

[3] Note that cash used in M&A transactions may be sourced either from past operations or from additional debt; the source of accumulated cash is beyond the scope of this work. The point I wish to make here is that, regardless of the source of cash, rated bidders might have higher propensity to make use of it due to their ease of access to the credit markets in the future.

measure debt capacity (see Faccio and Masulis (2005), Harford et al. (2009), and Uysal (2011)) or other factors such as growth opportunities (see Martin (1996)), information asymmetry about the bidding or target firm value (see Eckbo, Giammarino and Heinkel (1990), Hansen (1987), and Chemmanur, Paeglis and Simonyan (2009)), corporate control issues (see Amihud, Lev and Travlos (1990), Ghosh and Ruland (1998), Martin (1996), and Faccio and Masulis (2005)), concerns relating to the potential competition for the target (see Fishman (1989), and Berkovitch and Narayanan (1990)), agency costs of free cash flow (see Jensen (1986)), market timing (see Shleifer and Vishny (2003), and Rhodes-Kropf and Viswanathan (2004)), target status and diversification effects (see Faccio and Masulis (2005)), and the mode of acquisition (see Martin (1996)). Therefore, I am examining if these hypotheses are still valid, after taking into account the impact of all the above factors. In my investigations I control for these determinants by including the variables suggested in prior studies.

Different econometric methodologies are employed to estimate the probability of the choice of payment method and it is found that: 1) The likelihood of a cash offer or fraction of cash used as payment method in the takeover bid are not significantly associated with bidder credit rating existence; 2) The likelihood of a cash offer or fraction of cash used in the acquisition bid have a strong positive relationship with bidding firm credit rating level. In economic terms, after transforming the coefficients of the regressions into average marginal effects, one point rise in bidder rating level increases the likelihood of cash means of financing used in an M&A transaction by 6.52% over the sample average; 3) Unused debt capacity, measured with the relative credit rating level of bidder to target, also appears to be a determinant of cash financing in M&As corroborating the view that credit ratings are related with the choice of payment method in acquisitions; 4) My main results continue to hold even after taking into account the possible endogenous nature of the main variables of interest, credit rating existence and credit rating level.

This study has several contributions in the M&As, capital structure and credit ratings literature. First, it adds to the existing literature on the determinants of method of payment, and especially the relationship between a firm's credit rating and the use of cash or stock financing in acquisitions. Second, it investigates both credit rating existence and credit rating level as measures of the firm's capability to access public debt markets. Third, it presents more evidence regarding the association between credit ratings and firm's capital structure policies; in particular, the financing decision in takeover bids. Generally, my results imply that credit ratings ameliorate information asymmetry and, consequently, reduce bidding firms' cost of capital; firms having a high rating incur lower financial constraints and can issue public debt for investment purposes with relatively less frictions. My findings also provide straightforward implications for academics and practitioners. Specifically, bidding firms with high credit quality and access to public debt markets are able to conduct cash acquisitions and, therefore, rip the benefits related to that form of payment. In particular, prior literature demonstrates that bidders using cash currency enjoy non-negative abnormal returns in acquisitions of both public (see Brown and Ryngaert (1991), Moeller, Schlingemann and Stulz (2004), Travlos (1987), and Schlingemann (2004)), and private targets (see Chang (1998), Moeller et al. (2004), and Officer, Poulsen and Stegemoller (2009)). Furthermore, there exists empirical evidence that the usage of cash meets low target managerial resistance and inhibits competition from rival bidders during takeover contests (see Betton, Eckbo and Thorburn (2009), Fishman (1989), Jennings and Mazzeo (1993), and Chemmanur et al. (2009)).

This study is related to a number of previous works. For instance, studies that investigate the determinants of the method of payment choice, such as (Amihud et al. (1990), Berkovitch and Narayanan (1990), Eckbo et al. (1990), Fishman (1989), Hansen (1987), Jensen (1986), Martin (1996), Shleifer and Vishny (2003), Chemmanur et al. (2009), Faccio and Masulis (2005), Harford et al. (2009), Rhodes-Kropf and Viswanathan (2004), and Uysal (2011)). In fact, Faccio and Masulis (2005), Harford et al. (2009), and Uysal (2011) who study particularly the impact of a firm's debt capacity on the cash-stock choice of payment are more directly associated to this work. Faccio and Masulis (2005), employ bidder's leverage, collateral and interlocking directorships, while Harford et al. (2009), and Uysal (2011) use the deviation from bidder's target debt ratios as a proxy of debt capacity. I, instead, apply credit ratings as measures of debt capacity and credit quality. Sufi (2009) examines the impact of the introduction of syndicated bank loan ratings on various firm financing and investment decisions, including the decision to pay with cash for the consummation of an acquisition. In this work, I concentrate on the relationship between long term bond ratings and payment method in corporate acquisitions. More recently, Alshwer, Sibilkov and Zaiats (2011) examine the relationship between financial constraints and the choice of payment method in M&As. My study focuses specifically on the direct impact of credit ratings in the M&As' financing method by employing various credit rating variables in the empirical analysis. Moreover, Harford and Uysal (2012) study the effect of bidding firm access to bond markets, as implied by the existence of credit ratings, on the decision to undertake a takeover and shareholders' wealth creation. In this study, I focus on the influence of both credit rating existence and credit rating level in a different acquisition decision; that is, the choice of payment method. Faulkender and Petersen (2006), Lemmon and Zender (2010), and Kisgen (2006, 2009) investigate the impact of credit ratings on firms' capital structure policy. Here, I examine the effect of credit ratings on firms' financing decision – that is, in turn, associated with their capital structure – in the context of M&As.

The remainder of the chapter is organized as follows. Section 2.2 discusses the determinants of the choice of method of payment in M&As documented in prior literature providing also the variables definitions used in the empirical analysis. Section 2.3 describes the sample. Section 2.4 analyzes the methodology and findings of the empirical tests. I present further robustness checks of my results in Section 2.5. Finally, Section 2.6 concludes the chapter.

2.2 Determinants of the Method of Payment Choice and Variables Definitions

2.2.1 *Debt Capacity, Financial Condition, Market Credit Risk and Method of Payment*

Prior literature has shown that there are several factors that capture debt capacity. Faccio and Masulis (2005) use the *collateral* variable, which is the ratio of property, plant and equipment (PPE) to book value of total assets at the year-end prior to the acquisition announcement to proxy for debt capacity. Hovakimian, Opler and Titman (2001) report a strong positive effect of tangible assets to the firm's level of debt. The bidder's size is another variable of relevance, as larger firms are more diversified and, hence, have a lower probability of default, enabling them to issue more debt. To account for this effect, the variable *size* is used, which is the natural logarithm of the market value of equity 4 weeks prior to the acquisition announcement. Furthermore, financial leverage controls for bidder's financial condition. The variable *leverage* is measured by the ratio of a firm's total financial debt (long-term debt plus debt in current liabilities) to the book value of total assets in the fiscal year prior to the acquisition announcement. The predicted sign of this variable is ambiguous as Faccio and Masulis (2005) find a negative association between leverage and the likelihood of cash, while Harford et al. (2009) report a positive relation. Finally, in order to capture the effect of market credit conditions, Harford (2005) uses the variable *interest rate spread*, which is the spread between the average rate on commercial and industrial loans and the Federal Funds rate. This variable is provided by the Federal Reserve Senior Loan Officer's (SLO) survey and proxies for the ease of financing or credit constraints in the economy.[4] When the spread is low, and therefore firms face relatively lower cost of debt capital, the likelihood of cash acquisition should be higher. Therefore, a negative relationship between the interest rate spread and the likelihood of cash deals is predicted.

2.2.2 *Growth Opportunities, Market Timing and Method of Payment*

The investment opportunities theory posits that a relation between acquirer valuation and mode of acquisition exists, as long as the firms with more growth opportunities avoid underinvestment problems caused by high levels of debt finance; in response to that, they prefer to use stock (see Martin (1996), and Jung, Kim and Stulz (1996)). To proxy for growth opportunities, the bidder's book to market ratio is used and a positive relationship with the likelihood of a cash consideration is expected. The variable *book-to-market* is defined as the book value of equity at the fiscal year-end prior to the acquisition announcement divided by the market value of equity 4 weeks prior to the acquisition announcement.

Moreover, according to the market overvaluation theory (see Shleifer and Vishny (2003), and Rhodes-Kropf and Viswanathan (2004)) acquirers favor stock acquisitions when their equity is relatively overvalued to target firms' equity in order to decrease acquisition costs. Faccio and Masulis (2005) use *run-up* to measure bidder overvaluation. *Run-up* is the bidder market-adjusted buy-and-hold returns over the period (-205, -6) days prior to the acquisition announcement.

[4] I also use in the robustness section analysis an additional proxy of market credit conditions; this is the yield spread between BBB-AAA bonds (see Longstaff (2004)).

2.2.3 Asymmetric Information, Target Status and Method of Payment

Hansen (1987), and Chemmanur et al. (2009) suggest that bidder information asymmetry plays a significant role in the choice of payment method in M&As. Particularly, in cases where bidders possess proprietary information about their own value, they are more likely to use stock when their firm stock is considered relatively "overvalued" and cash when their firms stock is considered relatively "undervalued". Accordingly, the higher the degree of information asymmetry faced by target firms when evaluating bidders' offer, the higher the likelihood of accepting a cash offer as the acceptance of bidder's equity might turn out to be a costly option if the bidder is overvalued. To control for information asymmetry, the variable *intangibles* is employed, which is estimated as the ratio of the firm's total intangible assets to the book value of total assets in the fiscal year-end prior to the acquisition.[5] Barth and Kasznik (1999), and Officer et al. (2009) argue that information asymmetry increases with the level of intangible assets.

Additionally, Faccio and Masulis (2005) take into account the effect of target status on the choice of payment method. This is justified on the grounds that in deals where an unlisted target is involved, the seller's consumption/liquidity needs have to be considered. These sellers are likely to prefer cash due to the illiquid and concentrated nature of their portfolio holdings in a timely attempt to cash out their wealth opportunities. To capture target status, the *private* variable is used, which is an indicator variable taking the value of 1 for an unlisted target and 0 otherwise.

[5] Following Krishnaswami and Subramaniam (1999), and Chemmanur et al. (2009) I also use other measures of information asymmetry such as the *analysts forecasts' error* and the *standard deviation of analysts' forecasts* with data retrieved from IBES for the last month or three last months of the fiscal year preceding the acquisition; the results remain qualitatively similar, however, the sample reduces significantly due to the low coverage of analysts forecasts' data.

2.2.4 Firm Control, Monitoring and Method of Payment

In the spirit of Stulz (1988), and Jung et al. (1996) the likelihood of losing control in their firm leads managers to prefer debt or internal resources relative to equity when deciding to finance an acquisition; this is due to the fact that issuance of new stock is likely to dilute their stake in the bidding firm leading to a loss of control and outside intervention. Thus, managers with higher ownership stakes in the bidding firm are more likely to use cash as a payment form in takeover bids (see Amihud et al. (1990), Ghosh and Ruland (1998), Martin (1996), and Faccio and Masulis (2005)).

Furthermore, Shleifer and Vishny (1997), and Burkart, Gromb and Panunzi (1997) argue that blockholders can monitor the action of corporate managers which helps align the interests of managers and shareholders and leads to better corporate performance. Among others, one of the major actions that large investors can take to improve corporate performance is to advise and put pressure on bidder's managers to proceed to a potential bid or abandon it. These actions include judgments about the terms of the acquisition bid such as the choice of the payment method. Given the empirical evidence on the wealth effects of stock-financed public acquisitions, which demonstrates a significant reduction of bidder's shareholders wealth (see Brown and Ryngaert (1991), Travlos (1987), and Schlingemann (2004)) the likelihood of pure stock takeover deals should be lower when blockholdings are higher. To capture these effects, the variable *blockholder ownership* is employed, which is a measure of the aggregate holdings of blockholders who own at least 5% of the firm's stock.

2.2.5 Pecking Order, Free Cash Flow and Method of Payment

Myers (1984) in his pecking order theory, argues that managers follow a financing hierarchy; that is, they use firstly internal finance, then debt, and finally external equity financing. Moreover, Jensen (1986) states that firms with large amounts of free cash flow are likely to conduct value destroying acquisitions with cash. In particular, firms with large amounts of cash, cash flow or sufficient amount of debt capacity are more likely to use cash to finance their various investment projects. To control for this effect, *cash flows to assets* variable is used, which represents the income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by firm's book value of total assets at the fiscal year-end immediately prior to the acquisition announcement. It is expected a positive association between this variable and the likelihood of a cash acquisition.

2.2.6 Hostility, Competition, Mode of Acquisition, Relative Size, Intra-Industry Deals and Method of Payment

In addition, the characteristics of a takeover deal might have an influence on the payment method. In hostile acquisitions or in cases where more than one bidders compete for a particular target, the bidder might want to consummate the deal relatively quickly and deter competition (see Fishman (1989), and Berkovitch and Narayanan (1990)) thus choosing cash as medium of exchange. Therefore, *hostile deals* variable is used, which is an indicator variable taking the value of 1 for hostile acquisitions and 0 otherwise. The variable *competition* proxies for the degree of competition the bidder faces during a takeover; this is an indicator variable taking the value of 1 when more than one bidders enter the bidding contest and 0 otherwise.

Furthermore, in tender offers when the bidder incumbent management desires to close the deal earlier, cash is also preferred. That is because tender offers with stock must be made in accordance with the Securities Act of 1933, which entails a substantial delay, mainly because the registration statement must be reviewed by the SEC (see Martin (1996)). *Tender offers* is a dummy variable taking the value of 1 for acquisitions labeled as tender offers and 0 otherwise.

Moreover, the likelihood of using cash is likely to decrease by the size of the target relative to the bidder, because it is more difficult to raise large amounts of cash as the size of the deal increases to very high levels. To control for this effect, Harford et al. (2009) employ the variable *relative size. Relative size* is defined as the value of the transaction divided by bidder market value of equity 4 weeks prior to the acquisition announcement.

Finally, the industry diversification effect is another important determinant of the choice of the payment method. Faccio and Masulis (2005) argue that in unrelated industries in which sellers are not well acquainted with the industry risks and prospects of the bidder's business sector, they should be relatively more reluctant to accept stock as a method of payment, primarily because of bidder's overvaluation risk. In this case, sellers are likely to prefer cash in order to mitigate the overvaluation problem. To capture this effect, the *diversifying deals* variable is used, which is a dummy variable taking the value of 1 for inter-industry transactions, and 0 for intra-industry transactions. Industries are defined at the 2-digit SIC level from the Thomson Financial SDC.

2.3 Sample and Data

2.3.1 *Sample Selection Criteria*

I download a sample of US domestic acquisitions announced over the period January 1, 1998 and December 31, 2009 from the Thomson Financial SDC Mergers and Acquisitions Database. The start date of the sample was driven by the availability of data for all variables used in the empirical analysis.[6] The sample consists of both successful and unsuccessful deals. It is required deals to have non-missing transaction value and payment method information. Bidders are listed firms and targets are either listed or private firms. The original

[6] Specifically, this is due to availability of blockholder ownership data from the Thomson ONE ownership database. This database provides ownership data starting from 31st March 1997 and therefore I prefer to start the sample from 1st January 1998 in order to have a more coherent collection of years. In fact, the main results are similar when I include the remaining observations of the year 1997.

sample includes 13,048 deals. I remove from the sample all deals classified as repurchases, liquidations, restructurings, divestitures, leveraged buyouts, reverse takeovers, privatizations, bankruptcy acquisitions and going private transactions. This reduces the sample to 10,828 observations. Furthermore, to include in the sample deals that represent a transfer of control, it is required that the bidder owns less than 10% of target shares before the announcement and seeks to acquire more than 50% after the acquisition. There are 10,166 transactions that meet these criteria. Furthermore, deals worth less than US$ 1 million and less than 1% of a bidder market value are dropped to avoid noise in the analysis. Eventually, there are 6,819 deals that satisfy the above requirements.

Credit rating information for the bidder is collected from COMPUSTAT. Credit ratings represent the Standard & Poor's (S&P) long-term domestic issuer credit ratings. In my sample, the highest level of bidder one month prior to the acquisition announcement is AAA and the lowest is CCC. Out of the 6,819 transactions, 1,747 transactions involve bidders with a credit rating and 5,072 transactions with unrated firms. The main variables of interest are i) the *rating existence*, which is an indicator taking the value of 1 if a bidding firm has a credit rating one month prior to the acquisition announcement, and 0 otherwise; and ii) the *rating level*, which is an ordinal variable ranging from 1 to 22.[7,8]

2.3.2 *Sample Statistics*

Table 2.1 presents descriptive statistics for the overall sample and by payment method (i.e., more than 50% cash and less than 50% cash). For the entire sample of 6,819 acquisitions, 3,156 targets are acquired with more than 50% cash and 3,583 acquisitions comprise less than 50% cash means of transaction. There are also 80 acquisitions that are

[7] A higher rating level corresponds to a larger number (i.e., 22 for AAA and 1 for D – in my case the lowest number is 5 as the lower credit rating level is CCC). See Appendix B for a correspondence between each credit rating level and the number assigned to it.
[8] In the robustness checks section I also proxy for bidders' credit quality by using a dummy variable for investment-grade firms (i.e., firms with a credit rating BBB- or above).

financed exactly with 50% cash and 50% stock. Panel A demonstrates bidder specific characteristics, which appear to differ between the two payment types. The proportion of bidders holding a credit rating (*rating existence*) is higher in cash-dominated financed deals (27.8%) than bidders in acquisitions with less than 50% cash (24.1%). The mean difference is statistically significant at the 1% level. Mean bidder *size* for cash-dominated deals is US$ 3,672.396 million, whereas the average bidder size for non-cash dominated deals is larger (US$ 5,092.108 million). Bidders in cash-dominated deals have significantly higher mean and median *leverage* and *collateral* relative to bidders in non-cash dominated deals. Furthermore, bidders *book-to-market* mean (median) ratio is significantly higher in cash-financed acquisitions 0.530 (0.417), than in acquisitions with less than 50% cash (0.442 (0.339)), which is consistent with the growth opportunities story. Additionally, bidders mean (median) *run-up* is significantly lower in cash deals (0.010 (-0.069)) relative to non-cash dominated acquisitions (0.209 (-0.027)). The figures from the *run-up* variable support the overvaluation theory. Regarding *blockholder ownership*, in cash acquisitions bidders have relatively more concentrated ownership with a mean (median) of 25.97% (22.63%), while in non-cash dominated deals they are the more widely diffused (17.59% (11.82%)). This finding is in line with the corporate control hypothesis. *Cash flows to assets* is significantly higher in cash acquisitions with a mean (median) of 0.052 (0.074) than in non-cash dominated acquisitions (-0.046 (0.013)), in support of the free cash flow hypothesis. Finally, *intangibles* appear to differ between the two methods of payment, as the mean (median) intangibles are 0.205 (0.142) for cash deals and 0.123 (0.034) for less than 50% cash financed deals, respectively.

Panel B presents the statistics for target characteristics. Target mean (median) *leverage* is significantly lower in cash deals (0.174 (0.108)) than in non-cash dominated deals (0.204 (0.153)). Concerning target *book-to-market* ratio I am not able to establish a significant mean or median difference between the two methods of payment. Additionally, target mean and median *blockholder ownership, intangibles and profitability* are significantly higher in cash deals than in non-cash dominated financed deals.

Panel C presents the statistics for deal-specific characteristics, which, again, appear to differ between the two financing categories. The mean (median) *interest rate spread* is significantly higher in cash-financed acquisitions 2.188 (2.120), than in less than 50% cash financed acquisitions (2.090 (2.050)). The average (median) size of the target relative to the bidder (*relative size*) is lower for cash deals 23.0% (8.6%), than the relative size of non-cash dominated deals 33.2% (13.0%). Consistent with the previous analysis, the percentage of bidders and targets being in the same industry is lower for non-cash dominated deals (34.22%), while cash deals have a higher proportion of diversifying deals (38.47%). The statistics for the *hostile* deals support the mode of acquisition hypothesis as the percentage of hostile acquisitions is higher in cash deals (2.19%) than in less than 50% cash acquisitions (0.81%). Moreover, 8.40% of cash-financed acquisitions represent *tender offers*, while only 1.28% of non-cash dominated form of financing are tender offers. In cash deals the percentage of acquisitions of *private* targets accounts for 72.66% of the overall sample, while in non-cash dominated deals acquisitions of private targets represent the 57.10% of the overall sample. Finally, the *number of bidders* is significantly higher, on average, in cash deals (1.035) than in non-cash dominated deals (1.024).

[Please Look Table 2.1]

Table 2.2 presents the descriptive statistics by rated and unrated bidders. The statistics from this table will shed further light on the relation between the method of payment and credit ratings. Panel A presents bidder characteristics. Rated bidders are, on average, larger (US$ 12,920.240 million) than unrated ones (US$ 1,508.230 million). Further, rated bidders have significantly higher mean and median *leverage*, *collateral*, *book-to-market* and lower mean and median pre-acquisition *run-up* than unrated bidders. The average (median) *blockholder ownership* is lower for the rated bidders (18.30% (13.88%)) relative to the unrated ones (22.90% (18.71%)). Finally, rated bidders also exhibit higher mean and median *cash holdings* and *intangibles* than bidders without a credit rating.

Panel B reports statistics for targets characteristics by rated and unrated bidders. Target firms receiving bid offers by rated bidders appear to have higher mean and median *leverage*, *book-to-market*, *intangibles* and *profitability* ratios than target firms associated with unrated bidders.

With respect to deal characteristics, the relative size of the transactions appears to differ as the median value of the rated group is 0.086 and is significantly lower than the unrated group (0.111). Further, in the rated group the mean (median) fraction of cash that is used as method of payment is greater (0.506 (0.505)) than the unrated group (0.457 (0.424)). Concerning hostile acquisitions and tender offers, rated bidders execute more deals of these types compared to unrated ones. Finally, I find that rated bidders are involved in less private deals and face a higher degree of competition in the takeover contest than unrated ones.

[Please Look Table 2.2]

From the analysis so far, it has been noticed that rated bidders have, for instance, significantly larger size and higher leverage, among others, than unrated bidders. Additionally, size and leverage are important determinants of the financing method in M&As. Therefore, in order to establish a more concrete statistical relationship and uncover the net effects of the credit rating variables, I present, in the next section, multivariate analysis controlling for several determinants of the choice of payment method. The correlation matrix of the above variables is presented in Table 2.3. The main variables of interest - *rating* *existence* and *rating level* - do not exhibit high correlation with the control variables. This should moderate econometric difficulties (such as multicollinearity concerns) in disentangling any effects of the credit rating variables on the choice of the payment method in takeover deals.

[Please Look Table 2.3]

2.4 Empirical Analysis

2.4.1 *Fractional Logit Regressions*

In order to investigate the relationship between credit ratings and the choice of payment form in acquisitions, I firstly use as dependent variable the fraction of cash as part of the total price offered by the bidder. Since by definition this variable is a fractional response and lies in the interval [0, 1], I follow Papke and Wooldridge (1996) and use a Generalized Linear Model (GLM) Logit regression where the parameters of the model are obtained by the Quasi-Maximum Likelihood Estimator (QMLE).

2.4.2 *Credit Rating Existence and Method of Payment*

Initially, it is examined the relation between bidder credit rating existence and method of payment by controlling for various bidder-, and deal-specific characteristics. All regressions also control for year fixed effects whose coefficients are suppressed. Additionally, I use heteroskedasticity-robust standard errors adjusted also for bidder clustering due to the presence of repeated acquirers in the sample. Table 2.4 presents the results, in which the first main variable of interest is the *rating existence*. Specification (1) also includes bidder *size*. I find that the rating existence coefficient is positive and statistically significant at the 1% significance level. Bidder *size* has a negative association with the cash consideration in contrast to my hypothesis for debt capacity.[9] In specification (2) I add further bidder- and deal-specific characteristics. Noticeably, I observe that the significant relationship between cash deals and rating existence disappears. This finding is in line with the prediction that the mere existence of credit rating does not prove *ex-ante* the superior debt capacity of rated firms.

Additionally, in the regression I am able to confirm the results from the past literature as I find that most of the control variables have a significant relationship with the cash consideration. More specifically, independent variables that capture firm's financial condition, such as *Leverage* and *Collateral* carry positive and significant coefficients. *Book-to-market* is consistent with the growth opportunities theory as it is positively related with the use of cash. Further, I am able to confirm the market timing hypothesis, since I find that *run-up* is negatively associated with cash method of payment. That is firms with high pre-acquisition valuations are less likely to use cash in the transaction. In addition, I find that the higher the concentration of ownership the more likely the use of cash consideration, as *blockholder ownership* holds a positive and statistically significant coefficient at conventional levels. The free cash flow hypothesis is also supported by my results; *cash flows to assets* carries a positive and significant coefficient at the 1% significance level. With respect to information asymmetry, I corroborate the past literature and find that the bidder *intangibles* are positively associated with the use of cash. *Relative size* is negatively related with the use of cash in M&As, while the target *private* status is positively associated with cash financing. Lastly, I document that in *diversifying*, *hostile* and *tender offer* deals, cash is more likely to be the means of payment.

[9] My results should not be affected by any potential multicollinearity, given the large sample size with sufficient variation in our explanatory variables. I still perform a multicollinearity (VIF) test for all specifications throughout the study and find that correlation between explanatory variables does not have any material effect on the estimates.

2.4.3 *Credit Rating Level and Method of Payment*

In the previous section it is documented that when I take into account a variety of factors known to affect the method of payment decision, the relation between the existence of credit ratings and the use of cash disappears. In this section, I attempt to shed light on the second research question: How is credit quality related with the method of payment in M&As? In this respect, I use the *rating level* as the main variable of interest. Table 2.4 (specifications (3) and (4)) presents the results for this analysis. First, in specification (3) I also add bidder *size*. The variable of interest has a positive and significant coefficient at the 1% significance level. Bidder *size* exhibits a negative relationship with the use of cash. In specification (4) I also control for other bidder- and deal-specific characteristics in the sample. Consistent with my prediction, the higher the credit rating level, the higher the likelihood of a cash acquisition. This result has a strong economic significance, as one point rise in the rating level increases the likelihood of using cash mode of payment in acquisitions in the overall sample by 6.52%.[10] From the remaining control variables, *size, book-to-market, cash flows to assets, relative size, diversifying, hostile, tender offers* and *private* acquisitions carry significant coefficients at conventional levels with signs consistent to the prior M&A literature.

[Please Look Table 2.4]

2.4.4 *Probit Regressions*

In this section we try to distinguish the qualitative nature of the choice of the medium of payment by using Probit regressions. The parameters of the Probit model are computed with the method of Maximum Likelihood Estimator (MLE). In this respect, the dependent

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[10] This is estimated by calculating average marginal effects and dividing the coefficient of the main independent variable of interest to the mean value of the percentage of cash that is used for acquisitions in the total sample.

variable takes the value of 1 for deals financed with more than 50% cash and 0 for deals financed with more than 50% stock. Table 2.5 presents the results for the Probit regressions.[11]

2.4.5 *Credit Rating Existence and Method of Payment*

Consistent with the above analysis I examine the relation between credit rating existence and the likelihood of using cash as the consideration in M&As. My main variable of interest is the *rating existence* and the control variables are the same as above. The results are qualitatively similar with the analysis in Table 2.4, since in specification (1), which includes only one control variable (i.e. bidder size), the main variable of interest exhibits a positive and significant coefficient, whereas in the full model (2) the significant association between credit rating existence and the probability of a cash acquisition disappears. All other control variables generally exhibit the same relationship with the choice of cash method of payment as in Table 2.4.

2.4.6 *Credit Rating Level and Method of Payment*

Next, I test the relation between credit rating levels and the likelihood of using cash as the method of payment in M&As. The main variable of interest is the *rating level* and the control variables are as above. In specification (3), which adds only bidder *size* as control variable, the rating level is significant at the 1% significance level, and in specification (4) which comprises the full model, the rating level is also positive and significant at the 1%

[11] A benefit of a Probit regression is that it allows one to focus on the qualitative decision of firms to finance with cash or stock. In many mixed deals the acquirer does not always specify the actual percentage of cash financing, as target shareholders are offered with a choice of cash or stock financing. Thus, the decision can also be specified as choosing among cash, stock or a mixture. In that respect, an Ordered Probit regression is preferred, in which the dependent variable is 0 for pure stock deals, 1 for mixed deals, and 2 for all cash deals as in Faccio and Masulis (2005). In the robustness section I present the analysis by using Ordered Probit and my results are qualitatively similar.

significance level. That is, the higher the credit rating the more likely bidders to use cash in a takeover deal. [12]

[Please Look Table 2.5]

2.4.7 *Unused Debt Capacity and Method of Payment*

Myers and Majluf (1984) propose a specific financial rationale for M&As based on the complementary fit between different levels of debt capacity of bidders and targets. Bruner (1988) concentrates particularly in the case in which target firms with increased growth opportunities face capital constraints regarding the financing of their investment opportunities; the author suggests that it always pays for a bidder with higher debt capacity and lower growth opportunities to acquire a capital constrained target, since the higher debt capacity of the combined firm will help the firm to put forward all the positive NPV projects that the constrained firm might pass up. On the other hand, Smith and Kim (1994) empirically document that the positive effect of unused debt capacity materializes to the opposite direction; that is, a capital constrained bidder acquires an unconstrained target. Hence, considerations of unused debt capacity between the merging firms can influence the likelihood of using cash as a method of payment; this is mainly due to the fact that the unused debt capacity in one of the two merging parties will lead bidders to use cash for the consummation of the deal, since any increase in leverage associated with cash payments will be absorbed by the unused debt capacity of the combined firm.

To measure unused debt capacity, the *BRating/TRating* variable is proposed, which is the ratio of the bidder credit rating level to target firm credit rating level measuring the difference in debt capacity between the two merging participants. Additionally, given the

[12] In the robustness section I also put as dependent variable the value of 1 for deals financed with more than 50% stock and 0 for deals with more than 50% cash and find the opposite result. In particular, the dependent variable experiences a negative relationship with rating levels, implying that stock method of payment is a decreasing function of rating levels.

arguments for the existence of a non-linear relationship described above, I include the quadratic form of the above variable, $(BRating/TRating)^2$, which is simply a polynomial term. Furthermore, I follow Bruner (1988) and create an interaction variable between *BRating/TRating* and *Relative Size* of the deal.[13] This can be justified by the fact that the impact of unused debt capacity of the merging firms on the choice of cash method of payment should decrease in large transaction values, since it is more difficult to raise large amounts of cash as the size of the deal increases to very high levels. It is worth mentioning that in my sample of 353 deals where both bidders and targets possess a credit rating, roughly 69% of the deals consists of bidders with a higher credit rating level than targets with a mean (median) value of 1.21 (1.13). This is translated in bidders holding approximately 3 (2) notches higher credit ratings than targets.

Table 2.6 presents the results for this analysis, which runs second-order polynomial (GLM) Logit regressions where the dependent variable is the fraction of cash used in the acquisition. We notice that the number of observations reduces significantly due to the requirement that target firms should also hold a credit rating, which leaves private deals out of this analysis. In specification (1) I also add bidder *size*. The *BRating/TRating* coefficient is positive and statistically significant at the 1% level, while the $(BRating/TRating)^2$ variable carries a negative and significant coefficient at the 10% significance level. These results confirm my prediction for the existence of a non-linear relationship between the unused debt capacity of the merging parties and the choice of payment method. Particularly, the relationship seems to follow an inverted *U-shape* (Parabola) curve. This means that the positive effect of bidders' higher credit rating relative to targets increases at a decreasing rate and implies that beyond a specific point the effect becomes negative, consistent to the notion that the relationship can be positive even when the *BRating/TRating* is decreasing (i.e., the

[13] The variables *BRating/TRating* and $(BRating/TRating)^2$ are centered around their mean values to avoid any multicollinearity issues related with the use of polynomial terms in these regressions.

target firm holds a higher credit rating than the bidding firm). In specification (2) I also add all control variables used in the previous analysis as well as the interaction variable *BRating/TRating X Relative Size*. The *BRating/TRating* carries a positive and significant coefficient at the 1% and the $(BRating/TRating)^2$ carries a negative and significant coefficient at the 5% significance level, respectively. Moreover, as expected, the coefficient of the interaction variable is negative and significant at the 5% level. This suggests that the incremental effect of unused debt capacity on the proportion of cash financing decreases as the relative size of the deal increases. Overall, the results imply that the existence of unused debt capacity constitutes a determinant of the use of cash as a method of payment in M&As lending further support to the importance of credit ratings in the choice of acquisition financing.

[Please Look Table 2.6]

2.5 Further Robustness Tests

In the previous analysis I provided evidence that firms with high credit quality (i.e., firms holding a higher credit rating) are more likely to use cash or a higher fraction of cash when they finance an acquisition, while I did not find any strong evidence of a relationship between the choice of cash method of payment and credit rating existence. In this section, I offer additional auxiliary tests to check the validity of my findings.

2.5.1 *Investment-Grade Vs Speculative-Grade Firms*

In order to shed further light on the relationship between credit rating quality and the choice of payment method in M&As, I investigate, for robustness reasons, the impact of investment grade credit ratings. Investment-grade firms are the ones rated with BBB- or above as in An and Chan (2008). These firms are, in general, of higher creditworthiness relative to the speculative-grade firms (i.e. firms with a credit rating below BBB-). In this respect, Longstaff, Mithal and Neis (2005), and Chen et al. (2007) demonstrate that investment grade firms generate lower bond yield spreads relative to the speculative grade ones. Additionally, Molina (2005), and Almeida and Philippon (2007) empirically document that default costs are considerably lower for investment-grade firms than for the speculative-grade ones. Furthermore, due to the absence of regulation restrictions regarding allocations in securities of investment grade firms (see Kisgen (2007), and Kisgen and Strahan (2010)) these firms enjoy a larger clientele base and a higher demand for their debt securities. If investment grade firms face lower cost of debt capital and have a wider access to investors, then it is plausible that they are able to borrow more and use cash more frequently as a method of payment in a takeover deal. Thus, I create the variable *investment grade* dummy taking the value of 1 for firms rated BBB- and above, and 0 otherwise. Table 2.7 reports the results.

In specification (1) the dependent variable is the fraction of cash as part of the total price offered by the bidder and in specification (2) the dependent variable is the choice between more than 50% cash and more than 50% stock consideration. In both specifications I also incorporate the control variables employed in previous analyses. The coefficient of the *investment grade* carries a positive and significant coefficient at the 1% significance level in both specifications. In economic terms, being an investment grade bidder increases the likelihood of using cash as a payment form by 18.94% over the sample average. Overall, the results of this analysis add further support to the hypothesis that firms with high credit quality are more likely to use cash financing in M&As.

[Please Look Table 2.7]

2.5.2 *Endogeneity Control*

2.5.2.1 Propensity Score Matching

So far, in the analysis I treated the credit rating variables as exogenous to my model; that is the decision to obtain a credit rating and the level of credit ratings are randomly allocated across the sample firms. However, Liu and Malatesta (2005), An and Chan (2008), and Harford and Uysal (2012) argue that firms determine, at least partially, whether to obtain a credit rating or have a higher rating level after considering the benefits against the potential costs. Therefore, it is likely that the decision to obtain a (high) credit rating is based on firm specific characteristics and failure to account for these characteristics would lead to biased estimates in my analysis. Initially, I use a propensity score matching (PSM) approach to reduce the potential selection bias in the estimation of the effect of being rated on the choice of payment method under a univariate setting. This is of particular interest since in Table 2.2 I found that the difference in the fraction of cash used between the rated and unrated bidders is significantly different. In that respect, I first estimate a Probit model including variables that determine the outcome (i.e., *fraction of cash* and *cash-dominated*) as well as variables that determine the choice of being rated (i.e., *rating existence*).[14] I then use the results from the Probit regression to compute the bidder's propensity score (i.e., the probability that the firm is rated, given my set of control variables); and finally, I examine the difference in mean values of the fraction of cash used in M&As between the treated and matched control firms based on the results of the propensity scores. In order to obtain robust estimates from this analysis, I use four different matching methods to examine the impact of being rated: 1) One-to-One Matching; 2) 50^{th} Nearest-Neighbor Matching; 3) Local Linear Matching with a Gaussian Kernel; and 4) Local Linear Matching with an Epanechnikov Kernel.[15]

[14] I refrain from a discussion of the variables that affect the choice of being rated in this section and examine the issue extensively in Section 5.2.3 below.

[15] However, according to Rosenbaum (2002) the use of the PSM comes with some limitations. Especially in the choice of instruments there might be found departures from random assignment and consequently, this can lead

Table 2.8 provides the results of this analysis. In Panel A I report the results from the unmatched sample (i.e., without taking into account of the propensity scores) and observe that rated bidders are more likely to use cash as a payment mode relative to unrated bidders. However, after matching the statistical significance of the difference disappears with all four different methodologies (Panels B, C, D and E). This confirms the earlier multivariate regressions results which suggest that just holding a credit rating irrespective of its level does not prove *ex-ante* that a bidding firm possesses a higher capability to access public debt markets.

[Please Look Table 2.8]

2.5.2.2 ***Quasi-Natural Experiment for Change in Rating Status***

To further alleviate concerns that my results might be driven by firm characteristics that are correlated with *rating existence*, I use an approach similar to Harford and Uysal (2012) and investigate whether a change in rating status has an effect on the likelihood of using cash means of financing in M&As. In particular, I restrict the multivariate regressions in a sub-sample of bidders that did not have a rating two years prior to the acquisition (*t-2*) and examine whether holding a rating at the announcement year (*t-0*) has a significant impact on the payment choice decisions at *t-0*, relative to a sample of firms which did not hold a rating at *t-2*. Specifically, I obtain 255 bidders that satisfy these criteria and run the regressions together with all remaining unrated bidders. The results of this analysis are presented in Table 2.9. Specifications (1) and (2) present the results for GLM (Logit) and specifications (3) and (4) show the findings for Probit analysis. I find that the effect of *rating existence* replicates the findings of Tables 2.4 and 2.5. The *rating existence* variable carries a positive and

to biased inferences. Furthermore, the PSM and the corresponding *t*-test that is used in order to examine the difference in the proportion of cash are all based on the normality assumptions and this can further lead to erroneous inferences. To tackle this issue one can use the permutation and non-parametric methods that are discussed in Rosenbaum (2002).

significant coefficient only in the preliminary regressions (1) and (3), in which I include only bidder size as control variable, whereas in the full models (2) and (4) the statistical significance ceases to exist.

[Please Look Table 2.9]

2.5.2.3 *Control Function Approach*

Finally, in order to control for a potential endogeneity bias of either *rating existence* or *rating level*, I use a two-step Control Function Approach. Smith and Blundell (1986), and Rivers and Vuong (1988) use this method to account for endogeneity when the second stage regression is a Limited Dependent Variable (LDV) model and the Endogenous Explanatory Variables (EEVs) are continuous. However, in a recent paper Wooldridge (2013) extends this estimator to cases where the structural regression can be a binary or fractional response model, and the EEVs can be either continuous or discrete in nature; this is particularly true in my case. Control Function estimators firstly calculate the model of endogenous regressor as a function of instruments, like the "first stage" of Two Stage Least Squares (2SLS), and then use the errors from the reduced model as an additional regressor in the structural model. If the coefficient of the included error is not statistically significant, then the null hypothesis of no endogeneity cannot be rejected.[16] In order to apply this approach and get unbiased estimates, instruments are essential; that is, variables that determine the probability of a bidder holding a credit rating or having a high rating, and concurrently are not related with the main dependent variables (*fraction of cash* and *cash-dominated*) in the structural models. It is likely that factors influencing firm's decision to access public debt markets might also influence firm's decision to use cash as a payment method in acquisitions. In this respect, a better strategy would be to avoid firm-specific attributes that determine the probability of having a debt

[16] In that case the coefficient of the included residual captures the degree of correlation "ρ" among the residuals in the reduced and structural regressions, which is a valid and simple test of endogeneity (Wooldridge (2002)).

rating and use industry-specific attributes instead. To accomplish this task I follow the literature on firms' "debt composition" and "determinants of credit rating levels" (Cantillo and Wright (2000), Denis and Mihov (2003), Faulkender and Petersen (2006), Johnson (1997), Krishnaswami, Spindt and Subramaniam (1999), and Ashbaugh-Skaife, Collins and LaFond (2006)) and use variables that have been proposed to account for these effects.

Specifically, Faulkender and Petersen (2006), and An and Chan (2008) suggest that a firm is more likely to issue a public bond and obtain a credit rating when it operates in a well established industry, since it is possible that the bond market investors already know the competitors and are familiar with the economic condition of the industry. Therefore, this reduces the potential costs of information collection that the banks incur when they agree to underwrite a bond issue. To control for this effect, I compute the fraction of firms with credit ratings in the same 3-digit SIC industry group at the fiscal year-end prior to the acquisition and use the log of 1 plus this fraction (*industry fraction*). Johnson (1997), and Cantillo and Wright (2000) argue that public credit markets cater to profitable or safe industries with low default risk. Obviously, bondholders prefer to invest their money in safe securities that yield a periodical interest (i.e., in effect their opportunity cost of capital), and expect at the maturity to collect normally their principal in full. Industries with high and steady cash flows face low default probability, since an abundance or low volatility of cash flows serves as a guarantee that the firms are likely to fulfill timely their debt obligations. To control for the effect of profitability I calculate the median industry profitability (defined as the ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets) of bidders' same 3-digit SIC industry group at the fiscal year-end preceding the acquisition (*industry profitability*). Accordingly, to measure the impact of credit risk I use the standard deviation of the industry's profitability (*industry risk*).

Finally, a number of studies (Smith (1986), Smith and Watts (1992), Krishnaswami, Spindt and Subramaniam (1999), and Ashbaugh-Skaife et al. (2006)) contend that regulated firms tap the public capital markets more frequently, thus revealing firm's cost of capital, which is beneficiary for firms in the process of setting their rating. The periodic use of capital markets disciplines management and constrains their discretion in investment and operating decisions. Furthermore, these papers suggest that, relative to unregulated firms, regulated firms engage more rarely in asset substitution and underinvestment as state utility commissions and other regulatory authorities supervise managerial decisions. To sum up, it follows that firms in regulated industries exhibit low agency costs and, hence, the need for the monitoring role of private debt is limited, a fact that leads to a higher reliance on public debt when debt capital is required. To deal with this effect, I use an indicator variable that equals with 1 if the firm is a financial institution or utility firm (1-digit SIC level 6 or 2-digits SIC level 49), and 0 otherwise (*regulated industry*).

Table 2.10 presents the results of this analysis for different methodologies (i.e., Fractional Probit and Probit).[17] Specification (1) presents the reduced Probit model measuring the probability of having a credit rating. Two of the excluded instruments, *industry fraction* and *industry profitability* carry the expected signs and are significant at the 1% and 5% level, respectively. To examine the strength of the instruments I follow Stock and Yogo (2002) and use the *weak identification test critical values* for the "maximal IV Wald size distortion". However, as Nichols (2007) notes, these identification statistics only apply to the linear case - not the nonlinear analogs - including those estimated with generalized linear models. Therefore, in practice researchers should report the identification statistics for the closest

[17] Note that in this section I use a (GLM) Fractional Probit instead of a Fractional Logit to be consistent with the methodology of Wooldridge (2013) who extends the use of the control function approach in fractional response models by using as a casework example the Fractional Probit. However, this shift in the model does not affect the qualitative nature of my findings since it has been demonstrated that Logit coefficients are roughly 1.6 times the Probit coefficients, and the validity of the inferences is generally irrelevant of whether one uses a Logit or a Probit model (Amemiya (1981)).

linear analog (i.e., in the case of fractional Probit the closest linear analogs for the first stage is a Linear Probability Model (LPM) and for the second stage is a Linear Regression Model) and be careful when drawing inferences from their values.[18] In the lower panel of Table 2.10, I report the *F-test* for the joint significance of the excluded instruments in the first-stage regression, and the critical values for the desired 10% size distortion on a nominal 5% Wald test, computed by the Limited Information Maximum Likelihood (LIML) estimator. In both models (2) and (3) the *F-test* is larger than the corresponding critical values and, hence, I can reject the null of excluded instruments' weakness. Finally, in both structural equations (2) and (3), the *rating existence residual* is insignificant at conventional levels. These findings imply that the variable *rating existence* is exogenous to my model, which mitigates any concerns of confounding effects due to a potential endogeneity bias.

[Please Look Table 2.10]

With regards to the correction for endogeneity in the case of the variable *rating level,* I apply the same method as above, with the rating level choice equation (OLS) being the reduced form, and the method of payment equations (Fractional Probit and Probit) being the structural forms. Additionally, I substitute the instrument *industry fraction* with the variable *industry level,* which is the median credit rating level of the bidders' same 3-digit SIC industry group at the fiscal year-end preceding the acquisition, to control for the credit quality level of the industry. Table 2.11 shows the results for this analysis. In the reduced model (1) three out of the four instruments (*industry level, industry risk* and *regulated industry*) carry the expected coefficients and are all statistically significant at the 1% level. Furthermore, the results from the identification statistics reject the null of excluded instruments' weakness. In both structural equations (2) and (3), the variable of interest *rating level residual,* is

[18] This is indeed the case as the *F-test* from the Probit regression has a value of 44.01 and is significantly higher than the reported *F-test* values from the LPM regression in Table 2.10. This is due to the fact that the rating choice is a binary variable and the Probit regression specifies better this decision than the LPM regression.

insignificant at conventional levels. These results imply that the *rating level* variable appears to be exogenous in my models. Therefore, given that I am not able to identify any existence of endogeneity bias for the rating level in these regressions, I can base my inferences on the results of Tables 2.4 and 2.5, in which the regressions are consistent and efficient.[19] Overall, the findings support my hypothesis of a positive association between credit rating level and the likelihood of using cash as a method of payment in acquisitions.

[Please Look Table 2.11]

2.5.3 *Target Firm Characteristics and Method of Payment*

Finally, in this section, I focus on a subsample of public acquisitions and include in my regressions target firm characteristics known from the literature to affect the method of payment in M&As. In particular, it has been suggested that a target firm's leverage (Hansen (1987)), growth opportunities (Martin (1996)), share ownership (Ghosh and Ruland (1998)), and information asymmetry (Chemmanur et al. (2009)) exert an impact on the likelihood of using cash as a payment form. In particular, target's growth opportunities, share ownership and information asymmetry are expected to have a negative association with the choice of cash in acquisitions, while the predicted relationship of a target firm's leverage with the likelihood of using cash is ambiguous. To control for these effects I add on the top of the control variables used in the previous analysis supplementary target firm's variables (*Tleverage*, *Tbook-to-market*, *Tblockholder ownership*, *Tintangibles* and *Tprofitability*) and report the results in Table 2.12. I use GLM Logit regressions in specifications (1) and (3) and probit regressions in specifications (2) and (4). Specifications (1) and (2) present the results where the main variable of interest is the *rating existence* and specifications (3) and (4) show

[19] It is worth noting that since I employ instruments to measure the choice of credit rating level, by construction the coefficients of rating level in the Control Function Approach regressions exhibit higher standard errors (i.e., loss in efficiency) than the regressions which do not account for endogeneity and, hence, it is likely in some cases the rating level to appear statistically insignificant at conventional levels.

the findings for the *rating level* variable as main variable of interest. With regards to the *rating existence,* I am not able to establish any significant relationship at conventional levels; however, the *rating level* variable continues to be strongly positively associated with cash acquisitions as it carries positive and significant coefficients at the 1% level in both specifications. From the target control variables only *Tleverage* is negative and statistically significant at the 5% level in specification (3). This last set of results adds more evidence regarding the robustness of the basic findings and implies that firms' credit quality is an important determinant of the financing decision in M&As.[20]

[Please Look Table 2.12]

2.5.4 Other Sensitivity Tests

In this subsection the robustness of my results is tested with various additional tests. In an alternative attempt to capture the impact of market conditions on the cost of debt which the bidding firms face, I use the variable *BBB-AAA spread.* This variable measures the difference in yield rates between the average BBB and AAA U.S rated utilities and industrial bonds, retrieved from the Federal Reserve's Selected Interest Rates H.15 release. In Table 2.13 and Table 2.14 I present the results for the (GLM) logit models and probit models respectively. In Table 2.13 the variable *rating existence* is insignificant while the variable *rating level* is significant at the 1% level thus, corroborating my findings so far. The same hold true in Table 2.14 for the two main control variables while I observe that the variable *BBB-AAA spread* does not carry a significant coefficient at any conventional levels.

[Please Look Tables 2.13 & 2.14]

[20] I also employ the Control Function Approach discussed above for the existence of endogeneity on this set of regressions which include target firm characteristics and again we do not find any evidence of endogeneity bias.

Moreover, in Table 2.15 I try to measure the relationship between method of payment and credit ratings by using an ordered probit model. In that case I use as a dependent variable an ordinal variable taking the value of 0 for stock deals, 1 for mixed deals, and 2 for cash deals. In specifications (1) through (2) I present the results for the *rating existence* and in specifications (3) through (4) the results for the *rating level.* I observe that the *rating existence* holds a positive and significant coefficient at the 1% level in both models. The same holds for the effect of *rating level* where I observe that it carries positive and significant coefficients at the 1% level in both specifications. These results corroborate my hypotheses about the impact of credit quality on the choice of cash while on the same time provide some indication about the impact of ratings existence on the method of payment during acquisitions.

[Please Look Table 2.15]

Finally, in Table 2.16 I try to measure the effect of credit ratings on the choice of payment method by using a probit model where the dependent variable takes the value of 1 when the deal is financed with over than 50% stock and 0 when it is financed with more than 50% cash. If the assumptions regarding the positive effect of credit rating levels on the likelihood to pay with cash are correct, I would expect in this alternative specification to find a negative relationship with the likelihood of paying by stock. In models (1) through (2) I present the findings for the *rating existence,* and in models (3) through (4) the findings for the *rating level.* In the full model (2) the rating existence does not exhibit any significant association with the likelihood of paying by stock whereas in the full model (4), the *rating level* holds a negative and highly significant coefficient at the 1% level. These findings further validate the main hypotheses of this study.

[Please Look Table 2.16]

2.6 Conclusion

In this chapter I present direct empirical analysis of the relation between credit ratings and the choice of method of payment in mergers and acquisitions. In particular, I examine whether rating existence and rating level affect the likelihood of cash being used as a form of financing in a takeover bid. In the empirical analysis, I use different econometric approaches to examine this relationship and I am able to establish a positive relation between a bidders' credit rating level and cash payment method. The results are attributed to the lower financial constraints of firms with a high credit rating, as implied by their higher credit quality. The investment grade results also confirm the findings on rating level analysis corroborating the view that cash method of payment is an increasing function of credit quality. Further, unused debt capacity between the counterparties appears to determine the choice of cash method of payment lending further support to the relationship of credit ratings with the financing choice. Moreover, my results have a strong economic significance and are robust even after controlling for endogeneity issues regarding the main variables of interest.

Additionally, in response to the questions raised in the introduction, the findings of this study imply that higher capability to access public debt markets affects the choice of payment method in M&As. In particular, high credit quality associated with lower cost and higher demand for debt securities allows highly rated bidding firms to be less reluctant to use cash in an acquisition investment as it is less painful for them to find cash for new investments in the future.

This study adds to the prior literature by providing further evidence on how credit ratings affect firm capital structure decisions in general, and financing decisions in the M&As process more specifically. In particular, I establish a direct relationship of credit ratings as a determinant of the choice of payment method. The positive likelihood of using cash as a method of payment in acquisitions in which firms have high credit quality can be considered as a high value asset for bidders' shareholders, given the well-documented fact that cash consideration is related with various beneficial outcomes for bidders' shareholders, such as favorable valuation effects and determent of competition in the market for corporate control. Overall, this chapter highlights the role of CRAs in firm's capital structure decisions related particularly with the financing decision in takeover bids.

Appendix A. Variable Definitions

Variable	Definition
	Panel A: Measures of Payment Form
Fraction of Cash	Fraction of cash as part of the total price offered by the bidder to the target shareholders from Thomson Financial SDC.
Cash-dominated	Dummy variable: 1 for deals financed with more than 50% cash, 0 for deals financed with more than 50% stock from Thomson Financial SDC.
	Panel B: Credit Rating Variable
Rating Existence	Dummy variable: 1 for rated bidders, 0 for unrated bidders.
Rating Level	Continuous variable for rated bidders: 1 to 22, AAA level takes 22 and D takes 1.
Investment Grade	Dummy variable: 1 for investment grade bidders (above BBB- threshold), 0 for speculative grade bidders (below BBB- threshold).
BRating/TRating	The ratio of bidder credit rating level to target credit rating level.
	Panel C: Firm Characteristics
Size	Firm market value of equity 4 weeks prior to the acquisition announcement from CRSP in US$ million.
Leverage	Firm total financial debt (long-term debt plus debt in current liabilities) divided by the book value of total assets in the fiscal year prior to the acquisition announcement from COMPUSTAT.
Collateral	The ratio of firm's property, plant and equipment to total assets at the fiscal year immediately prior to the acquisition announcement from COMPUSTAT.
Book-to-Market (B/M)	Book value of equity at the fiscal year-end prior to the acquisition announcement divided by the market value of equity 4 weeks prior to the acquisition announcement. Book value of equity is from COMPUSTAT, market value of equity is from CRSP.
Run-Up	Market-adjusted buy-and-hold returns of the firm over the period starting (-205, -6) days prior to the acquisition announcement from CRSP.
Blockholder Ownership	Aggregate holdings of blockholders who own at least 5% of the company's stock from Thomson One ownership database.
Cash Flows to Assets	Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the total assets at the fiscal year-end immediately prior to the announcement from COMPUSTAT.
Intangibles	The ratio of firm's total intangible assets scaled by total assets at the fiscal year immediately prior to the acquisition announcement from COMPUSTAT.
Profitability	The ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets at the fiscal year immediately prior to the acquisition announcement from COMPUSTAT.

Panel D: Deal Characteristics	
Interest Rate Spread	The spread on the interest rate charged for all industrial and commercial loans over intended federal funds rate. The spread is from the Survey of Terms of Business Lending published by the Federal Reserve Bank of New York in its E2 release.
Relative Size	The ratio of the deal's value to bidder's market value of equity 4 weeks prior to the acquisition announcement from CRSP in US$ million.
Diversifying Deals	Dummy variable: 1 for inter-industry transactions, 0 for intra-industry transactions. Industries are defined at the 2-digit SIC level from Thomson Financial SDC.
Hostile Deals	Dummy variable: 1 for deals defined as "hostile" or "unsolicited" by Thomson Financial SDC, 0 otherwise.
Tender Offers	Dummy variable: 1 for tender offers from Thomson Financial SDC, 0 otherwise.
Private	Dummy variable: 1 for private targets from Thomson Financial SDC, 0 otherwise.
Number of Bidders	Number of bidders during the takeover deal from Thomson Financial SDC.
Competition	Dummy variable: 1 if more than one bidders enter the contest, 0 otherwise.
Panel E: Instrumental Variables	
Industry Fraction	Log of 1 plus the fraction of firms in the same 3-digit SIC industry group that have credit ratings at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.
Industry Profitability	The median ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets of firms in the same 3-digit SIC industry group at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.
Industry Risk	The standard deviation of the ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets of firms in the same 3-digit SIC industry group at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.
Industry Level	The median credit rating level of firms in the same 3-digit SIC industry group at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.
Regulated Industry	Dummy variable: 1 if firm is a financial institution (1-digit SIC level 6) or a utility firm (2-digit SIC level 49), 0 otherwise.

Appendix B. Credit Rating Levels

Credit Rating Level	Numerical Value	Rating Description
AAA	22	Prime
AA+	21	High Grade
AA	20	High Grade
AA-	19	High Grade
A+	18	Upper Medium Grade
A	17	Upper Medium Grade
A-	16	Upper Medium Grade
BBB+	15	Lower Medium Grade
BBB	14	Lower Medium Grade
BBB-	13	Lower Medium Grade
BB+	12	Non-Investment Grade Speculative
BB	11	Non-Investment Grade Speculative
BB-	10	Non-Investment Grade Speculative
B+	9	Highly Speculative
B	8	Highly Speculative
B-	7	Highly Speculative
CCC+	6	Substantial Risks
CCC	5	Substantial Risks
CCC-	4	Substantial Risks
CC	3	Extremely Speculative
C	2	Extremely Speculative
D	1	In Default

Table 2.1

Sample Descriptive Statistics by Payment Method

The table presents descriptive statistics for a sample of US public and private acquisitions announced over the period between January 1, 1998 and December 31, 2009 drawn from the Thomson Financial SDC Mergers and Acquisitions Database. The sample is further classified by the method of payment used in the transaction. The financing category "Cash>50%" includes payments where the percentage of cash used is more than 50%. The financing category "Cash<50%" includes payments consisting of less than 50% cash. Panels A, B and C describe the mean and median values for bidder-, target- and deal-specific characteristics, respectively. Credit ratings represent the Standard & Poor's (S&P) long-term domestic issuer credit ratings from COMPUSTAT. Stock price data is from CRSP, accounting data is from COMPUSTAT. All variables are defined in Appendix A. Statistical tests for differences in means and equality of medians for each characteristic between the two methods of payment are also presented in parentheses.

			Method of Payment					
	Total Sample (N=6,819)		(1) Cash>50% (N=3,156)		(2) Cash<50% (N=3,583)		Difference (1) – (2)	
Variable	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean (p-value)**	**Median (p-value)**
Panel A: Bidder Characteristics								
% Rating Existence	25.620	-	27.788	-	24.114	-	(0.000)	-
Size	4,431.941	491.321	3,672.396	499.581	5,092.108	491.973	(0.002)	(0.875)
Leverage	0.182	0.133	0.189	0.149	0.175	0.124	(0.004)	(0.001)
Collateral	0.351	0.241	0.364	0.256	0.339	0.226	(0.008)	(0.001)
Book-to-Market	0.484	0.377	0.530	0.417	0.442	0.339	(0.000)	(0.000)
Run-Up	0.114	-0.050	0.010	-0.069	0.209	-0.027	(0.000)	(0.001)
% Blockholder Ownership	21.652	17.190	25.966	22.630	17.588	11.820	(0.000)	(0.000)
Cash Flows to Assets	0.001	0.049	0.052	0.074	-0.046	0.013	(0.000)	(0.000)
Intangibles	0.163	0.075	0.205	0.142	0.123	0.034	(0.000)	(0.000)
Panel B: Target Characteristics								
Leverage	0.192	0.135	0.174	0.108	0.204	0.153	(0.003)	(0.000)
Book-to-Market	0.732	0.525	0.737	0.553	0.730	0.513	(0.902)	(0.042)
% Blockholder Ownership	21.000	16.110	26.770	24.040	17.95	11.990	(0.000)	(0.000)
Intangibles	0.105	0.022	0.125	0.044	0.093	0.017	(0.000)	(0.000)
Profitability	0.030	0.057	0.057	0.089	0.014	0.034	(0.000)	(0.000)
Panel C: Deal Characteristics								
Interest Rate Spread	2.137	2.09	2.188	2.120	2.090	2.050	(0.000)	(0.000)
Relative Size	0.283	0.105	0.230	0.086	0.332	0.130	(0.000)	(0.000)
% Diversifying Deals	36.090	-	38.466	-	34.217	-	(0.000)	-
% Hostile Deals	1.466	-	2.19	-	0.809	-	(0.000)	-
% Tender Offers	4.561	-	8.400	-	1.284	-	(0.000)	-
% Private	64.482	-	72.655	-	57.103	-	(0.000)	-
Number of Bidders	1.028	1	1.035	1	1.024	1	(0.032)	-

Table 2.2

Sample Descriptive Statistics by Credit Ratings

The table presents descriptive statistics for a sample of US public and private acquisitions announced over the period between January 1, 1998 and December 31, 2009 drawn from the Thomson Financial SDC Mergers and Acquisitions Database. Panels A, B and C describe the mean, median and number of observations for bidder-, target- and deal-specific characteristics, respectively, for rated and unrated bidders. Credit ratings represent the Standard & Poor's (S&P) long-term domestic issuer credit ratings from COMPUSTAT. Stock price data is from CRSP, accounting data is from COMPUSTAT. All variables are defined in Appendix A. Statistical tests for differences in means and equality of medians for each characteristic for rated versus unrated bidders are also presented in parentheses.

	With Credit Rating (1)			Without Credit Rating (2)			Difference (1)-(2)	
Panel A: Bidder Characteristics	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean (p-value)**	**Median (p-value)**
Size	12,920.240	3,092.009	1,747	1,508.230	296.317	5,072	(0.000)	(0.000)
Leverage	0.306	0.273	1,718	0.137	0.072	4,782	(0.000)	(0.000)
Collateral	0.477	0.346	1,436	0.305	0.210	3,930	(0.000)	(0.000)
Book-to-Market	0.427	0.360	1,725	0.504	0.386	4,798	(0.000)	(0.001)
Run-Up	0.018	-0.038	1,707	0.150	-0.054	4.566	(0.000)	(0.840)
% Blockholder Ownership	18.298	13.880	1,563	22.898	18.705	4,206	(0.000)	(0.000)
Cash Flows to Assets	0.062	0.061	1,681	-0.021	0.041	4,728	(0.000)	(0.000)
Intangibles	0.202	0.130	1,544	0.149	0.060	4,310	(0.000)	(0.000)
Panel B: Target Characteristics								
Leverage	0.252	0.219	830	0.137	0.084	893	(0.000)	(0.000)
Book-to-Market	0.561	0.471	916	0.889	0.617	1,003	(0.000)	(0.000)
% Blockholder Ownership	21.634	17.400	1,023	20.536	14.920	1,399	(0.206)	(0.128)
Intangibles	0.123	0.039	831	0.088	0.011	894	(0.000)	(0.000)
Profitability	0.084	0.100	904	-0.019	0.024	992	(0.000)	(0.000)
Panel C: Deal Characteristics								
Interest Rate Spread	2.137	2.090	1,747	2.138	2.090	5,072	(0.906)	(0.735)
Relative Size	0.275	0.086	1,747	0.286	0.111	5,072	(0.665)	(0.000)
Fraction of Cash	0.506	0.505	1,747	0.457	0.424	5,072	(0.000)	(0.000)
% Diversifying Deals	36.463	-	1,747	35.962	-	5,072	(0.707)	-
% Hostile Deals	3.034	-	1,747	0.927	-	5,072	(0.000)	-
% Tender Offers	9.788	-	1,747	2.760	-	5,072	(0.000)	-
% Private	41.442	-	1,747	72.417	-	5,072	(0.000)	-
Number of Bidders	1.057	1	1,747	1.018	1	5,072	(0.000)	-

Table 2.3

Variables Correlation Matrix

The table presents pair-wise correlations of the variables. The sample consists of US public and private acquisitions announced over the period between January 1, 1998 and December 31, 2009. All variables are defined in Appendix A.

	Rating Existence	Rating Level	Size	Leverage	Collateral	Interest Rate Spread	Book-to-Market	Run-Up	Blockholder Ownership	Cash Flows to Assets	Intangibles
Rating Existence	1.000										
Rating Level	-	1.000									
Size	0.257	0.451	1.000								
Leverage	0.385	-0.448	0.014	1.000							
Collateral	0.225	0.099	0.035	0.299	1.000						
Interest Rate Spread	-0.001	-0.020	0.018	-0.066	-0.009	1.000					
Book-to-Market	-0.057	-0.091	-0.082	-0.043	-0.008	0.115	1.000				
Run-Up	-0.061	-0.142	0.021	0.004	-0.032	-0.058	-0.199	1.000			
Blockholder Ownership	-0.099	-0.331	-0.125	-0.038	-0.033	0.223	0.078	-0.036	1.000		
Cash Flows to Assets	0.127	0.162	0.064	0.010	0.066	-0.001	-0.066	-0.033	0.017	1.000	
Intangibles	0.119	-0.232	0.002	0.142	-0.281	0.084	0.029	-0.001	0.142	0.044	1.000
TLeverage	0.284	-0.067	0.088	0.399	0.298	-0.022	0.012	-0.023	-0.047	0.103	0.016
TBook-to-Market	-0.134	-0.091	-0.096	-0.041	-0.042	0.069	0.170	-0.097	0.127	-0.154	-0.056
TBlockholder Ownership	0.026	-0.159	-0.017	0.005	-0.054	0.257	0.043	-0.012	0.304	0.022	0.202
TIntangibles	0.109	-0.046	0.066	0.042	-0.137	0.077	-0.051	0.008	0.119	0.103	0.415
TProfitability	0.226	0.074	0.104	0.163	0.222	-0.089	-0.138	0.024	-0.108	0.332	0.057
Relative Size	-0.005	-0.132	-0.029	0.061	0.095	-0.002	0.201	-0.037	-0.012	-0.058	-0.038
Diversifying	0.005	0.022	0.004	0.041	-0.059	-0.029	0.012	0.002	0.003	-0.012	0.066
Hostile Deals	0.077	0.009	0.043	0.059	0.087	0.007	0.022	-0.021	0.010	0.029	-0.003
Tender Offers	0.147	0.119	0.057	0.012	0.058	0.024	0.004	-0.037	-0.004	0.057	0.030
Private	-0.283	-0.383	-0.198	-0.076	-0.164	0.003	-0.017	0.055	0.155	-0.032	0.121
Competition	0.088	0.042	0.061	0.046	0.076	0.017	0.012	-0.016	-0.004	0.027	-0.002

	TLeverage	TBook-to-Market	TBlockholder Ownership	TIntangibles	TProfitability	Relative Size	Diversifying	Hostile Deals	Tender Offers	Private	Competition
TLeverage	1.000										
TBook-to-Market	-0.076	1.000									
TBlockholder Ownership	-0.013	0.059	1.000								
TIntangibles	0.148	0.082	0.085	1.000							
Tprofitability	0.119	-0.098	-0.015	0.115	1.000						
Relative Size	0.118	0.009	-0.022	0.025	0.079	1.000					
Diversifying	0.008	0.021	0.068	0.145	0.052	-0.001	1.000				
Hostile Deals	0.060	0.009	0.045	0.036	0.055	0.087	-0.021	1.000			
Tender Offers	0.001	0.009	0.148	0.053	0.019	0.014	0.032	0.155	1.000		
Private	-	-	-	-	-	-0.107	0.075	-0.164	-0.292	1.000	
Competition	0.016	0.002	0.033	-0.019	0.078	0.078	-0.028	0.346	0.158	-0.192	1.000

Table 2.4

(GLM) Logit Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level

The table presents the results of the (GLM) Logit regression analysis of the fraction of cash financing on credit rating existence, credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	All Sample		Sample with Rating Data	
	(1)	(2)	(3)	(4)
Constant	-0.3135***	-2.1626***	0.6590**	-0.9300
	(-2.90)	(-4.51)	(2.15)	(-0.76)
Rating Existence	0.3496***	0.1590		
	(4.72)	(1.51)		
Rating Level			0.0875***	0.1843***
			(3.65)	(5.51)
Ln (Size)	-0.0746***	0.0318	-0.3455***	-0.4290***
	(-4.41)	(1.13)	(-7.02)	(-6.41)
Leverage		0.4711**		-0.1681
		(2.03)		(-0.41)
Collateral		0.2387**		-0.1244
		(2.31)		(-0.74)
Interest Rate Spread		0.0161		0.2148
		(0.07)		(0.35)
Book-to-Market		0.3715***		-0.3330*
		(3.32)		(-1.80)
Run-Up		-0.2311***		-0.2313
		(-4.20)		(-1.46)
Blockholder Ownership		0.0038**		-0.0004
		(2.12)		(-0.11)
Cash Flows to Assets		2.0221***		2.5623***
		(7.64)		(2.60)
Intangibles		0.7765***		0.5359
		(3.91)		(1.29)
Relative Size		-0.2178*		-0.4154**
		(-1.65)		(-2.24)
Diversifying Deals		0.1286**		0.2763**
		(2.00)		(2.06)
Hostile Deals		0.8861***		0.8722*
		(2.85)		(1.85)
Tender Offers		2.1325***		2.1774***
		(12.16)		(8.99)
Private		1.0574***		1.1596***
		(11.13)		(7.12)
Competition		0.1744		-0.0361
		(0.82)		(-0.12)
N	6,819	3,793	1,747	1,106
Pseudo R^2	0.084	0.181	0.137	0.271

Table 2.5

Probit Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level

The table presents the results of the Probit regression analysis of the choice between more than 50% cash and more than 50% stock on credit rating existence, credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. In all models the dependent variable takes the value of 1 for more than 50% cash deals, and 0 for more than 50% stock deals. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	All Sample		Sample with Rating Data	
	(1)	(2)	(3)	(4)
Constant	0.1505*	-1.2564***	0.9169***	0.1136
	(1.82)	(-3.03)	(4.00)	(0.11)
Rating Existence	0.3174***	0.1406		
	(5.55)	(1.59)		
Rating Level			0.0505***	0.1432***
			(2.91)	(5.24)
Ln (Size)	-0.0924***	-0.0123	-0.2650***	-0.3610***
	(-7.19)	(-0.55)	(-7.16)	(-6.46)
Leverage		0.3975**		-0.2094
		(2.06)		(-0.61)
Collateral		0.2310***		0.0734
		(2.61)		(0.48)
Interest Rate Spread		-0.0368		-0.1300
		(-0.18)		(-0.26)
Book-to-Market		0.2748***		-0.1921
		(2.99)		(-1.21)
Run-Up		-0.1491***		-0.0974
		(-3.61)		(-0.78)
Blockholder Ownership		0.0023		-0.0027
		(1.57)		(-0.89)
Cash Flows to Assets		1.4864***		1.3157*
		(7.54)		(1.94)
Intangibles		0.6219***		0.3675
		(3.61)		(1.01)
Relative Size		-0.0642		-0.1726
		(-0.95)		(-1.40)
Diversifying Deals		0.1090**		0.1479
		(1.98)		(1.24)
Hostile Deals		0.5366**		0.5081
		(2.00)		(1.32)
Tender Offers		1.6620***		1.6816***
		(10.45)		(7.24)
Private		0.9253***		1.0507***
		(12.81)		(7.70)
Competition		0.2252		0.0573
		(1.32)		(0.21)
N	6,204	3,394	1,607	999
Pseudo R^2	0.099	0.261	0.157	0.351

Table 2.6

(GLM) Logit Polynomial Regressions of the Payment Form on the Unused Debt Capacity

The table presents the results of the (GLM) Logit Polynomial regression analysis of the fraction of cash financing on the ratio of the bidder to target credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	(1)	(2)
Constant	0.4224	2.4402
	(0.65)	(0.75)
BRating/TRating	1.4233***	2.2692***
	(3.41)	(3.26)
(BRating/TRating)^2	-0.5035*	-1.0096**
	(-1.83)	(-2.56)
BRating/TRating X Relative Size		-2.9639**
		(-2.27)
Ln (Size)	-0.2720***	-0.2668**
	(-4.20)	(-2.30)
Leverage		0.0096
		(0.01)
Collateral		-0.0815
		(-0.25)
Interest Rate Spread		-1.2209
		(-0.78)
Book-to-Market		-0.1249
		(-0.28)
Run-Up		-0.3699
		(-1.28)
Blockholder Ownership		-0.0020
		(-0.29)
Cash Flows to Assets		1.8742
		(1.22)
Intangibles		0.2811
		(0.35)
Relative Size		-0.5964
		(-1.45)
Diversifying Deals		0.2746
		(1.03)
Hostile Deals		0.7667*
		(1.80)
Tender Offers		1.8470***
		(4.38)
Competition		-0.2688
		(-0.70)
N	353	229
Pseudo R^2	0.136	0.264

Table 2.7

Regressions of the Payment Form on the Investment Grade

The table presents the results of the (GLM) Logit (specification (1)), and Probit (specification (2)) regression analyses of the choice of the method of payment on investment grade and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	GLM (Logit)	Probit
	(1)	(2)
Constant	0.0092	0.9689
	(0.01)	(1.01)
Investment Grade	0.5245***	0.5139***
	(2.93)	(3.33)
Ln (Size)	-0.2576***	-0.2423***
	(-4.61)	(-5.21)
Leverage	-0.3205	-0.2966
	(-0.76)	(-0.85)
Collateral	-0.0988	0.0842
	(-0.59)	(0.56)
Interest Rate Spread	0.1869	-0.1964
	(0.32)	(-0.41)
Book-to-Market	-0.2310	-0.1284
	(-1.24)	(-0.82)
Run-Up	-0.3068**	-0.1490
	(-2.03)	(-1.23)
Blockholder Ownership	-0.0021	-0.0042
	(-0.54)	(-1.32)
Cash Flows to Assets	2.9747***	1.7265***
	(3.02)	(2.59)
Intangibles	0.4322	0.3068
	(1.02)	(0.84)
Relative Size	-0.4425**	-0.1833
	(-2.30)	(-1.49)
Diversifying Deals	0.2780**	0.1369
	(2.08)	(1.18)
Hostile Deals	0.8386*	0.4399
	(1.75)	(1.12)
Tender Offers	2.1490***	1.6582***
	(8.65)	(7.07)
Private	1.1020***	1.0042***
	(6.71)	(7.32)
Competition	0.0197	0.1105
	(0.06)	(0.42)
N	1,106	999
Pseudo R^2	0.256	0.332

Table 2.8

Endogeneity Control for Credit Rating Existence: Propensity Score Matching

The table presents the results of the propensity score matching for the credit rating existence and the differences in mean values of the fraction of cash financing for the treated and control groups for a sample of US acquisitions over the period 1998-2009. I use four matching methods: One-to-One Matching, Nearest Neighbor Matching with 50 neighbors, Local Linear Matching using a Gaussian, and Epanechnikov Kernel. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. N denotes the number of observations. P-values are in parentheses.

Procedure	**Mean**		**Difference**	
	Treated (N=1,056)	**Control (N=2,573)**	**(Treated-Control)**	
Panel A:				
Unmatched	0.506	0.457	0.049***	(0.000)
Panel B:				
One-to-One Matching	0.604	0.606	-0.002	(0.917)
Panel C:				
Nearest Neighbor Matching	0.604	0.616	-0.012	(0.512)
Panel D:				
Local Linear Matching Gaussian	0.604	0.603	0.001	(0.933)
Panel E:				
Local Linear Matching Epanechnikov	0.604	0.589	0.015	(0.405)

Table 2.9

Regressions of the Payment Form of Subsample of Non-Rated Firms Two Years Prior to the Acquisition

The table presents the results of the (GLM) Logit (specifications (1) and (2)) and Probit (specifications (3) and (4)) regression analyses of the choice of method of payment on credit rating existence and other bidder-, and deal-specific characteristics for a subsample of firms that did not have a rating at *t-2*. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	GLM (Logit)		Probit	
	(1)	(2)	(3)	(4)
Constant	-0.4301***	-2.3740***	0.0735	-1.5604***
	(-3.64)	(-4.57)	(0.81)	(-3.42)
Rating Existence	0.2825**	-0.0645	0.2802***	0.0218
	(1.96)	(-0.35)	(2.68)	(0.14)
Ln (Size)	-0.0395**	0.0716**	-0.0685***	0.0130
	(-2.09)	(2.14)	(-4.76)	(0.48)
Leverage		0.7003**		0.5820**
		(2.51)		(2.57)
Collateral		0.4140***		0.2963***
		(3.06)		(2.63)
Interest Rate Spread		-0.0182		0.0351
		(-0.07)		(0.16)
Book-to-Market		0.5098***		0.3571***
		(3.77)		(3.06)
Run-Up		-0.2162***		-0.1375***
		(-3.84)		(-3.17)
Blockholder Ownership		0.0060***		0.0058***
		(3.05)		(3.44)
Cash Flows to Assets		1.9383***		1.4593***
		(7.41)		(7.19)
Intangibles		0.8175***		0.6807***
		(3.78)		(3.60)
Relative Size		-0.1393		-0.0235
		(-0.98)		(-0.33)
Diversifying Deals		-0.0073		0.0365
		(-0.10)		(0.58)
Hostile Deals		1.1202***		0.8615***
		(3.13)		(2.87)
Tender Offers		2.2212***		1.7357***
		(9.42)		(8.90)
Private		1.0850***		0.9528***
		(9.59)		(11.16)
Competition		0.3243		0.3008
		(1.17)		(1.41)
N	5,327	2,842	4,833	2,538
Pseudo R^2	0.072	0.170	0.088	0.257

Table 2.10

Endogeneity Control for Credit Rating Existence: Control Function Approach

The table presents the results of the control function regression approach to test for potential endogeneity of credit rating existence for a sample of US acquisitions over the period 1998-2009. Specification (1) is the reduced regression. Specification (2) is the structural regression for the (GLM) Probit regression. Specification (3) is the structural regression for the Probit regression. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations. The lower part of the table shows the *F*-test from the linear first-stage regression testing the joint significance of the excluded instruments and the Stock and Yogo (2002) (LIML) critical values of the 10% expected size distortion on a 5% nominal Wald test.

		(GLM) Probit	Probit
	Reduced	Structural	Structural
	(1)	(2)	(3)
Constant	-6.3832***	-1.4113***	-1.2650***
	(-12.77)	(-4.66)	(-2.88)
Rating Existence		-0.1788	0.0250
		(-0.87)	(0.09)
Rating Existence Residual		0.1261	0.0520
		(1.40)	(0.41)
Industry Fraction	1.5498***		
	(4.51)		
Industry Profitability	1.1482**		
	(2.45)		
Industry Risk	-0.0013		
	(-0.75)		
Regulated Industry	0.1518		
	(0.96)		
Ln (Size)	0.6540***	0.0513*	0.0044
	(17.19)	(1.92)	(0.12)
Leverage	3.6083***	0.4515**	0.4295*
	(12.44)	(2.46)	(1.65)
Collateral	0.3152**	0.1513**	0.2254**
	(2.52)	(2.29)	(2.40)
Interest Rate Spread	-0.1495	-0.0165	-0.0719
	(-0.66)	(-0.12)	(-0.34)
Book-to-Market	0.5343***	0.2280***	0.2855***
	(3.91)	(3.79)	(3.06)
Run-Up	-0.3005***	-0.1380***	-0.1463***
	(-5.13)	(-4.09)	(-3.30)
Blockholder Ownership	-0.0004	0.0019*	0.0025
	(-0.20)	(1.75)	(1.64)
Cash Flows to Assets	1.0245**	1.0992***	1.4444***
	(2.48)	(8.24)	(7.36)
Intangibles	0.9938***	0.4769***	0.6018***
	(4.30)	(3.82)	(3.31)
Relative Size	-0.0031	-0.0806	-0.0533
	(-0.03)	(-1.30)	(-0.82)
Diversifying Deals	0.2101***	0.1028**	0.1304**
	(2.97)	(2.53)	(2.26)
Hostile Deals	-0.4525**	0.4288**	0.5230*
	(-2.00)	(2.27)	(1.83)
Tender Offers	0.3188**	1.2838***	1.6769***
	(2.51)	(12.69)	(10.38)
Private	-0.2392***	0.6183***	0.9089***
	(-2.70)	(10.61)	(11.97)
Competition	0.0220	0.1191	0.2657
	(0.12)	(0.96)	(1.53)
N	3,629	3,629	3,249
Pseudo R^2	0.529	0.178	0.258
***F*-test**		11.02	10.53
LIML size of nominal 5% Wald		5.44	5.44

Table 2.11

Endogeneity Control for Credit Rating Level: Control Function Approach

The table presents the results of the control function regression approach to test for potential endogeneity of credit rating level for a sample of US acquisitions over the period 1998-2009. Specification (1) is the reduced regression. Specification (2) is the structural regression for the (GLM) Probit regression. Specification (3) is the structural regression for the Probit regression. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics in the reduced regression and z-statistics in the structural regressions reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations. The lower part of the table shows the *F*-test from the linear first-stage regression testing the joint significance of the excluded instruments and the Stock and Yogo (2002) (LIML) critical values of the 10% expected size distortion on a 5% nominal Wald test.

		(GLM) Probit	Probit
	Reduced	Structural	Structural
	(1)	(2)	(3)
Constant	0.2306	-0.3680	0.0936
	(0.18)	(-0.52)	(0.09)
Rating Level		0.0363	0.1601*
		(0.60)	(1.85)
Rating Level Residual		0.0735	-0.0211
		(1.17)	(-0.24)
Industry Level	0.1559***		
	(4.18)		
Industry Profitability	0.8229		
	(0.90)		
Industry Risk	-0.0111***		
	(-2.70)		
Regulated Industry	1.1696***		
	(3.48)		
Ln (Size)	1.3599***	-0.1442	-0.3810***
	(19.29)	(-1.61)	(-2.99)
Leverage	-2.3378***	-0.2298	-0.2075
	(-4.18)	(-0.81)	(-0.54)
Collateral	0.6527**	-0.0259	0.0978
	(2.45)	(-0.25)	(0.62)
Interest Rate Spread	0.2304	0.0872	-0.1629
	(0.47)	(0.25)	(-0.32)
Book-to-Market	0.6789**	-0.1273	-0.1851
	(2.45)	(-1.05)	(-1.04)
Run-Up	-0.6959***	-0.1757*	-0.0681
	(-3.84)	(-1.64)	(-0.48)
Blockholder Ownership	-0.0061	-0.0006	-0.0027
	(-1.47)	(-0.26)	(-0.84)
Cash Flows to Assets	3.8777***	1.6047***	1.1237
	(2.76)	(2.68)	(1.53)
Intangibles	0.4018	0.2856	0.3693
	(0.73)	(1.13)	(0.98)
Relative Size	-0.1910	-0.2429**	-0.1875
	(-1.17)	(-2.43)	(-1.47)
Diversifying Deals	0.4120***	0.2027**	0.1632
	(2.67)	(2.45)	(1.30)
Hostile Deals	-0.6256*	0.4341	0.5499
	(-1.84)	(1.46)	(1.22)
Tender Offers	0.5465**	1.2870***	1.7081***
	(2.27)	(9.41)	(7.06)
Private	-0.1506	0.6711***	1.0431***
	(-0.83)	(7.08)	(7.75)
Competition	0.3408	0.0588	0.1554
	(1.23)	(0.32)	(0.53)
N	1,039	1,039	939
Adjusted R^2 (Pseudo R^2)	0.653	(0.270)	(0.350)
F-test		14.70	13.58
LIML size of nominal 5% Wald		5.44	5.44

Table 2.12

Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level with Target Firm Control Variables

The table presents the results of the (GLM) Logit (specifications (1) and (3)) and Probit (specifications (2) and (4)) regression analyses of the choice of method of payment on credit rating existence, credit rating level and other bidder-, target- and deal-specific characteristics for a sample of US public acquisitions over the period 1998-2009. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	All Sample		Sample with Rating Data	
	GLM Logit (1)	Probit (2)	GLM Logit (3)	Probit (4)
Constant	-2.0389*	-0.8654	-0.5299	0.4064
	(-1.71)	(-0.98)	(-0.26)	(0.29)
Rating Existence	0.1397	0.0366		
	(0.75)	(0.25)		
Rating Level			0.1607***	0.1097***
			(3.56)	(3.08)
Ln (Size)	0.0556	0.0448	-0.2881***	-0.2035***
	(1.04)	(1.17)	(-2.93)	(-2.62)
Leverage	-0.4092	-0.4478	-0.6564	-0.5708
	(-0.88)	(-1.27)	(-1.00)	(-1.10)
Collateral	-0.2748	-0.0939	-0.2591	0.0633
	(-1.43)	(-0.61)	(-1.02)	(0.30)
Interest Rate Spread	0.1377	-0.2316	-0.1790	-0.5886
	(0.22)	(-0.49)	(-0.17)	(-0.81)
Book-to-Market	0.2761	0.1913	-0.1151	-0.0528
	(1.38)	(1.48)	(-0.44)	(-0.23)
Run-Up	-0.3405	-0.1360	-0.0807	0.0013
	(-1.53)	(-1.15)	(-0.31)	(0.01)
Blockholder Ownership	-0.0017	-0.0013	-0.0059	-0.0047
	(-0.44)	(-0.44)	(-1.07)	(-1.03)
Cash Flows to Assets	1.9646***	1.2421***	2.0976*	0.8136
	(3.71)	(3.34)	(1.81)	(0.99)
Intangibles	0.1283	0.2495	0.5133	0.7595
	(0.30)	(0.77)	(0.86)	(1.50)
TLeverage	-0.7016**	0.1554	-0.9811**	-0.2084
	(-2.19)	(0.56)	(-2.56)	(-0.57)
TBook-to-Market	0.0233	0.0350	-0.0828	-0.1659
	(0.54)	(1.07)	(-0.54)	(-1.04)
TBlockholder Ownership	0.0021	0.0017	0.0062	0.0050
	(0.56)	(0.62)	(1.13)	(1.16)
TIntangibles	-0.5868	-0.4858	-0.3230	-0.3466
	(-1.43)	(-1.52)	(-0.61)	(-0.78)
TProfitability	0.2239	0.1378	-0.7600	-0.6258
	(0.67)	(0.58)	(-1.36)	(-1.34)
Relative Size	-0.1601	-0.0655	-0.3718*	-0.1962
	(-0.61)	(-0.63)	(-1.78)	(-1.19)
Diversifying Deals	0.1497	0.0553	-0.0326	-0.0513
	(1.02)	(0.49)	(-0.17)	(-0.32)
Hostile Deals	0.8654**	0.4916*	0.8894	0.5196
	(2.34)	(1.69)	(1.60)	(1.21)
Tender Offers	2.1811***	1.6126***	1.9321***	1.4421***
	(10.33)	(9.22)	(6.88)	(5.97)
Competition	0.0675	0.1783	0.0145	0.0512
	(0.27)	(0.96)	(0.04)	(0.19)
N	912	851	497	451
Pseudo R^2	0.243	0.272	0.279	0.301

Table 2.13

(GLM) Logit Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level

The table presents the results of the (GLM) Logit regression analysis of the fraction of cash financing on credit rating existence, credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	(1)	(2)
Constant	-2.1308***	-0.4267
	(-7.94)	(-0.72)
Rating Existence	0.1588	
	(1.51)	
Rating Level		0.1856***
		(5.52)
Ln (Size)	0.0319	-0.4307***
	(1.13)	(-6.42)
Leverage	0.4711**	-0.1610
	(2.03)	(-0.39)
Collateral	0.2385**	-0.1329
	(2.30)	(-0.79)
BBB-AAA Spread	-0.0046	-0.1836
	(-0.04)	(-0.65)
Book-to-Market	0.3719***	-0.3239*
	(3.32)	(-1.79)
Run-Up	-0.2310***	-0.2231
	(-4.19)	(-1.41)
Blockholder Ownership	0.0038**	-0.0005
	(2.12)	(-0.12)
Cash Flows to Assets	2.0220***	2.5667***
	(7.65)	(2.61)
Intangibles	0.7758***	0.5287
	(3.91)	(1.27)
Relative Size	-0.2177*	-0.4153**
	(-1.65)	(-2.24)
Diversifying Deals	0.1287**	0.2815**
	(2.00)	(2.12)
Hostile Deals	0.8858***	0.8727*
	(2.85)	(1.86)
Tender Offers	2.1324***	2.1733***
	(12.16)	(8.97)
Private	1.0573***	1.1581***
	(11.12)	(7.10)
Competition	0.1747	-0.0282
	(0.82)	(-0.09)
N	3,793	1,106
Pseudo R^2	0.181	0.272

Table 2.14

Probit Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level

The table presents the results of the Probit regression analysis of the choice between more than 50% cash and more than 50% stock on credit rating existence, credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. In all models the dependent variable takes the value of 1 for over 50% cash deals, and 0 for less than 50% cash deals. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	(1)	(2)
Constant	-1.2432***	0.0653
	(-5.82)	(0.13)
Rating Existence	0.1400	
	(1.59)	
Rating Level		0.1453***
		(5.30)
Ln (Size)	-0.0117	-0.3650***
	(-0.52)	(-6.51)
Leverage	0.3975**	-0.2094
	(2.06)	(-0.61)
Collateral	0.2296***	0.0628
	(2.59)	(0.41)
BBB-AAA Spread	-0.1150	-0.2497
	(-1.09)	(-1.00)
Book-to-Market	0.2795***	-0.1986
	(3.03)	(-1.29)
Run-Up	-0.1481***	-0.0939
	(-3.60)	(-0.75)
Blockholder Ownership	0.0029*	-0.0028
	(1.92)	(-0.92)
Cash Flows to Assets	1.4874***	1.3036*
	(7.54)	(1.92)
Intangibles	0.6142***	0.3585
	(3.56)	(0.98)
Relative Size	-0.0631	-0.1650
	(-0.94)	(-1.33)
Diversifying Deals	0.1096**	0.1477
	(1.99)	(1.25)
Hostile Deals	0.5367**	0.5206
	(2.01)	(1.36)
Tender Offers	1.6656***	1.6806***
	(10.46)	(7.25)
Private	0.9241***	1.0516***
	(12.81)	(7.68)
Competition	0.2271	0.0535
	(1.33)	(0.20)
N	3,394	999
Pseudo R^2	0.261	0.352

Table 2.15

Ordered Probit Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level

The table presents the results of the Ordered Probit regression analysis of the choice between stock, mixed, and cash on credit rating existence, credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. In all models the dependent variable takes the value of 1 for over 50% cash deals, and 0 for less than 50% cash deals. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	All Sample		Sample with Rating Data	
	(1)	(2)	(3)	(4)
Constant1	-0.4069***	0.7013**	-1.0297***	0.6150
	(-6.11)	(2.37)	(-5.54)	(0.85)
Constant2	0.7744***	2.1345***	0.1174	2.0929***
	(11.55)	(7.15)	(0.63)	(2.84)
Rating Existence	0.3043***	0.1965***		
	(6.34)	(3.00)		
Rating Level			0.0414***	0.1186***
			(2.84)	(5.78)
Ln (Size)	-0.0520***	0.0242	-0.1821***	-0.2250***
	(-4.98)	(1.45)	(-6.32)	(-5.42)
Leverage		0.3035**		0.1574
		(2.39)		(0.60)
Collateral		0.1945***		0.0852
		(2.99)		(0.84)
Interest Rate Spread		0.1143		0.3833
		(0.79)		(1.08)
Book-to-Market		0.1753***		-0.1382
		(2.94)		(-1.25)
Run-Up		-0.1147***		-0.1119
		(-2.79)		(-1.20)
Blockholder Ownership		0.0019*		0.0024
		(1.68)		(0.98)
Cash Flows to Assets		0.6834***		1.5619***
		(5.08)		(2.63)
Intangibles		0.4333***		0.4339*
		(3.55)		(1.73)
Relative Size		-0.1120*		-0.2000**
		(-1.73)		(-2.20)
Diversifying Deals		0.0746*		0.2022**
		(1.83)		(2.43)
Hostile Deals		0.5405***		0.4037
		(2.84)		(1.55)
Tender Offers		1.1421***		0.9745***
		(10.62)		(6.79)
Private		0.5992***		0.6436***
		(9.77)		(6.59)
Competition		0.0560		-0.0226
		(0.42)		(-0.13)
N	6,819	3,793	1,747	1,106
Pseudo R^2	0.0669	0.123	0.0925	0.178

Table 2.16

Probit Regressions of the Payment Form on Credit Rating Existence and Credit Rating Level

The table presents the results of the Probit regression analysis of the choice between more than 50% stock and more than 50% cash on credit rating existence, credit rating level and other bidder- and deal-specific characteristics for a sample of US acquisitions over the period 1998-2009. In all models the dependent variable takes the value of 1 for over 50% stock deals, and 0 for less than 50% stock deals. See Appendix A for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	All Sample		Sample with Rating Data	
	(1)	(2)	(3)	(4)
Constant	-0.1505*	1.2564***	-0.9169***	-0.1136
	(-1.82)	(3.03)	(-4.00)	(-0.11)
Rating Existence	-0.3174***	-0.1406		
	(-5.55)	(-1.59)		
Rating Level			-0.0505***	-0.1432***
			(-2.91)	(-5.24)
Ln (Size)	0.0924***	0.0114	0.2650***	0.3610***
	(7.19)	(0.50)	(7.16)	(6.46)
Leverage		-0.3965**		0.2094
		(-2.06)		(0.61)
Collateral		-0.2320***		-0.0734
		(-2.62)		(-0.48)
Interest Rate Spread		0.0379		0.1300
		(0.18)		(0.26)
Book-to-Market		-0.2752***		0.1921
		(-3.00)		(1.21)
Run-Up		0.1487***		0.0974
		(3.59)		(0.78)
Blockholder Ownership		-0.0029*		0.0027
		(-1.90)		(0.89)
Cash Flows to Assets		-1.4839***		-1.3157*
		(-7.53)		(-1.94)
Intangibles		-0.6229***		-0.3675
		(-3.61)		(-1.01)
Relative Size		0.0638		0.1726
		(0.95)		(1.40)
Diversifying Deals		-0.1096**		-0.1479
		(-1.99)		(-1.24)
Hostile Deals		-0.5345**		-0.5081
		(-2.00)		(-1.32)
Tender Offers		-1.6615***		-1.6816***
		(-10.44)		(-7.24)
Private		-0.9253***		-1.0507***
		(-12.80)		(-7.70)
Competition		-0.2252		-0.0573
		(-1.32)		(-0.21)
N	6,204	3,394	1,607	999
Pseudo R^2	0.0994	0.261	0.157	0.351

Chapter 3

Do Expectations for Credit Rating Level Changes Drive Corporate Investments? Evidence from Acquisitions

3.1 Introduction

Credit Rating Agencies (CRAs) provide qualitative statements on the creditworthiness of corporate entities and their financial obligations. Particularly in the recent years the importance of credit ratings has enhanced with survey evidence (Graham and Harvey (2001)) demonstrating that managers consider them as one of the most important factors when deciding their firms' corporate policy. Specifically, Faulkender and Petersen (2006) show that firms holding credit ratings, thus having access to the public debt markets, have a 50% higher leverage ratios relative to the ones without ratings. Additionally, Kisgen (2006, 2009) argues that given several discrete benefits (costs) from changes in credit rating levels, firms adjust their capital structure policies towards the issuance of less leverage (more equity), in order to preserve or even achieve a better credit rating. While there is plenty of recent evidence regarding the impact of credit ratings on financial decisions,[21] very few studies (with the exceptions of Nini Smith and Sufi (2009), Chernenko and Sunderam (2012), and Harford and Uysal (2012)), have investigated the relationship between credit ratings and firm real investment decisions.

Theoretically, in perfect frictionless capital markets firms' investment policies should be based only on their investment opportunities and the source of financing should be irrelevant (Modigliani and Miller (1958)). However, in the presence of information asymmetries the source of financing plays an important role in corporate investments (Stiglitz and Weiss (1981), Greenwald et al. (1984), Myers and Majluf (1984), and Myers (1984)) and

[21] Among others, see Cantillo and Wright (2000), Denis and Mihov (2003), Faulkender and Petersen (2006), Mittoo and Zhang (2008), Kisgen (2006, 2009), Sufi (2009), and Rauh and Sufi (2010).

might distort "optimal investment" (Myers (1977), Jensen (1986), Hart and Moore (1995), and Stein (2003)) leading to over or underinvestment. In this respect, given that credit ratings have direct implications on the access to debt financing, the model by John and Nachman (1985) provides supportive arguments that high credit ratings ameliorate the underinvestment problem.[22]

This study examines the effect of credit ratings on firms' acquisition investment policy – perhaps the most important corporate event with tremendous reallocation of resources (Harford and Li (2007)). Prior literature has shown that acquisitions increase bidders' default risk (Dennis and McConnell (1986), Billett, King and Mauer (2004), Furfine and Rosen (2011), Vallascas and Hagendorff (2011), and Bargeron, Lehn, Moeller and Schlingemann (2012)), and leverage levels in the post-merger period (Ghosh and Jain (2000), Morellec and Zhdanov (2008), and Harford et al. (2009)). Therefore, acquisitions are very likely to lead to a downward pressure on bidders' credit ratings, creating concerns about preserving the rating level, which should, in turn, have a considerable impact on firms' acquisition decisions.

Following the theoretical rationale and empirical findings of Kisgen (2006, 2009), Gul, Zhao and Zhou (2011), Chernenko and Sunderam (2012), Flannery, Nikolova and Öztekin (2012), Jung et al. (2012), and Alissa et al. (2013), I examine a setting of firms with managers that have strong incentives to maintain or obtain higher credit ratings, and the relationship of these incentives with acquisition decisions. These are firms which exhibit a close proximity to a future credit rating change (upgrade or downgrade), implying that the expected benefits or costs associated with these potential rating transitions are major for managers' investment decision making. The above argument must hold true especially for the investment-grade cut-

[22] In particular John and Nachman (1985) link firms' decision to invest in high quality (high cash flows) projects , and ultimately their ability to repay their debt obligations on time with the assignment of a high credit rating. In their dynamic sequential equilibrium model firms' reputation derived from the high quality rating at time t has a consequent beneficial effect in all the future time periods $t+n$ which the firms will try to access the bond markets, in the form of low interest rates, and less restrictive constraints in the bond covenants on maximal payouts or minimum investment than those of the low rated firms. Eventually, this state of affairs reduces the agency cost of debt and mitigates the underinvestment problem (Myers (1977)).

off (i.e., BBB-); this cutoff is the distinction between investment- and speculative- grade firms and is considered as one of the most prominent market segmentations in the capital market (Chernenko and Sunderam (2012)). *Ex ante*, it would be expected that the relationship between credit rating levels (credit quality) and real investment to be linear as the higher the credit rating level (i.e., the lower the cost of debt) the easier it is for firms to access credit markets and invest. Nevertheless, Kisgen (2006, 2009) show the importance of seeking or maintaining specific rating levels (i.e., investment grade cut-off) in their corporate policy, since on that distinction a large number of regulations, contracts and investment charters base their policies. Therefore, firms with a rating around the investment grade cut-off will deviate from the conventional linear relationship between cost of capital and investments and will avoid acquisition investments. Based on the preceding discussion, my first hypothesis is the following:

H1: The relationship between credit rating levels (credit quality) and the likelihood to conduct an acquisition investment is non-monotonic, as firms around the investment-grade threshold should exhibit a more conservative investment policy (i.e., abstain from takeovers) in order to secure or achieve an investment-grade rating on their publicly traded debt. Nevertheless, before and after this cut-off it is expected the traditional finance intuition to hold; that is a positive relationship between credit rating levels and acquisition investments.

In addition to the hypothesized significance of the generic rating class (i.e., investment grade cut-off) on acquisition investments, I follow Kisgen (2006, 2009) and consider further measures for estimating the proximity to credit rating changes on various micro levels (i.e., A-, BBB+, BB-, etc). In general, rating transitions on a micro level are considered all the upgrades/downgrades that might incur to the firms' creditworthiness, irrespective of the prior credit rating that the firm might hold. That is, a downgrade of a firm's rating from BB+ to BB is defined as a rating change to a lower micro level. Similarly an upgrade from A- to A is defined as a rating change to a higher micro level. One of the measures I use to capture the closeness to a rating change includes S&P's outlook reports. A rating outlook is a report from a rating agency analyst and is similar to reports provided by an equity analyst or an investment bank (Hull, Predescu and White (2004)). Prior literature suggests that rating outlooks are the strongest predictors of future credit rating changes (Hamilton and Cantor (2004), and Hill, Brooks and Faff (2010)). They can be viewed as an indication that a shift in firm's risk profile has been observed, but its permanence has not yet been established (Hamilton and Cantor (2004)). Usually rating outlooks represent agencies' opinions over the medium term (12-24 months) and can fall into four categories: negative, positive, developing and stable (Standard & Poor's (2008)). Additionally, credit ratings are determined by CRAs' evaluation of the distribution of future cash flows to bondholders, which, is in turn, related to firms' future cash flows. Hence, changes in credit ratings represent shifts in firms' fundamentals. In this respect, Whited (1992) argues that credit ratings measure firms' future growth opportunities, while CRAs state that their assessment of rating factors are forward looking and expand into the future (Standard & Poor's (2008)). [23] Given that credit rating outlooks represent forward-looking agencies' opinions, I would expect a firm with a positive (negative) outlook on its debt to conduct more (less) acquisitions, since these firms are likely to face lower (higher) "expected" cost of debt and higher (lower) growth opportunities. The above discussion leads to the following hypothesis:

H2: Firms with positive (negative) credit rating outlooks have higher (lower) likelihood to conduct acquisitions.

[23] A list of various factors that CRAs consider when they evaluate firms' creditworthiness contains: 1) product positioning and brand reputation; 2) market shares, the installed customer base and geographic coverage; 3) distribution capabilities; 4) customer relationships; 5) technology/manufacturing capabilities; and 6) meaningful barriers to entry (Standard & Poor's (2008)).

Furthermore, previous literature has demonstrated that credit ratings affect firms' cost of borrowing (West (1973), Liu and Thakor (1984), Ederington et al. (1987), Ziebart and Reiter (1992), Chen et al. (2007), and Radhakrishnan et al. (2013)). Moreover, Jensen and Meckling (1976), Myers (1977), and Myers and Majluf (1984) argue that firms with better creditworthiness are less constrained by the debt overhang problem and have higher investment levels. When firms' default risk is declining (increasing), firms' bargaining power in the credit markets is likely to increase (decrease), and thus firms' financial constraints will be less (more) severe. Hence, firms with higher (lower) creditworthiness face lower (higher) cost of debt capital, which, in turn, is likely to result in higher (lower) levels of M&A investments. I employ lagged rating actions as another measure of the proximity to credit rating changes. Altman and Kao (1992), Lando and Skødeberg (2002), and Christensen, Hansen and Lando (2004) demonstrate that credit rating changes exhibit a positive serial autocorrelation ("rating momentum"). That is a past downgrade tends to be followed by another downgrade. Since past credit rating changes serve as a good signal for upcoming rating shifts, I expect that they should exert an influence on firms' management takeover decisions. This leads to the following testable hypothesis:

H3: Firms received an upgrade (downgrade) on their publicly traded debt in the recent past are more (less) likely to conduct an acquisition.

Finally, I employ my last proxy to capture the possible direction of a rating change, by examining the deviation of an empirically modeled ("expected") credit rating from firm's ratings at time *t-1* (where *t-1* is the fiscal year-end immediately prior to the acquisition). Kisgen (2006), Hovakimian, Kayhan and Titman (2009), Alissa et al. (2013), and Baghai et al. (2013) employ a similar approach to investigate firms' capital structure, as well as investment and earnings management decisions, when firms exhibit a large estimated deviation from the "expected" credit rating at a given year. Following this rationale, I would anticipate that a large deviation might serve as a good candidate for measuring the likelihood and direction of credit ratings transitions in the future; this should, in turn, impact firms' management acquisition decisions.

H4: Given the positive relationship between the absolute difference from the expected-rating and the probability of a future credit rating change, below- (above-) expected-rating firms are more (less) likely to conduct acquisitions.

Using a sample of US acquisitions of publicly traded bidders over the period 1996-2009, I explore the effect of credit ratings on acquisition investments and find strong support to my conjectures. In particular, this study provides evidence of i) a non linear association between credit rating levels (credit quality) and acquisition decisions at the 1% significance level; ii) a strong positive (negative) association between positive (negative) rating outlooks and acquisition decisions at the 1% significance level; iii) a positive (negative) relationship between past upgrades (downgrades) and acquisition decisions; and iv) a positive association between the estimated deviation from an "expected" credit rating and takeover decisions. My results appear to be both statistically and economically significant, even after controlling for potential endogeneity of credit ratings. Economically, firms having a positive (negative) outlook on their debt increase (decrease) their acquisition investments by approximately 30% (34%) over the sample average. Similarly, firms experiencing an upgrade (downgrade) on their debt increase (decrease) their acquisition investments by roughly 20% (68%) over the sample average. Furthermore, a one point increase in the estimated credit rating deviation leads to an increase in acquisitions of approximately 5% over the sample average. Overall the findings in this work support my hypotheses and highlight the importance of CRAs on firms' acquisition policy.

This study has several contributions to the M&As and credit ratings literature. First, it provides evidence on the importance of credit ratings on corporate control decisions.

Particularly, I show that the relationship between credit quality and takeover decisions is non-linear since firms near the investment-grade cutoff follow a more conservative investment policy in order to avoid being downgraded in the junk status or achieve being upgraded in the investment grade status. To my knowledge, this is the first study to examine and uncover this non-linear association between credit rating levels and corporate investment decisions. Second, I offer new evidence regarding the relationship between different types of rating information, such as rating outlooks and lagged rating changes, and acquisition investments. Third, it adds to the existing literature on the determinants of M&A likelihood and particularly the association between credit ratings and the propensity of an acquisition investment. Fourth, it provides further evidence to the recent literature that investigates how credit supply frictions affect investment decisions (Cantillo and Wright (2000), Faulkender and Petersen (2006), Chava and Roberts (2008), Leary (2009), Nini, Smith and Sufi (2009), Lemmon and Roberts (2010), and Chernenko and Sunderam (2012)); in particular, I study the effect of credit rating benchmarks (i.e., investment-grade cut-off) and specific CRAs' opinions (i.e, outlooks) on acquisition investments.

Finally, it can reasonably be argued that this study has implications regarding the impact of credit supply uncertainty on corporate policies (Morellec (2010), and Massa, Yasuda and Zhang (2013)). It has been argued contrary to the irrelevance theorem of Modigliani and Miller (1958), and the demand-driven approach to corporate finance, that firms can face uncertainty related with their future access to credit markets, and as a consequence they have to seek for creditors when raising debt financing. The implications derived from the above setting are numerous with some examples including the hampering of investments, and the usage of less than optimal leverage on capital structures. The findings in this study imply that the function of debt certification in the form of rating outlook opinions that are provided by the CRAs, is likely to mitigate firms' credit supply uncertainty when considering their future access to credit markets, and therefore makes them less reluctant to conduct an investment. Outlook opinions are perceived as a form of certification on the firms' ability to repay their debt obligations in the future, and therefore provide a signal to potential creditors regarding their decisions to borrow capital to the firms. Since, the rating outlook is public information known both to firms, and the creditors it can help mitigate information asymmetries (Healy and Palepu (2001)), and narrow the gap between the demand and supply side of capital thus, enhancing market clearance, reducing supply uncertainty, and helping firms' investment decisions.

This work is related with a number of different branches of literature. For instance, it is related with studies that examine the predictability of takeovers such as Palepu (1986), Ambrose and Megginson (1992), Comment and Schwert (1995), Billett (1996), Harford (1999), Almazan, De Motta, Titman and Uysal (2010), Billett, Jiang and Lie (2010), Uysal (2011), and Harford and Uysal (2012). This study is particularly related with papers that investigate the acquisition likelihood from the bidder's side (Harford (1999), Almazan et al. (2010), Uysal (2011), and Harford and Uysal (2012)). These studies use the amount of cash reserves (Harford (1999)), firms' locations (Almazan et al. (2010)), and the deviation from target leverage (Uysal (2011)) as the main predictor variables in their analysis. In this work, instead, I use credit rating level as the main variable of interest. A very recent study which is close to my work is the one by Harford and Uysal (2012), who examine the effect of credit rating *existence* on the likelihood of an acquisition. Their study pools together rated and unrated firms without considering the particular effect of credit rating levels; my study differentiates to the extent that the focus is solely on a sample of rated firms and therefore I am able to examine the impact of credit quality on acquisition decisions considering also different types of rating information. Furthermore, another paper closely to my study is by Billett (1996), who examines the relationship between the likelihood of a target firm receiving a takeover bid and its debt riskiness as measured by the investment and speculative grade differential. This study differs from Billett (1996), since it examines the effect of bidder credit rating level on acquisition probability. Moreover, Kisgen (2006), Shah (2008), Hovakimian et al. (2009), Jung et al. (2012), and Alissa et al. (2013) demonstrate that firms are concerned about their credit rating levels and adjust their corporate policies accordingly in order to attain or maintain these rating targets. My work is in line with these studies offering evidence in an M&A setting.

The remainder of the chapter is organized as follows. Section 3.2 presents my sample. Section 3.3 analyzes the methodology and findings of the empirical tests. I present further robustness tests to my results in Section 3.4. Finally, Section 3.5 concludes the chapter.

3.2 Sample and Data

3.2.1 *Sample Statistics*

The sample consists of all NYSE, AMEX, and NASDAQ firms listed on the COMPUSTAT annual industrial files, with a credit rating over the period from 1995 to 2008.[24] The sample is composed of 3,205 firms for a total of 23,044 firm/year observations. Acquisition data are obtained from Thomson Financial SDC Mergers and Acquisitions Database and the sample includes successful and unsuccessful acquisitions of rated bidders over the period 1996 to 2009. I require deals to have non-missing transaction value and payment method information. Bidders are listed firms and targets are either listed or private firms. I remove from the sample all deals classified as repurchases, liquidations, restructurings, divestitures, leveraged buyouts, reverse takeovers, privatizations, bankruptcy acquisitions and going private transactions. Furthermore, to include in the sample deals that

[24] Firms with a rating of D (default) or SD (selective default) are the most severely vulnerable firms and, hence, are excluded from the analysis similar to Alissa et al. (2013), and Alp (2013).

represent a transfer of control, I require that the bidder owns less than 10% of target shares before the announcement and seeks to acquire more than 50% after the acquisition. Furthermore, I drop deals worth less than US$ 1 million and less than 1% of a bidder market value to avoid noise in the analysis. All these restrictions results in a sample of 1,695 acquisition deals. After merging the two samples, I find that 926 acquirers conducted 1,695 transactions over the sample period.

Table 3.1 presents the sample of acquisitions by announcement year. On average, takeovers of publicly listed targets represent the 61% of the M&A activity in the sample. Further, the vast majority (92.98%) of the deals announced during the whole sample period were successfully consummated. Finally, the average target size relative to the bidder is 24.71%; however, this magnitude varies considerably across the full sample period.

[Please Look Table 3.1]

In this study I use the S&P domestic long term issuer credit rating as a measure of firms' credit quality from COMPUSTAT.[25] Table 3.2 presents data for the average credit quality in the full sample partitioned by the acquisition announcement year. The average credit quality of US firms exhibits a decreasing trend consistent with Blume, Lim and Mackinlay (1998), Alp (2013), and Baghai et al. (2013). Moreover, a noticeable result is the monotonic decrease in the volatility of the US firms' credit quality, a finding which entails a trend towards the stability of CRAs' opinions about firms' creditworthiness.[26]

[Please Look Table 3.2]

[25] The credit rating level is an ordinal variable ranging from 1 to 22. A higher rating corresponds to a larger number (i.e., 22 for AAA and 1 for D-, in my sample the lowest number is 3 as the lower credit rating is CC).

[26] According to CRAs a credit rating system's performance can be measured mainly by two objectives. Rating accuracy (i.e., the correlation between ratings and defaults) and rating stability (i.e., the frequency and magnitude of ratings changes) (Cantor and Mann (2003)).

In addition to firms' credit rating levels, in this study I apply other information produced or derived by CRAs in order to measure firms' proximity to a future credit rating change. Specifically, I use: i) the credit rating outlooks[27]; ii) the change in credit ratings between firms' time *t-1* and time *t-2* (where *t-1* represents fiscal year-end immediately prior to the acquisition year); and iii) the estimated deviation from an empirically modeled expected-rating. Particularly, in the case of the empirically modeled difference I follow Kisgen (2006), and use a surrogate expected-rating model of the form:

$$Rating_{it-1} = 4.7307 + 1.2743Log(AT)_{it-1} - 3.8790Leverage_{it-1} + 9.7189Profitability_{it-1} \quad (1)$$ [28, 29]

Table 3.3 presents descriptive statistics for these credit rating related variables.[30] Panel A shows the number of rating outlooks partitioned by type in the full sample. The total number of firm/year observations with rating outlooks reported in COMPUSTAT's RatingsXpress is 15,546. I observe that the positive outlooks represent the 9.71% of the full sample while the negative outlooks represent the 20% of the full sample. Moreover, the percentage of stable outlooks over the full sample is 69.79% while the percentage for developing outlooks is a marginal 0.005%. Panel B presents the number of rating changes and the average number of notches' transitions partitioned by the direction of change. Upgrades amount to 2,074 with a mean upgrade change of 1.32 notches. Downgrades amount to 2,953 with an average downgrade change of 1.67 notches. The remaining 15,870 firm/year observations constitute data unaffected by any shift in credit risk. Finally, Panel C shows the number and average values for the estimated deviation of the expected rating of model (1) from firms' original rating at time *t-1*. The 50.87% of the observations is comprised of firms rated below their expected-rating, implying that these firms anticipate a possible upgrade on

[27] Rating outlooks were collected from the COMPUSTAT RatingsXpress database.
[28] The model is estimated using OLS with year and industry (12 Fama-French industries) fixed effects and heteroskedasticity-robust standard errors adjusted also for clustering at firm level. The adjusted R^2 of this model is a satisfactory 0.618, similar with the results in Kisgen (2006).
[29] Where *i* represent firms and *t-1* represent time.
[30] All the variables are defined later in the variables selection subsection and in the Appendix A.

their rated debt. The remaining 49.13% constitutes firms rated above their expected-rating reflecting that these firms expect a likely downgrade on their rated debt.

[Please Look Table 3.3]

3.2.2 *Variables Selection*

In the empirical analysis I control for a number of variables that are known from the prior literature to affect the propensity of an acquisition investment. Large firms are more likely to make an acquisition, since they are more diversified and are able to obtain capital in order to finance acquisitions in a short notice (Almazan et al. (2010), and Uysal (2011)). Hence, I include the market value of the firm at the fiscal year-end as proxy for *size.*[31]

To control for the operating performance of the firms, I include the ratio of EBITDA to total assets (*profitability*) as more profitable firms have a higher propensity to conduct acquisitions (Harford (1999), and Uysal (2011)). Furthermore, cash rich firms are more likely to undertake acquisitions according to Jensen (1986), Harford (1999), and Faccio and Masulis (2005). For that reason I include the variable *cash reserves* which is defined as the ratio of cash holdings over total assets.

I also control for firms' age as older firms might be more likely to engage in acquisitions (Almazan et al. (2010)). The *age* variable is defined as the number of years the firm is covered in COMPUSTAT until the time *t* (year of the acquisition announcement). Moreover, to control for the potential effects of growth opportunities and misvaluation (Harford (1999), Shleifer and Vishny (2003), Uysal (2011), and Harford and Uysal (2012)) I add *stock-return* and *market-to-book*. The former variable is defined as the market adjusted (relative to the value weighted CRSP index) monthly excess return for the last fiscal year before the acquisition announcement, and the latter is defined as the ratio of market value of

[31] I also use the log of sales and log of total assets as another way to measure size and the results are qualitatively similar.

equity to the book value of equity, at the fiscal year-end prior to the acquisition announcement.

I also include the *leverage* variable, which is defined as the ratio of total debt (short- and long-term debt) over the total assets of the firm, to disentangle the effects of credit rating levels from leverage. The relationship of leverage with the acquisition propensity is mixed; in particular, Harford (1999) finds no evidence that leverage affects the probability to buy other firms, while Faccio and Masulis (2005) document a positive relation between leverage and the propensity of an acquisition. Uysal (2011) observes that overleveraged firms are less likely to carry out acquisitions.

To account for the liquidity of corporate assets within an industry (i.e., M&A waves), I include in my regressions the *M&A liquidity* variable, similar to Uysal (2011) and Harford and Uysal (2012). Industry concentration might also influence the propensity of firms to conduct acquisitions as firms in highly concentrated industries have fewer competitors that can serve as targets, a fact that can hamper the number of within-industry acquisitions. Hence, I add the variable *Herfindhal Index* following Uysal (2011), and Harford and Uysal (2012), to control for this effect.

Table 3.4 presents summary statistics for the above control variables. The average market capitalization in the sample is $7.64 billion. Further, the mean profitability is 11.70% and the average age is 20 years. Moreover, the mean market value is 3.34 times larger than the book value, and the average leverage is 36.28%. Finally, the average (median) industry concentration is 0.15 (0.10), a finding which implies the existence of unconcentrated industries.

[Please Look Table 3.4]

3.3 Empirical Analysis

3.3.1 *Credit quality and acquisition investments*

In this section I present a multivariate analysis including several variables that might affect the propensity to engage in acquisitions.[32] The main variable of interest is the *rating level* which measures firms' credit quality. According to hypothesis (***H1***) it is expected a non-linear relationship between *rating level* and the likelihood of acquisitions. Thus, in order to measure this anticipated non-linearity, I include in my main regressions polynomial terms of the variable *rating level* up to the 3rd order.[33,34] Therefore, I also add in my regressions the *rating level squared* and *rating level cubic* along with all the other control variables in my sample. Finally, in my regressions I include year- and industry- (12 Fama-French industries) fixed effects whose coefficients are suppressed. Moreover, I use heteroskedasticity-robust standard errors adjusted also for clustering at firm level. Table 3.5 presents the results. Specifications (1) through (3) show the results for probit analysis, where the dependent variable is the *acquisition dummy*, which takes the value of 1 if the firm made at least one acquisition in a given year, and 0 otherwise. In specifications (4) through (6) I present the results for the tobit analysis, where the dependent variable is the *DVA /TA*, which is the sum of the deal values of acquisitions made in a given year scaled by firms' total assets in the previous year. In models (1) and (2) the coefficients on both variables of interest (i.e., *rating level* and *rating level squared*) are negative and statistically significant at the 1% level, a

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[32] In Appendix B is presented the correlation matrix of all the variables used in the empirical analysis in order mitigate any concerns related with multicollinearity among the main and other control variables in the regressions. The results should not be affected by any potential multicollinearity, given the large sample size with sufficient variation in the explanatory variables. I still perform a multicollinearity (VIF) test for all specifications throughout the study and find that correlation between explanatory variables does not have any material effect on the estimates.

[33] The validity of the usage of 3rd order polynomials is examined by including in one step at a time a higher order polynomial (i.e., first the *rating level* to the power of 2 and then the *rating level* to the power of 3) and observing whether the Pseudo R^2 in every consequent model increases. Another rule of thumb that justifies the selection of 3rd order polynomials is the mere observation that the coefficients in the regressions are significant for all three polynomial terms of *rating level.*

[34] Since by construction the usage of higher order polynomials might create a multicollinearity bias in my regressions, I center the variable *rating level* around its mean value and derive accordingly the higher order polynomials from that centered variable.

result that is a first indication of a non-linear relation. Finally, in model (3) which comprises the full model I observe that the coefficient on *rating level cubic* is positive and statistically significant at the 5% level. This finding implies that the cubic polynomial has a positive leading coefficient and the functional relationship between credit rating levels and probability of acquisition has two turning points indicating a non-linear relationship. In particular, it firstly exhibits a local maximum, and secondly a local minimum.[35]

Moreover, I measure the specific turning points in this non-linear relationship between credit quality and the likelihood of acquisitions which allows to accept or reject the hypothesis about the impact of the investment-grade cut-off on acquisition investments.[36] According to hypothesis ***H1***, I predict the turning points of the above relationship to be close to the investment-grade cut-off. In particular, I identify the first turning point (local maximum) around the credit rating level BB which is two notches below the rating level BBB-. This means that when firms' debt is rated two notches away from an upgrade to the investment-grade status (located in the broad rating category BB), bidding firm's managers are not likely to invest in M&As, in order to avoid jeopardizing their firms' creditworthiness and secure the beneficial investment grade status. Regarding the second turning point, I estimate the change in firms' investment behaviour around the rating level A-, which implies that firms exiting from the broad rating category BBB start to increase their M&As investments. This is probably due to the fact that an imminent downgrade to a junk status is considered a relatively remote incident.[37] The coefficient estimates for the other control variables are consistent with the existing literature. For instance, the coefficient on *size* is positive and similar to the findings of Cai and Vijh (2007), and Harford and Uysal (2012).

[35] In mathematical terms this result is translated as: $(f(x) \to -\infty \; as \; x \to -\infty)$ and $(f(x) \to +\infty \; as \; x \to +\infty)$.

[36] I compute the turning points of the 3rd order polynomial by using the formula: $t_{1,2} = \frac{-\beta 2 \pm \sqrt{\beta 2^2 - 3\beta 1 \beta 3}}{3\beta 3}$, where $\beta 1$, $\beta 2$ and $\beta 3$ are the estimated coefficients from the full model in specification (3) as in Plassmann and Khanna (2007).

[37] In order to measure the non-linear relationship between credit quality and likelihood of acquisitions in the robustness section I also employ linear spline and restricted cubic spline regressions.

Profitability, *age*, *stock-return* and *M&A liquidity* hold positive and significant coefficients corroborating the findings of Harford (1999), Uysal (2011), and Harford and Uysal (2012). Finally *leverage* exhibits a negative association with the likelihood of undertaking an acquisition, consistent with the findings by Almazan et al. (2010).

Regarding the results of the tobit analysis in specifications (4) through (6) similar patterns are obtained to the findings of the probit analysis. Specifically, I am able to uncover a non-linear relationship between credit quality and acquisition likelihood, since the coefficient on *rating level cubic* is positive and significant at the 5% level. The remaining control variables have coefficients consistent with the previous literature on the M&As' likelihood.

[Please Look Table 3.5]

3.3.2 *Proximity to credit rating changes and acquisition investments*

This section presents an analysis of the relationship between the various variables used to measure the proximity to a future credit rating change and acquisition decisions. I use the credit rating outlooks as the first measure. In particular, the variable *outlook positive* is a dummy variable taking the value of 1 when the firm is assigned an outlook with a positive direction on its debt and 0 otherwise.[38] Further, I use the variable *outlook negative,* which is a dummy variable taking the value of 1 when the firm is assigned an outlook with a negative direction on its debt and 0 otherwise.[39] Additionally, I include in my regressions the variable *investment-grade*, which controls for the firm closeness to an upgrade in the investment-grade status along with closeness to a downgrade in the speculative-grade status. Specifically, I construct this variable following Kisgen (2006), and calculate the expected-rating derived

[38] In that case the value of 0 is assigned to firms with other types of outlooks (i.e., negative, stable and developing) and firms without any rating outlook.

[39] In this analysis I do not assign any particular values on the other two types of outlooks (stable and developing) as, *ex-ante*, these types should not have any meaningful effect on firms' investments.

by equation (1) for firms with rating BB+ or BBB- at time *t-1*. Then I create the expected-rating score quartiles for each of these two rating categories, and assign the value of 1 to the lowest quartile BBB- firms and highest quartile BB+ firms, and 0 otherwise. By this way the dummy *investment-grade* measures the firms that are very close to a potential upgrade/downgrade according to their credit score. The other control variables are the same as in the analysis of section 3.3.1.

Table 3.6 presents the results of this analysis. In specifications (1) and (2) the coefficients on the *outlook positive* and *outlook negative* carry the expected positive and negative signs accordingly, and are highly statistically significant. However, the effect of negative outlooks is larger than the effect of positive outlooks, a finding which implies that firms target minimum rating levels, similar to the results of Kisgen (2009).[40] Further, these findings confirm hypothesis ***H2*** and imply that firms with positive (negative) outlooks regarding their public debt conduct more (less) acquisitions, since firms' management conceive the future state of business affairs more optimistic (pessimistic). Another noteworthy result is the negative sign on *investment-grade* in specification (I) which corroborates my expectations about firm conservative behavior when the impact of market segmentation (investment-/speculative-status) is more pronounced. The remaining control variables hold coefficients which are according with the M&As' likelihood literature.[41]

[Please Look Table 3.6]

Table 3.6 also presents the results for the second proxy of closeness to future rating changes; that is the lagged credit rating changes. The *lagged upgrade* is a dummy variable

[40] The Wald test for the difference between the two coefficients rejects the null of equality at the 1% significance level.

[41] In all the main regressions that are reported in this section and specifically in table 3.6, I also control for credit rating level in untabulated analysis, and the results remain qualitative similar.

which takes the value of 1 for firms that were upgraded over the last year prior to the acquisition announcement year, and 0 otherwise. The *lagged downgrade* is a dummy variable which takes the value of 1 for firms that were downgraded over the last year prior to the acquisition announcement year, and 0 otherwise. Given, the notion of "rating momentum", these variables serve as another proxy for potential credit rating change. The results in specifications (3) and (4) show that *lagged upgrade* (*downgrade*) has a positive (negative) association with acquisition investments at conventional significance levels. Again, the impact of the downgrade appears to be stronger than the impact of the upgrade, implying that potential downgrades are conceived by firms' management as more important events for their creditworthiness than upgrades. These findings corroborate hypothesis ***H3*** regarding the differential firm acquisition investment strategy based on their expected credit rating level. The remaining control variables exhibit signs according to the related M&As likelihood literature.

Finally, Table 3.6 presents in specifications (5) and (6) the results for the third measure of firms' proximity to future credit rating changes. This variable measures the deviation of the expected-rating derived from equation (1) from the credit rating of the firms in my sample at time *t-1*. I label this variable *difference.* According to hypothesis ***H4***, it is expected that the higher the estimated deviation, the higher the probability of an upgrade and *vice versa.* In models (5) and (6) the main variable of interest, *difference*, has a positive and highly significant relationship with the acquisition propensity, a result that validates the hypothesis ***H4***. The remaining control variables hold coefficients with signs consistent to the existing M&As related literature on M&As. In summary, the results in this section corroborate my hypotheses regarding the proximity of credit rating changes and acquisition investments highlighting that firm corporate investments are conditional upon anticipated credit quality.

3.4 Robustness Tests

3.4.1 *Endogeneity of credit rating levels*

So far, in my analysis I treated the *rating level* variable as exogenous to my model; that is the decision to obtain a specific credit rating level is randomly allocated across the sample firms. However, Liu and Malatesta (2005), and An and Chan (2008) argue that firms determine, at least partially, whether to obtain a higher rating level after considering the benefits against the potential costs. Therefore, it is likely that the decision to obtain a high credit rating is based on firm- and industry- specific characteristics, and failure to account for these characteristics would lead to biased estimates in my analysis. Given that in the main regressions the potential endogenous variable is the *rating level* with its polynomial terms (squared and cubic), a simple two-stage procedure with appropriate instruments is not sufficient and can lead to erroneous inferences associated with the "forbidden regression" problem discussed in Wooldridge (2002). Therefore, in order to overcome the problem of erroneous instrumental variables (IVs) estimation, correcting for the endogeneity bias of the *rating level*, I follow the method proposed by Wooldridge (2002). Specifically, I firstly use a list of instruments for the *rating level* and compute the predicted value $\widehat{rating\ level}$ from this (OLS) regression. As a second step, I choose as a single instrument for *rating level squared* the above predicted value raised to the power of 2, that is $\widehat{rating\ level}^2$. Finally, as an instrument for *rating level cubic* I follow the same process and use the predicted value of the first regression raised to the power of 3, that is $\widehat{rating\ level}^3$.

The choice of instruments for the *rating level* is justified by considering the relevant literature on firm "debt composition" and "credit rating endogeneity" (Cantillo and Wright (2000), Johnson (1997), Denis and Mihov (2003), Liu and Malatesta (2005), Faulkender and Petersen (2006), and An and Chan (2008)). In particular, Johnson (1997), and Cantillo and Wright (2000) argue that public credit markets cater to safe industries with low default risk and high credit quality. Hence, I use the variable *industry level,* which is the median credit rating level of the bidders' same 3-digit SIC industry group at the fiscal year-end preceding the acquisition, to control for the credit quality level of the industry. Moreover, Denis and Mihov (2003), Liu and Malatesta (2005), and An and Chan (2008) propose that the credit quality of the issuer is the primary determinant of the rating level, and firms with the highest credit quality are assigned the highest credit rating level. Thus, in order to account for this effect I add as an instrument the variable *Altman-Z* (Altman (1968)); the *Altman-Z* score measures the probability of a public firm to default on its debt within 1or 2 years. Finally, I employ the two-step minimum chi-square estimator of Newey (1987), which is an asymptotically efficient estimator for cases where the main dependent variable is of discrete nature, and the endogenous explanatory variables (EEVs) are continuous;[42] that is precisely my case.

Table 3.7 presents the results of this analysis. Specifications (1), (2) and (3) present the results for the reduced form regressions measuring the choice of credit rating level for the *rating level*, *rating level squared* and *rating level cubic*, respectively. I find that the four instruments, *industry level, Altman-Z,* $\widehat{rating\ level}^2$ and $\widehat{rating\ level}^3$ are highly significant in all three models. This finding implies that my instruments predict satisfactorily the choice of credit rating levels and should mitigate any concerns regarding the weak instruments bias.[43] Finally, in model (4) which comprises the structural regression for the probit model, I observe that the main variables of interest, *rating level*, *rating level squared* and *rating level cubic* hold the same signs as in section 3.3.1 and are all statistically significant at conventional levels. This finding suggests that the variable *rating level* with its polynomial terms is endogenous and gives a justification for the analysis in this section. In

[42] Specifically, the rating level variable is an ordinal variable but it can be modelled without any particular bias with an OLS regression (Horrigan (1966), Kisgen (2006), and Baghai et al. (2013)).
[43] I also conduct a Sargan test (Sargan (1958)) in order to examine the validity of the instruments and I am unable to reject the null of instruments validity.

addition, in the lower part of Table 3.7 I present the χ^2 value of the Wald test for endogeneity, which shows that the test rejects the null hypothesis of no endogeneity at the 1% level; this result adds further validity to my inferences about the existence of endogeneity bias in the main results.

[Please Look Table 3.7]

Table 3.8 presents the results for the endogeneity analysis when the main dependent variable is *DVA/AT*. Specifications (1), (2) and (3) present the results for the reduced form regressions measuring the choice of credit rating level for the *rating level*, *rating level squared* and *rating level cubic*, respectively. In the model (4) which comprises the structural regression for the tobit model, I observe that the main variables of interest, *rating level*, *rating level squared* and *rating level cubic* hold the same signs as in section 3.3.1 and are all statistically significant at conventional levels. This result indicate that the variable *rating level* with its polynomial terms is endogenous and corroborates the findings in Table 3.7 above for the case of the probit model. Additionally, in the lower part of Table 3.8 I present the χ^2 value of the Wald test for endogeneity, which shows that the test rejects the null hypothesis of no endogeneity at the 1% level; this result support my inferences about the existence of endogeneity bias in the main results.

[Please Look Table 3.8]

3.4.2 *What does the CreditWatch tells us?*

Finally, as an additional robustness check I examine the impact of CreditWatches on firms' acquisition investments. CreditWatches are stronger statements than outlooks, and indicate the potential direction of a rating change that may follow the resolution of particular events or trends, usually in a shorter time frame (3 months). A company is placed under review as a result of mergers, recapitalizations, regulatory actions or unanticipated operating developments (Standard & Poor's (2008)). A rating might be put on a review for a possible downgrade or upgrade or with uncertain direction. During the watchlist the rating agency collects additional information about the firms it rates, which typically leads to an interaction between rating analysts and firms' management (Bannier and Hirsch (2010)). The CreditWatch is finally resolved by the announcement of either a rating change or confirmation of the initial rating. Boot, Milbourn and Schmeits (2006) construct a theoretical model that explores the function of CRAs in capital markets and suggest that CreditWatches serve as monitoring devices of firm performance. As long as credit watches exert an influence and require particular actions from the firm management, it should be expected that CreditWatches play an important role on firms' acquisition policy. Similarly, Michelsen and Klein (2011), and Kemper and Rao (2013) examine the effect of CreditWatches on firms' capital structure decisions and find conflicting and moderate effects, respectively.

Therefore, I download all CreditWatch placements assigned to firms during the last month of the fiscal year preceding the acquisition year. The data were collected from COMPUSTAT's RatingsXpress and consist of 59 positive, 199 negative, and 23 developing CreditWatch observations, respectively. Table 3.9 presents the results for the association between CreditWatch actions and acquisition investments. The main variables of interest are the *watch positive* and *watch negative*. They are both indicator variables taking the value of 1 if the designation is positive or negative, respectively, and 0 otherwise.[44] I find that *watch positive* holds a large positive while *watch negative* holds a large negative coefficient respectively at the 10% level in both specifications (1) and (2). These findings suggest that CreditWatches exert an influence of firms' management acquisition decisions. The weak significance level can be attributed either to the low number of CreditWatch observations in

[44] In this analysis I do not consider the effect of developing CreditWatches as the sign and interpretation of this type of CRAs' action is ambiguous.

the sample or to the fact that CreditWatch actions by definition have duration of 90 days, and an examination of acquisition investments in the year following the CreditWatch placement might not be too revealing.

[Please Look Table 3.9]

3.4.3 *Other Sensitivity Tests*

In section 3.3.1 I was able to uncover a non-linear relationship between credit rating levels (credit quality), and acquisition decisions by using for this cause a 3rd order polynomial model. However, I can use other models to capture this non-linear association and validate my inferences so far. To accomplish this task in this section I employ linear spline and restricted cubic spline regressions (Harrell (2001)). In their general form spline regressions require an assignment of specific knots (turning points), in order to investigate the different firms' acquisition policies among the different intervals (credit rating levels). Fortunately, I already know from the analysis in section 3.3.1 that this relationship exhibits two turning points, the first around the BB rating level, and the second around the AA- rating level, so I can reasonably assign these levels as the turning points in my estimations of the linear and restricted cubic spline regressions.

Table 3.10 presents the findings for the linear spline where model (1) is the pobit regression with a dependent variable the *acquisition dummy,* and model (2) is the tobit regression with dependent variable the *DVA/AT.* I can observe from these two models that the signs and significance of *rating level* for the first two intervals are similar with the findings in Table 3.5 but, in the last interval the coefficient is negative and significant. This result might be driven by the inefficiency of the linear spline to capture very curved functions, since by construction the linear spline assume that the relationship is linear between the intervals. Assuming that the relationship is linear among the intervals is natural and useful simplification nevertheless, I am interested in the non-linearity of the association between credit rating levels and acquisition decisions, and a restricted cubic spline is a better choice than the linear spline (Harrell (2001)).

[Please Look Table 3.10]

Table 3.11 presents the results for the restricted cubic spline model where model (1) is the pobit regression with a dependent variable the *acquisition dummy,* and model (2) is the tobit regression with dependent variable the *DVA/AT.* I can observe that the signs and the significance for the different credit rating intervals in both of the models are similar with the results in Table 3.5. These findings validate, and add more support on my main inferences so far for the existence of a non-linear relationship between credit rating levels and firms' acquisition decisions.

[Please Look Table 3.11]

3.5 Conclusion

This chapter presents a direct empirical analysis of the impact of credit ratings on the firm acquisition propensity. In particular, I attempt to measure the effect of credit rating levels (credit quality) on the likelihood to undertake acquisitions and find that this relationship is non-linear. This finding is explained by the strategic importance of the investment-grade cut-off, since firms close to an upgrade (downgrade) to the investment-grade (speculative-grade) status exhibit a conservative investment behaviour which is not explained by the traditional finance theory. Furthermore, I apply three different proxies for the imminence of a credit rating change (Rating Outlooks, Lagged Rating Changes, and Deviation from Expected-Rating), and provide evidence that managerial concerns regarding potential rating changes influence their decisions to acquire. This finding suggests that different expected credit rating actions (upgrades/downgrades) signal a material change in firms' fundamentals and lead their management to perceive future states of the world under alternative perspectives (optimistically/pessimistically). The results support my hypotheses even after controlling for potential endogeneity. This study adds to the prior literature to the extent that provides anecdotal evidence for a non-linear relationship between credit rating levels and acquisition decisions. Additionally, my findings imply that firm management schedule their acquisition decisions conditional on their expected creditworthiness, as implied by the ratings assigned by CRAs.

Appendix A. Variable Definitions

Variable	Definition
	Panel A: Acquisition Decisions
Acquisition Dummy	Dummy variable: 1 if the firm announced at least one acquisition in year *t*, 0 otherwise. The variable is created using data from Thomson Financial SDC.
DVA/AT	It is the sum of the announced acquisition deal values in year *t* scaled by firm's total assets in year *t-1*. Deal values are from Thomson Financial SDC, firm's total assets are from COMPUSTAT.
	Panel B: Credit Rating Variables
Rating Level	Continuous variable for rated bidders: 1 to 22, AAA level takes 22 and D takes 1. The variable is created using data from COMPUSTAT.
Outlook Positive	Dummy variable: 1 for positive rating outlooks, 0 otherwise. The variable is created using data from COMPUSTAT RatingsXpress database.
Outlook Negative	Dummy variable: 1 for negative rating outlooks, 0 otherwise. The variable is created using data from COMPUSTAT RatingsXpress database.
Lagged Upgrade	Dummy variable: 1 for upgraded firms during the last year preceding the acquisition, 0 otherwise. The variable is created using data from COMPUSTAT.
Lagged Downgrade	Dummy variable: 1 for downgraded firms during the last year preceding the acquisition, 0 otherwise. The variable is created using data from COMPUSTAT
Difference	Deviation of rating at time t-1 from an empirically modeled expected-rating. The variable is created using data from COMPUSTAT
Watch Positive	Dummy variable: 1 for positive CreditWatch placements, 0 otherwise. The variable is created using data from COMPUSTAT RatingsXpress database.
Watch Negative	Dummy variable: 1 for negative CreditWatch placements, 0 otherwise. The variable is created using data from COMPUSTAT RatingsXpress database.
Investment-Grade	Dummy variable: 1 to the lowest quartile BBB- firms and highest quartile BB+ firms from an expected-rating model, 0 otherwise. The variable is created using data from COMPUSTAT.
	Panel C: Firm Characteristics
Size	Firm market value of equity at the fiscal year-end prior to the acquisition announcement from CRSP in US$ million.

Leverage	Firm total financial debt (long-term debt plus debt in current liabilities) divided by the book value of total assets in the fiscal year prior to the acquisition announcement from COMPUSTAT.
Stock-Return	Market adjusted (relative to the value weighted CRSP index) monthly excess return for the last fiscal year before the acquisition announcement.
Market-to-Book	Market value of equity at the fiscal year-end prior to the acquisition announcement divided by the book value of equity at the fiscal year-end prior to the acquisition announcement Market and book value of equity is from COMPUSTAT.
Cash Reserves	The ratio of cash holdings over total assets in the fiscal year-end prior to the acquisition announcement from COMPUSTAT.
Age	Number of years the firm is covered in COMPUSTAT until the time *t* (year) of the acquisition announcement.
Profitability	The ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets at the fiscal year immediately prior to the acquisition announcement from COMPUSTAT.
	Panel D: Industry Characteristics
M&A Liquidity	Sum of acquisitions value for each year and three-digit SIC code divided by the total assets of COMPUSTAT firms in the same three-digit SIC and year.
Herfindahl Index	Sum of squares of the market shares of all firms sharing the same three-digit SIC, where market share is defined as sales of the firm to sum of the sales with the industry.
	Panel E: Instrumental Variables
Industry Level	The median credit rating level of firms in the same 3-digit SIC industry group at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.
Altman-Z	Is calculated from the formula Z = 6.56 (Working Capital/Total Assets) + 3.26 (Retained Earnings/Total Assets) + 6.72 (EBIT/Total Assets) + 1.05 (Book Value of Equity/Book Value of Total Liabilities).

Appendix B. Variables Correlation Matrix

	Rating Level	Rating Level Squared	Rating Level Cubic	Outlook Positive	Outlook Negative	Lagged Upgrade	Lagged Downgrade	Difference	Investment Grade	Size	Profitability
Rating Level	1.0000										
Rating Level Squared	0.0346	1.0000									
Rating Level Cubic	0.8089	0.0873	1.0000								
Outlook Positive	-0.0433	-0.0790	-0.0271	1.0000							
Outlook Negative	0.0006	0.0208	-0.0200	-0.1046	1.0000						
Lagged Upgrade	-0.0265	-0.0563	-0.0137	0.0393	-0.1003	1.0000					
Lagged Downgrade	-0.1551	0.0989	-0.1873	-0.0879	0.1522	-0.1206	1.0000				
Difference	-0.6174	-0.1077	-0.5278	0.1176	-0.0359	0.0788	0.1116	1.0000			
Investment Grade	-0.0229	-0.1542	-0.0032	0.0485	0.0032	0.0175	0.0128	0.0222	1.0000		
Size	0.6860	0.0100	0.5674	0.0642	-0.0089	0.0536	-0.1303	-0.1484	-0.0143	1.0000	
Profitability	0.1612	-0.0859	0.1843	0.0548	-0.0823	0.0793	-0.1605	0.0000	-0.0088	0.1776	1.0000
Cash Reserves	-0.1011	0.1245	-0.0615	0.0103	-0.0331	0.0393	-0.0271	0.0448	0.0004	0.0841	-0.1170
Age	0.3396	-0.0206	0.2297	-0.0129	0.0670	-0.0192	0.0377	-0.1565	0.0049	0.2733	0.0803
Stock-Return	-0.0642	-0.0315	-0.0331	0.0430	-0.0315	0.0615	-0.1124	0.0634	0.0020	0.1011	0.0992
Market-to-Book	-0.0007	0.0015	0.0067	-0.0033	0.0177	-0.0036	-0.0107	-0.0129	-0.0044	0.0063	0.0140
Leverage	-0.4491	0.1414	-0.3549	-0.0409	0.0419	-0.0451	0.1049	0.0000	-0.0378	-0.4014	0.0094
M&A Liquidity	-0.0170	0.0111	-0.0058	-0.0037	-0.0268	0.0014	-0.0190	-0.0165	-0.0029	-0.0261	0.0246
Herfindahl Index	-0.0423	-0.0091	-0.0088	0.0054	0.0152	0.0031	0.0203	-0.0453	0.0261	-0.0513	0.0654

	Cash Reserves	Age	Stock-Return	Market-to-Book	Leverage	M&A Liquidity	Herfindhal Index
Cash Reserves	1.0000						
Age	-0.1053	1.0000					
Stock-Return	0.0878	-0.1506	1.0000				
Market-to-Book	0.0115	-0.0061	0.0168	1.0000			
Leverage	-0.1063	-0.1818	-0.0153	0.0162	1.0000		
M&A Liquidity	0.0397	-0.0398	0.0033	0.0029	0.0413	1.0000	
Herfindahl Index	-0.0302	0.0344	-0.0167	-0.0060	0.0194	0.0123	1.0000

Table 3.1

Descriptive Statistics on Acquisitions

The table presents yearly descriptive statistics for a sample of acquisitions by US rated publicly listed bidding firms announced over the period between January 1, 1996 and December 31, 2009. N denotes the number of acquisition announcements by year. An acquisition is considered public (private) when the target firm is a publicly listed (private) company. An acquisition is considered completed when the offer is successful and the deal consummated. Relative size is the ratio between the deal value and the market capitalization of the acquirer at the fiscal year-end prior to the acquisition announcement.

Year	N	Public	Private	Completed	Relative Size
1996	135	82	53	124	12.81%
1997	168	104	64	158	12.94%
1998	199	134	65	179	34.39%
1999	188	136	52	173	35.25%
2000	148	97	51	134	37.78%
2001	105	66	39	99	20.84%
2002	84	42	42	81	12.31%
2003	89	48	41	84	18.21%
2004	112	63	49	109	24.32%
2005	114	58	56	111	31.86%
2006	130	79	51	122	25.53%
2007	101	62	39	94	13.16%
2008	76	34	42	62	20.21%
2009	46	29	17	46	33.42%
Total	1,695	1,034	661	1,576	24.71%

Table 3.2

Descriptive Statistics on Credit Rating Levels

The table presents yearly descriptive statistics for the average credit quality of the universe of US rated publicly listed firms over the period between January 1, 1995 and December 31, 2008. Specifically it reports the average, median and standard deviation of the credit rating level by year.

Year	Mean	Median	Std. Dev.	N
1995	13.88	14	3.79	1,307
1996	13.70	14	3.75	1,474
1997	13.47	14	3.72	1,607
1998	13.33	13.5	3.71	1,772
1999	13.15	13	3.72	1,792
2000	13.07	13	3.70	1,777
2001	12.99	13	3.71	1,733
2002	12.85	13	3.63	1,714
2003	12.80	13	3.55	1,724
2004	12.75	13	3.49	1,738
2005	12.79	13	3.45	1,693
2006	12.73	13	3.50	1,647
2007	12.73	13	3.53	1,581
2008	12.63	13	3.57	1,485
Total	13.05	13	3.65	23,044

Table 3.3

Descriptive Statistics on Credit Rating Changes Proximity Measures

The table presents yearly descriptive statistics for the various credit rating changes proximity measures of the universe of US rated publicly listed firms over the period between January 1, 1995 and December 31, 2008. Panel A reports the number of rating outlooks by type (positive, negative, stable and developing). Panel B reports the number and mean rating change by type (upgrade, downgrade and unchanged). Panel C reports the number and mean estimated deviation by type (above expected-rating and below expected-rating).

Panel A: Rating Outlooks	Positive	Negative	Stable	Developing
N	1,510	3,110	10,850	76
Mean	0.10	0.20	0.70	0.00

Panel B: Lagged Rating Changes	Upgrades	Downgrades	Unchanged
N	2,074	2,953	15,870
Mean	1.32	1.67	0.00

Panel C: Rating Deviations	Difference	Below	Above
N	21,903	11,142	10,761
Mean	4.23	1.71	1.77

Table 3.4

Descriptive Statistics on Firm and Industry Characteristics

The table presents descriptive statistics for the universe of US rated publicly listed firms over the period between January 1, 1996 and December 31, 2009. See Appendix A for definition of the variables. The average, median, standard deviation and number of observations for the control variables used in the empirical analysis are reported.

Year	Mean	Median	Std. Dev.	N
Size ($1,000,000)	7,642.24	7,655.46	1.8786	21,834
Profitability	0.1170	0.1140	0.0948	21,970
Cash Reserves	0.0804	0.0415	0.1074	22,982
Age	20.47	17.00	12.9293	23,044
Stock-Return	0.0074	0.0133	0.0317	20,835
Market-to-Book	3.3472	1.8807	65.9920	21,832
Leverage	0.3628	0.3289	0.2479	22,915
M&A Liquidity	0.0243	0.0013	0.1378	23,044
Herfindhal Index	0.1505	0.1003	0.1478	23,044

Table 3.5

Credit Rating Levels and Acquisition Investments

The table presents the results for probit analysis in models (1) to (3) and the results for tobit analysis in models (4) to (6). The dependent variable in probit models takes the value of if the firm announced at least one acquisition in year *t*, and 0 otherwise. In tobit analysis, the dependent variable is the sum of the announced acquisition deal values in year *t* scaled by firm's total assets in year *t-1*. See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Probit Analysis			Tobit Analysis		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-2.1318***	-2.0912***	-2.0794***	-2.7495***	-2.7029***	-2.6868***
	(-14.50)	(-14.04)	(-13.93)	(-3.62)	(-3.62)	(-3.62)
Rating Level	-0.0448***	-0.0389***	-0.0527***	-0.0617***	-0.0549***	-0.0737***
	(-5.93)	(-5.04)	(-5.02)	(-3.08)	(-2.97)	(-2.97)
Rating Level Squared		-0.0040***	-0.0049***		-0.0047**	-0.0060***
		(-3.54)	(-4.19)		(-2.53)	(-2.74)
Rating Level Cubic			0.0005**			0.0006**
			(2.24)			(2.02)
Size	0.0924***	0.0911***	0.0913***	0.1297***	0.1283***	0.1288***
	(6.18)	(6.03)	(6.02)	(3.04)	(3.03)	(3.02)
Profitability	0.5738***	0.5029***	0.4751**	0.7959***	0.7139**	0.6736**
	(3.08)	(2.68)	(2.53)	(2.73)	(2.56)	(2.48)
Cash Reserves	-0.2272	-0.1422	-0.1298	-0.1119	-0.0107	0.0074
	(-1.39)	(-0.88)	(-0.80)	(-0.59)	(-0.06)	(0.04)
Age	0.0066***	0.0067***	0.0069***	0.0059***	0.0061***	0.0064***
	(4.12)	(4.22)	(4.35)	(2.74)	(2.80)	(2.87)
Stock-Return	2.2850***	2.3310***	2.3218***	2.7321***	2.7842***	2.7706***
	(5.46)	(5.49)	(5.43)	(3.15)	(3.15)	(3.15)
Market-to-Book	0.0001	0.0001	0.0001	0.0003	0.0003	0.0003
	(0.90)	(0.92)	(0.91)	(1.33)	(1.34)	(1.32)
Leverage	-0.2567***	-0.2026**	-0.2055**	-0.3418**	-0.2786**	-0.2819**
	(-3.19)	(-2.50)	(-2.51)	(-2.44)	(-2.17)	(-2.17)
M&A Liquidity	0.4713***	0.4649***	0.4671***	0.6635***	0.6564***	0.6588***
	(4.51)	(4.45)	(4.47)	(3.24)	(3.23)	(3.24)
Herfindahl Index	-0.1227	-0.1228	-0.1301	-0.1710	-0.1730	-0.1825
	(-0.95)	(-0.95)	(-1.00)	(-1.13)	(-1.14)	(-1.19)
N	19,305	19,305	19,305	19,305	19,305	19,305
Pseudo R^2	0.0596	0.0612	0.0617	0.0535	0.0549	0.0555

Table 3.6

Proximity to Credit Rating Changes and Acquisition Investments

The table presents the probit results in odd numbers models and the tobit results in even numbers specifications The dependent variable in probit models takes the value of if the firm announced at least one acquisition in year *t*, and 0 otherwise. In tobit analysis, the dependent variable is the sum of the announced acquisition deal values in year *t* scaled by firm's total assets in year *t-1*. See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Probit	Tobit	Probit	Tobit	Probit	Tobit
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-1.7436***	-2.2364***	-1.7133***	-2.1983***	-1.8097***	-2.3165***
	(-13.29)	(-3.62)	(-12.96)	(-3.60)	(-13.70)	(-3.63)
Outlook Positive	0.1551***	0.1677**				
	(2.94)	(2.51)				
Outlook Negative	-0.1742***	-0.2143***				
	(-3.62)	(-2.88)				
Lagged Upgrade			0.1025**	0.1711*		
			(2.28)	(1.93)		
Lagged Downgrade			-0.3499***	-0.4174***		
			(-6.68)	(-3.83)		
Difference					0.0237***	0.0291**
					(3.25)	(2.41)
Investment-Grade	-0.1544*	-0.0028	-0.1464*	0.0052	-0.1569*	-0.0073
	(-1.82)	(-0.02)	(-1.71)	(0.03)	(-1.84)	(-0.05)
Size	0.0362***	0.0537**	0.0344***	0.0511**	0.0412***	0.0595***
	(3.30)	(2.48)	(3.10)	(2.44)	(3.69)	(2.59)
Profitability	0.2817	0.3991*	0.1634	0.2486	0.3510*	0.4812**
	(1.55)	(1.72)	(0.90)	(1.12)	(1.86)	(1.96)
Cash Reserves	-0.0960	0.0758	-0.1090	0.0591	-0.1061	0.0644
	(-0.60)	(0.43)	(-0.68)	(0.33)	(-0.66)	(0.36)
Age	0.0053***	0.0040**	0.0055***	0.0043**	0.0055***	0.0044**
	(3.34)	(2.14)	(3.44)	(2.23)	(3.48)	(2.26)
Stock-Return	2.6954***	3.3441***	2.5021***	3.0761***	2.6387***	3.2568***
	(6.33)	(3.23)	(5.76)	(3.18)	(6.32)	(3.26)
Market-to-Book	0.0001	0.0003	0.0001	0.0002	0.0001	0.0003
	(1.01)	(1.36)	(0.75)	(1.20)	(0.93)	(1.30)
Leverage	-0.1292*	-0.1614	-0.1104	-0.1387	-0.1362*	-0.1694
	(-1.66)	(-1.58)	(-1.40)	(-1.38)	(-1.72)	(-1.63)
M&A Liquidity	0.4520***	0.6390***	0.4563***	0.6431***	0.4715***	0.6621***
	(4.24)	(3.17)	(4.24)	(3.17)	(4.46)	(3.22)
Herfindahl Index	-0.1373	-0.1941	-0.1299	-0.1863	-0.1139	-0.1668
	(-1.05)	(-1.24)	(-0.98)	(-1.18)	(-0.88)	(-1.08)
N	19,305	19,305	19,305	19,305	19,305	19,305
Pseudo R^2	0.0582	0.0508	0.0610	0.0537	0.0571	0.0500

Table 3.7

Endogeneity Control for Credit Rating Levels

The table presents the Newey (1987) two-step sequential estimator to test for potential endogeneity of credit rating levels. Specifications (1), (2) and (3) are the reduced form regressions for *rating level, rating level squared* and *rating level cubic,* respectively. Specification (4) is the structural regression for the *acquisition dummy.* See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are the two-step adjusted z statistics. N denotes the number of observations. The lower part of the table presents the χ^2 value for the Wald test of endogeneity.

	(1)	(2)	(3)	(4)
Constant	-11.8781***	6.5536***	-309.6855***	-1.8438***
	(-81.62)	(7.17)	(-39.50)	(-5.65)
Rating Level				-0.1652***
				(-3.67)
Rating Level Squared				-0.0089**
				(-1.98)
Rating Level Cubic				0.0046**
				(2.37)
Industry Level	0.2906***	0.1646***	6.2167***	
	(39.55)	(3.57)	(15.71)	
Altman-Z	0.0144***	-0.0588***	0.5855***	
	(5.41)	(-3.51)	(4.07)	
$\widehat{\text{Rating}}$ Level^2	0.0186***	0.8260***	1.8958***	
	(13.65)	(96.45)	(25.80)	
$\widehat{\text{Rating}}$ Level^3	-0.0031***	0.0452***	0.1786***	
	(-19.23)	(44.61)	(20.56)	
Size	1.1965***	-0.4550***	31.7917***	0.0674
	(112.93)	(-6.84)	(55.70)	(1.63)
Profitability	5.8539***	-7.6903***	171.8216***	0.2373
	(34.54)	(-7.23)	(18.82)	(0.79)
Cash Reserves	-3.7264***	13.7153***	-98.1613***	-0.0417
	(-26.81)	(15.71)	(-13.11)	(-0.20)
Age	0.0285***	-0.0334***	0.3262***	0.0080***
	(22.15)	(-4.13)	(4.70)	(5.28)
Stock-Return	-10.1188***	-14.4257***	-206.8417***	2.1450***
	(-21.50)	(-4.88)	(-8.16)	(3.98)
Market-to-Book	0.0003	-0.0012	0.0173	0.0001
	(1.57)	(-0.98)	(1.60)	(0.31)
Leverage	-3.0646***	0.8167*	-73.7994***	-0.2153*
	(-41.05)	(1.74)	(-18.35)	(-1.70)
M&A Liquidity	0.3575**	-2.3302***	3.6386	0.4750***
	(2.47)	(-2.57)	(0.47)	(4.48)
Herfindahl Index	0.3529***	0.6153	24.8709***	-0.2024*
	(3.39)	(0.94)	(4.44)	(-1.72)
Adjusted R^2 (Wald χ^2)	0.7145	0.3822	0.4538	(561.00)
N	19,305	19,305	19,305	19,305
χ^2				16.63
p(value)				(0.000)

Table 3.8

Endogeneity Control for Credit Rating Levels

The table presents the Newey (1987) two-step sequential estimator to test for potential endogeneity of credit rating levels. Specifications (1), (2) and (3) are the reduced form regressions for *rating level*, *rating level squared* and *rating level cubic*, respectively. Specification (4) is the structural regression for the *DVA/AT*. See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers reported in parentheses are the two-step adjusted z statistics. N denotes the number of observations. The lower part of the table presents the χ^2 value for the Wald test of endogeneity.

	(1)	(2)	(3)	(4)
Constant	-11.8781***	6.5536***	-309.6855***	-2.5169***
	(-81.62)	(7.17)	(-39.50)	(-6.30)
Rating Level				-0.1859***
				(-3.38)
Rating Level Squared				-0.0092*
				(-1.66)
Rating Level Cubic				0.0045*
				(1.90)
Industry Level	0.2906***	0.1646***	6.2167***	
	(39.55)	(3.57)	(15.71)	
Altman-Z	0.0144***	-0.0588***	0.5855***	
	(5.41)	(-3.51)	(4.07)	
$\widehat{\text{Rating Level}}^2$	0.0186***	0.8260***	1.8958***	
	(13.65)	(96.45)	(25.80)	
$\widehat{\text{Rating Level}}^3$	-0.0031***	0.0452***	0.1786***	
	(-19.23)	(44.61)	(20.56)	
Size	1.1965***	-0.4550***	31.7917***	0.1139**
	(112.93)	(-6.84)	(55.70)	(2.26)
Profitability	5.8539***	-7.6903***	171.8216***	0.4928
	(34.54)	(-7.23)	(18.82)	(1.34)
Cash Reserves	-3.7264***	13.7153***	-98.1613***	0.0559
	(-26.81)	(15.71)	(-13.11)	(0.22)
Age	0.0285***	-0.0334***	0.3262***	0.0076***
	(22.15)	(-4.13)	(4.70)	(4.08)
Stock-Return	-10.1188***	-14.4257***	-206.8417***	2.5405***
	(-21.50)	(-4.88)	(-8.16)	(3.89)
Market-to-Book	0.0003	-0.0012	0.0173	0.0002
	(1.57)	(-0.98)	(1.60)	(1.18)
Leverage	-3.0646***	0.8167*	-73.7994***	-0.3180**
	(-41.05)	(1.74)	(-18.35)	(-2.06)
M&A Liquidity	0.3575**	-2.3302***	3.6386	0.6681***
	(2.47)	(-2.57)	(0.47)	(5.54)
Herfindahl Index	0.3529***	0.6153	24.8709***	-0.2488*
	(3.39)	(0.94)	(4.44)	(-1.72)
Adjusted R^2 (Wald χ^2)	0.7145	0.3822	0.4538	(475.81)
N	19,305	19,305	19,305	19,305
χ^2				11.81
p(value)				(0.008)

Table 3.9

CreditWatch Placements and Acquisition Investments

The table presents the results for probit analysis in specification (1) and for tobit analysis in specification (2). The dependent variable in probit model takes the value of if the firm announced at least one acquisition in year *t*, and 0 otherwise. In tobit analysis, the dependent variable is the sum of the announced acquisition deal values in year *t* scaled by firm's total assets in year *t-1*. See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	(1)	(2)
Constant	-1.7601***	-2.2561***
	(-13.40)	(-3.63)
Watch Positive	0.3828*	0.5222*
	(1.74)	(1.90)
Watch Negative	-0.3579*	-0.4508*
	(-1.89)	(-1.84)
Investment-Grade	-0.1458*	0.0061
	(-1.71)	(0.04)
Size	0.0370***	0.0545**
	(3.35)	(2.50)
Profitability	0.3407*	0.4677**
	(1.87)	(1.97)
Cash Reserves	-0.0843	0.0902
	(-0.53)	(0.51)
Age	0.0049***	0.0036*
	(3.06)	(1.91)
Stock-Return	2.7366***	3.3811***
	(6.47)	(3.25)
Market-to-Book	0.0001	0.0003
	(0.83)	(1.24)
Leverage	-0.1418*	-0.1764*
	(-1.82)	(-1.70)
M&A Liquidity	0.4629***	0.6513***
	(4.39)	(3.21)
Herfindahl Index	-0.1277	-0.1821
	(-0.97)	(-1.15)
N	19,305	19,305
Pseudo R^2	0.0565	0.0495

Table 3.10

Credit Rating Levels and Acquisition Investments

The table presents the results for the linear spline probit analysis in models (1) to (3) and the results for the linear spline tobit analysis in models (4) to (6). The dependent variable in probit models takes the value of if the firm announced at least one acquisition in year *t*, and 0 otherwise. In tobit analysis, the dependent variable is the sum of the announced acquisition deal values in year *t* scaled by firm's total assets in year *t-1*. See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	(1)	(2)
Constant	-2.5064***	-3.1160***
	(-10.66)	(-3.61)
Rating Level<BB	0.0574**	0.0635**
	(2.47)	(2.03)
BB<=Rating Level<A-	-0.0546***	-0.0758***
	(-4.88)	(-2.98)
Rating Level>=A-	-0.0680***	-0.0851***
	(-3.76)	(-2.69)
Size	0.0913***	0.1287***
	(6.01)	(3.02)
Profitability	0.4497**	0.6443**
	(2.38)	(2.39)
Cash Reserves	-0.1050	0.0364
	(-0.64)	(0.20)
Age	0.0070***	0.0065***
	(4.39)	(2.89)
Stock-Return	2.3170***	2.7630***
	(5.41)	(3.15)
Market-to-Book	0.0001	0.0003
	(0.94)	(1.34)
Leverage	-0.2015**	-0.2791**
	(-2.46)	(-2.14)
M&A Liquidity	0.4653***	0.6571***
	(4.45)	(3.23)
Herfindahl Index	-0.1285	-0.1812
	(-0.99)	(-1.19)
N	19,305	19,305
Pseudo R^2	0.0622	0.0558

Table 3.11

Credit Rating Levels and Acquisition Investments

The table presents the results for restricted cubic spline probit analysis in models (1) to (3) and the results for the restricted cubic spline tobit analysis in models (4) to (6). The dependent variable in probit models takes the value of if the firm announced at least one acquisition in year *t*, and 0 otherwise. In tobit analysis, the dependent variable is the sum of the announced acquisition deal values in year *t* scaled by firm's total assets in year *t-1*. See Appendix A for definition of variables. All regressions control for year- and industry- fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The z-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	(1)	(2)
Constant	-2.5429***	-3.2489***
	(-9.02)	(-3.40)
Rating Level<BB	0.0824**	0.1066**
	(2.25)	(1.96)
BB<=Rating Level<A-	-0.1417***	-0.1918**
	(-3.01)	(-2.38)
Rating Level>=A-	0.4819**	0.6894**
	(2.11)	(2.00)
Size	0.0910***	0.1282***
	(6.00)	(3.02)
Profitability	0.4765**	0.6717**
	(2.54)	(2.48)
Cash Reserves	-0.1292	0.0106
	(-0.80)	(0.06)
Age	0.0069***	0.0064***
	(4.33)	(2.86)
Stock-Return	2.3240***	2.7731***
	(5.45)	(3.15)
Market-to-Book	0.0001	0.0003
	(0.92)	(1.33)
Leverage	-0.2058**	-0.2818**
	(-2.52)	(-2.18)
M&A Liquidity	0.4673***	0.6592***
	(4.47)	(3.24)
Herfindahl Index	-0.1296	-0.1825
	(-1.00)	(-1.19)
N	19,305	19,305
Pseudo R^2	0.0615	0.0553

Chapter 4

Bidders and Targets Made for Each Other: Credit Ratings and Acquisition Returns

4.1 Introduction

As mentioned in the previous chapters, the use of credit ratings has greatly expanded in recent years, mostly due to the globalization of financial markets, the growing complexity of financial products and their evolution in financial regulation and contracting (Kisgen (2006, 2009), and Frost (2007)). On theoretical grounds, prior literature uses credit ratings to measure debt capacity (Holmstrom and Tirole (1997), and Bolton and Freixas (2000)). On the empirical side, a number of studies consider credit ratings as a direct indicator of firms' debt capacity (Lemmon and Zender (2010), Leary and Roberts (2010), De Jong, Verbeek and Verwijmeren (2011), and Hess and Immenkötter (2012)). Additionally, the literature on firms' financial constraints use the existence of rated debt to identify unconstrained firms (Whited (1992), Gilchrist and Himmelberg (1995), Almeida et al. (2004), and Almeida and Campello (2007)). Recently, a still developing literature has examined the effect of credit ratings on firms' financial decisions. Among them, Cantillo and Wright (2000), Denis and Mihov (2003), Faulkender and Petersen (2006), Mittoo and Zhang (2008), Kisgen (2006, 2009), and Rauh and Sufi (2010) demonstrate that credit ratings affect the source of financing and the amounts of leverage which firms possess on their capital structures.

Surprisingly, despite the considerable amount of evidence on the implications of credit ratings on capital structure decisions, there is limited evidence of credit ratings impact on firms' investment decisions and their wealth effects. This examination is of a particular interest, since as it was explained previously in Chapter 3, due to information asymmetries the source of financing plays an important role in corporate investments and might lead to overinvestment or underinvestment respectively. Along these lines, the theoretical model of

John and Nachman (1985) proposes that high credit ratings ameliorate the underinvestment problem.[45] Thus, in so far as credit ratings' have real implications on the access to debt financing, considerations regarding credit ratings should affect also firms' investment choices.

Among firms' investment decisions, an M&A is a major corporate event, since it may be the largest investment that a company might ever undertake thus, entailing implications for the reallocations of resources within the boundaries of the firm (Harford and Li (2007)) and the economy as a whole. A recent study by Harford and Uysal (2012) attempts to address the impact of bidders' access to public debt markets on takeover decisions, and their value creation. In particular, the authors measure the access to debt markets by requiring the bidder to hold a credit rating, without giving emphasis on the quality and level of the rating *per se*. Consequently, they conduct their analysis and conclude that rated (unconstrained) bidders conduct less profitable marginal investment projects relative to the unrated (constrained) ones. Specifically, unrated bidders limit their investments to the highest Net Present Value (NPV) projects, whereas rated bidders can take all the positive NPV projects hence, the marginal project of unrated bidders creates more value than the marginal project of rated bidders.

However, it is plausible that credit ratings affect acquisition returns through other dimensions. First of all, I contend that credit ratings come into play during takeovers through the relative creditworthiness of the bidder to the target. Very often business combinations are formed in which the rating level between bidders and targets varies considerably; therefore the combined rating is determined by the credit quality difference between the merging parties. To exemplify this point, below I provide excerpts from Standard and Poor's credit ratings reports in relation to several acquisitions.

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[45] See footnote 22.

Standard and Poor's (2010): "Standard & Poor's Ratings Services recently placed its 'B' corporate credit rating for Continental on CreditWatch with negative implications, and its 'B-' corporate credit rating for UAL and subsidiary United Air Lines Inc. on CreditWatch with positive implications, pending completion of the merger." and "We currently hold a 'B' rating on Continental and a 'B-' rating on United, and we expect to assign the combined entity a corporate credit rating at one of those two levels. Reflecting this, we placed the corporate credit rating for each company, along with the obligations directly linked to it such as unsecured debt and bank loans, on CreditWatch with negative implications for Continental and positive implications for United."

Standard and Poor's (2012): "On Nov. 1, 2012, Standard & Poor's Ratings Services placed its 'BBB-', corporate credit rating on New York City-based The Warnaco Group Inc. on CreditWatch with negative implications following the announcement that PVH Corp. will acquire Warnaco." and "The CreditWatch placement reflects our expectation that we will lower our rating on Warnaco following the completion of the transaction, likely to 'BB+', based on PVH's weaker credit profile. We believe the combined company's business risk profile is likely "satisfactory" and its financial risk profile is likely "significant." The combination of these risk profiles could result in a corporate credit rating of 'BB+'."

In an adjacent theoretical setting, Myers and Majluf (1984) propose a specific rationale for the existence of mergers that is driven by information asymmetry. In the general version of their model, information asymmetry problems prohibit firms from issuing equity when investment funding is needed, due to their negative effect on firm valuation. Therefore firms forgo positive NPV projects which might lead to underinvestment. According to the authors, maintaining financial slack is a way to mitigate the impediment on firms' investment decisions imposed by information asymmetry. In their paper "financial slack" is defined as cash and liquid assets or *the ability to issue default risk free debt.* Myers and Majluf (1984) also propose that "underinvestment" can be resolved through the conduction of an acquisition. More specifically, a complementary fit between slack rich bidders (i.e. those with close to default-risk-free debt) and slack poor target firms can create value, through the undertaking of additional positive NPV projects by the slack rich bidder, which the slack poor target firm, might pass up. As Myers and Majluf (1984) state:

"[...] firms with plenty of slack should seek out acquisition targets which have good investment opportunities and limited slack, and about which investors have limited information. [...] A tender offer made directly to the slack poor firm's shareholders at a price

(above the discounted value but below the potential value) makes both the bidder and the target's shareholders better off ex ante [...]"

Additionally, the credit quality, which is often measured by the firm rating level (Radhakrishnan et al. (2013)), might also affect acquisition returns. It is likely that the value effects in M&As vary across the credit quality distribution, since highly rated firms face lower cost of debt capital than low rated ones (West (1973), Liu and Thakor (1984), Ederington et al. (1987), Ziebart and Reiter (1992), and Chen et al. (2007)). Consequently, bidders with lower cost of debt can achieve higher NPV for the same expected cash flows *ceteris paribus,* due to the lower discount rate that is applied in the valuation of the combined firm investment projects.

Motivated by the theoretical framework of Myers and Majluf (1984), the objective of this study is to examine the complementary impact of both bidder and target credit ratings, which capture debt capacity, and growth opportunities on acquisition returns. Specifically, I use a sample of US public acquisitions over the period from 1996 to 2009 and measure the effect of the complementary fit in debt capacity and growth opportunities between the bidder and the target in different settings of information asymmetry about the value of the target. To incorporate Myers (1984) argument that firms might wish to maintain "reserve borrowing power [...] to issue safe debt", I measure debt capacity by the firms' credit rating quality prior to the acquisition announcement. To this end, I use firstly the distinction between investment-grade and speculative-grade rated firms in line with Leary and Roberts (2010), and De Jong et al. (2011).[46] Molina (2005), and Almeida and Philippon (2007) empirically demonstrate that default costs are considerable lower for investment-grade firms than for the speculative-

[46] Longstaff et al. (2005), and Chen et al. (2007) demonstrate that investment grade firms generate lower bond yield spreads relative to the speculative grade ones. Furthermore, due to the absence of regulation restrictions regarding allocations in securities of investment grade firms (Kisgen (2007), and Kisgen and Strahan (2010)), these firms enjoy a larger clientele base and a higher demand for their debt securities lowers their cost of debt.

grade ones. Secondly, I use the level of firm credit ratings. Firms with higher credit ratings face lower cost of debt, which, *ceteris paribus,* leads to increased debt capacity (Billett et al. (2011)). Specifically, my prediction based on Myers and Majluf (1984) model is that when a bidder with investment-grade rating or highly rated in general (i.e., high debt capacity), and low growth opportunities acquires an unrated target or lowly rated in general (i.e., low debt capacity) with high growth opportunities and high information asymmetry, financial synergies are created. This is translated into higher synergistic gains, as well as bidder returns.

Overall, the empirical evidence of this study generally supports the hypotheses about the beneficial effect of financial complementarity on takeover gains. The main results I demonstrate are: 1) synergy gains are positively associated with the magnitude of complementarity in debt capacity and growth opportunities between the bidder and the target; 2) bidder returns are positively related with the degree of complementary fit between the bidder and the target; 3) target returns have a negative relationship with the amount of complementarity as it appears that bidders avoid overpayment; 4) the significant effect of the complementary fit on synergy, bidding and target firm returns is mainly driven by the group of target firms that operate under a high information asymmetry environment, a result which is perfectly aligned with the specific propositions of Myers and Majluf (1984); 5) the main results remain robust after testing for endogeneity bias in credit ratings.

This work contributes to the literature related with M&As wealth effects and credit ratings impact on investment outcomes. First, it supports empirically various propositions of the Myers and Majluf (1984) theoretical takeover model. Second, it sheds further light on the shareholders' wealth effects of credit ratings in corporate takeovers. Third, my results echo the findings of Maksimovic and Phillips (2001), and Rhodes–Kropf, Robinson and Viswanathan (2005), and the literature of "who buys whom?" suggesting that wealth effects can be generated when an acquirer with low asset valuation purchases a target with high asset valuation. Fourth, it provides further evidence on the importance of credit ratings in the value effects of corporate investments. My results have also important implications. First, to the extent that a complementary fit of debt capacity and growth opportunities between bidding and target firms lead to value creation in M&As, it implies that credit ratings help to reduce underinvestment in the spirit of Myers and Majluf (1984) proposition. Additionally, the evidence on the wealth effects of the combination where a low valuation bidder buys a high valuation target, suggests that it is against the conventional wisdom of the Q theories of takeovers (Lang, Stulz and Walkling (1989), Servaes (1991), Martin (1996), and Dong, Hirshleifer, Richardson and Teoh (2006)) where the typical merger involves a high valuation bidder purchasing a low valuation target. On the other hand, it is reminiscent of Jensen (1986) incentives for merger activity, where he proposes that bidders with low growth prospects use acquisitions as a channel for buying growth when their market's growth expectations are saturated.

This study is related with a number of previous works. Harford and Uysal (2012) examine the effect of bidder credit rating existence on takeover decisions and their value effects. This study we goes one step further and examines the joint impact of credit quality for both bidding and target firms on acquisition returns. Moreover, Bruner (1988), and Smith and Kim (1994) attempt to investigate the theoretical implications of Myers and Majluf (1984) takeover model. Bruner (1988) focuses only on the difference in debt capacity without considering the growth opportunities aspect. Further, he uses the net debt and debt ratio as a measure of debt capacity. Smith and Kim (1994), on the other hand, take into account both the difference in debt capacity and growth opportunities but they omit the information asymmetry element of the theory. Additionally, their evidence supports the complementary fit from the opposite side (i.e., slack poor bidder-slack rich target) than originally stated by

Myers and Majluf (1984), and they use as a measure of debt capacity variables related with the firm income generation ability. I, instead, take into account the complementary fit in debt capacity and growth opportunities along with the information asymmetry regarding the target firm. Further, I measure debt capacity by the quality of bidder credit ratings prior to the acquisition. Hennessy (2004), and Hennessy, Levy and Whited (2007) examine how debt is related with underinvestment and show that better rated companies exhibit higher firm values than lower rated ones, as measured by the Tobin's Q. In this work, I study the effect of credit quality on bidding firm returns in acquisitions as an implied outcome of mitigation in underinvestment. Finally, the Q theory of takeovers (Lang et al. (1989), Servaes (1991), Martin (1996), and Dong et al. (2006)) documents that the combination of bidders with higher investment opportunities or better management than the targets (high buys low) create value during acquisitions, mainly because target assets are redeployed more efficiently. In this study instead, motivated by the theoretical propositions in Myers and Majluf (1984), while considering as critical factor the information asymmetry of the firms as it was suggested by Rhodes–Kropf et al. (2005), I turn the Q theory on its head and find empirical support for value creation in deals where a "low buys high", resembling the findings in Rau and Vermaelen (1998), Maksimovic and Phillips (2001), and Rhodes–Kropf et al. (2005).

The remainder of the chapter is organized as follows. Section 4.2 describes the sample and presents univariate statistics. Section 4.3 analyzes the methodology and findings of the empirical tests. I check whether my results are biased due to endogeneity in Section 4.4 Finally, Section 4.5 concludes the chapter.

4.2 Sample and Data

4.2.1 *Sample Selection Criteria*

I download a sample of US domestic acquisitions announced over the period 1996 and 2009 from the Thomson Financial SDC Mergers and Acquisitions Database. I require deals to have non-missing transaction value and payment method information. In order to have credit rating data, bidders and targets are publicly-traded firms. The original sample includes 5,079 deals. I remove from the sample all deals classified as repurchases, liquidations, restructurings, divestitures, leveraged buyouts, reverse takeovers, privatizations, bankruptcy acquisitions and going private transactions. This reduces the sample to 4,847 observations. Furthermore, to include in the sample deals that represent a transfer of control, I require that the bidder owns less than 10% of target shares before the announcement and seeks to acquire more than 50% after the acquisition. There are 4,151 transactions that meet these criteria. Further, I drop deals worth less than $1 million and those that account for less than 1% of bidder market value to avoid noise in the analysis. There are 3,095 transactions that satisfy these requirements. I also require the bidding and the target firm to have sufficient data in the CRSP database (CRSP share codes 10 and 11; cases with multiple classes of common stock are excluded) to calculate announcement period returns. The remaining sample is 2,585 transactions.

Finally, I require that bidders are only rated firms and that credit rating information for the bidding and the target firms should be available from COMPUSTAT; this requirement leads to a final sample that includes 1,299 deals. Credit ratings represent the Standard & Poor's (S&P) long-term domestic issuer credit ratings. Appendix A presents the number of deals for each bidding and target firm credit rating level one month prior to the acquisition announcement. Credit ratings range from AAA (highest credit rating) to D (lowest credit rating). In my sample, the highest bidder level is AAA and the lowest is CCC. As for the target ratings, the highest level is AA+ and the lowest is CCC+. Out of the 1,299 acquisitions, 431 deals involve targets with a credit rating and 868 deals with unrated targets.

4.2.2 *Key variables*

I measure the complementarity of debt capacity and growth opportunities between the bidder and the target firm with two different variables. Firstly, I create the variable *ComplFit1*. To construct this variable, I primarily calculate the difference in debt capacity by creating an indicator variable *investment-grade* taking the value of 1 for bidders rated BBB- and above, and 0 otherwise for the group of bidders that merge with targets without a rating. This variable measures the impact of bidder's debt capacity level when acquiring a low debt capacity target; that is without access to public debt markets (Holmstrom and Tirole (1997), and Bolton and Freixas (2000)). According to my hypothesis the combination of "investment-grade bidder/unrated target" will create more value as it is a more optimal blending of merging parties' debt capacity than the combination "speculative-grade bidder/unrated target". As a second step, I measure the mismatch in growth opportunities following Rhodes-Kropf and Robinson (2008) with the surrogate variable *scaled ΔB/M,* which is computed by taking the difference between bidder's and target's *Ln (B/M)* and then scale this spread by the bidder's within-industry[47] standard deviation of *Ln (B/M)* for the fiscal year-end prior to the transaction announcement; a higher value of *scaled ΔB/M* is translated as the target having superior growth opportunities. A firm with a higher value of B/M is conceived as having lower growth opportunities.[48] I specifically use this transformed variable since, in the full sample approximately 66% of the transactions involve a bidder with a lower *Ln (B/M)* than

[47] Industries are defined according to the Fama-French 48 industry classification codes, retrieved from the website of Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html). My results are still consistent with the Fama-French 12 industry classification codes, but in this study I follow the same approach as in Rhodes-Kropf and Robinson (2008).

[48] M/B has been used as an empirical proxy of growth opportunities in other corporate finance contexts (Rajan and Zingales (1995), and Johnson (2003)).

its target,[49] and consequently this can lead to a reduced likelihood of encountering a positive value on the second part of the interaction term, thus producing biased results towards negative values. Particularly, the density distribution of the *Ln (B/M)* difference is mostly concentrated to the left hand side of the origin on the x-axis with a mean (median) value of -0.236 (-0.232). *ComplFit1* value is high when the source of financial synergy is high; that is the bidder has higher debt capacity while the target has superior growth opportunities (*scaled* $\Delta B/M$ carries a positive value). It is worth noting at this point that the construction of *ComplFit1* as a product of two components represents the financial synergy as a source of value. Hence, it does not capture the difference in individual components (debt capacity or growth opportunities), but their complementarity.

Secondly, I construct the variable *ComplFit2* based on the quality of credit rating when both bidding and target firms are rated. *ComplFit2* is similar to *ComplFit1*; it is an interaction variable between the individual components that capture the difference in debt capacity and growth opportunities. The first component *ΔRating* is calculated as the difference between bidder's and target's credit rating level. To construct this component I transform the credit ratings into an ordinal scale ranging from 1 to 22, where 22 represents a rating of AAA and 1 represents a rating of D, following Liu and Malatesta (2005), and An and Chan (2008).[50] However, because in my sample the number of target firms that hold a credit rating is very small (only 431 observations), I decide to use an empirically modelled rating "pseudo-rating" instead of the real rating which target firms hold, and obtain a larger sample of rated firms that will help my estimations. By this way, I examine the effect of target's debt capacity as it is measured by an *implicit* credit rating. This research design does not create any particular problems in the inferences, since one of the main objectives in this study is to investigate the

[49] These findings resemble Andrade et al. (2001), who report that 66% of acquisitions involve a bidder with a higher Q than its target, and Rhodes-Kropf and Robinson (2008) who show that deals with these characteristics occur roughly 60% of the time.
[50] See Appendix A for the correspondence between the number of deals and bidders' and targets' credit rating levels.

complementarity in firms' debt capacities under a generic credit ratings mindset. To derive the equation to calculate the pseudo-rating I regress target firms' real ratings on factors that are thought to predict ratings. Hence, I follow Kisgen (2006) and use a surrogate model of the form:

$$PseudoRating_{it} = 4.5535 + 1.1600Log(TA)_{it-1} - 2.7598Leverage_{it-1} + 4.8821Profitability_{it-1}{}^{51,52} \quad (1)$$

Equation (1) has a satisfactory adjusted R^2 of 0.635, roughly similar with the results in Kisgen (2006).[53] Finally, I conduct an out-of-sample calculation for each target firm in the sample, and round up the scores in order to obtain integer values of credit rating levels. After I compute target firms' pseudo-rating levels, I calculate *ΔRating* as the difference between bidder's *real* and target's *pseudo* credit rating level. A higher value of *ΔRating* implies a better debt capacity of the bidder relative to the target. In my sample approximately 78% of observations involve a bidder with a higher rating than the target. Moreover the average difference in rating levels between the bidder and target is 3 notches. The second component is the *scaled ΔB/M* which is defined as above. *ComplFit2* has a high value when both components are increasing and represents the second measure of the financial synergies created by the complementarity in debt capacity and growth opportunities between the merging firms. Additionally, I create an indicator variable *Negative Dummy* taking the value of 1 when both predictor variables in the interaction term are negative, and 0 otherwise. I construct this variable because the combination of low debt capacity bidder (negative ΔRating) and low growth opportunities target (negative *scaled ΔB/M*), while not the best match according with my story enters with a positive sign in the interaction *ComplFit2* as

[51] The model also includes year- and industry- (Fama-French 48 classification) fixed effects.
[52] Where *i* represents firms and *t* represent time.
[53] The high R^2 should mitigate any concerns about a potential errors-in-variables complication, since the measure for PseudoRating is measured with error.

though, by construction two negative numbers are multiplied together. The sign of the coefficient may misrepresent the real impact of my main control *ComplFit2* and therefore I aim to eliminate this bias from my tests.

4.2.3 Sample Statistics

Table 4.1 presents descriptive statistics for the overall sample and for the investment-grade and speculative-grade bidders sub-samples, respectively. All variables are defined in Appendix B. Panels A and B display statistics for bidder and target characteristics. The mean (median) bidder *size* in the sample is $16,209.280 ($4,639.001) million. Investment-grade bidders are substantially larger ($21,083.840 million) than speculative ones ($3,297.165 million). Moeller et al. (2004) demonstrate that bidder announcement returns are negatively associated with firm size. The mean (median) target size is $2,316.771 ($443.636) million. High debt capacity bidders acquire substantially larger firms. Schwert (2000) documents that larger targets have lower announcement returns.

The mean bidder (target) *book-to-market ratio* (B/M) in the sample is 0.427 (0.549). High debt capacity bidders seem to have lower B/M ratios. Servaes (1991) shows that bidders with higher B/M ratios enjoy lower announcement returns. Targets that are taken over by high debt capacity bidders appear to have lower B/M values. Dong et al. (2006) find a positive relation between target B/M and target abnormal returns.

The mean bidder (target) *run-up* in the sample is a negative -0.3% (-1.4%). Highly rated bidders experience a lower run-up. Rosen (2006) documents a negative impact of bidder's run-up to acquirer announcement returns. The magnitude of run-up among the takeover targets of different debt capacity bidders does not differ statistically. Schwert (1996) shows that target returns do not exhibit any significant relation with target run-up.

The mean bidder (target) *free cash flow-to-assets* is 0.06 (0.06) in my sample. High debt capacity bidders seem to have more free cash flow. Targets acquired by low debt capacity bidders appear to have higher levels of free cash flow. The inclusion of free cash flow variable is of specific importance for the consistency of my hypotheses as though, Myers and Majluf (1984) define financial slack by the amount of cash and liquid assets available to the firm or the ability to issue default risk free debt, and hence it is important to control for both parameters in my analysis and capture better the theoretical properties of their model. Jensen (1986) argues that high free cash flow leads to empire building takeovers. Additionally, Lang, Stulz and Walkling (1991) demonstrate that bidder returns are negatively related with bidder free cash flow. Smith and Kim (1994) report that target free cash flow is positively associated with target returns.

The mean bidder (target) leverage is 0.278 (0.248) in my sample. Highly rated bidders appear to be less leveraged than low rated ones. Masulis, Wang and Xie (2007) suggest that leverage provides incentives for firm managers to improve firm performance, though managers have to relinquish control to debtors and usually lose their jobs if their firms fall into financial distress. They find a positive link between leverage and bidder stock returns. Targets acquired by investment-grade bidders appear to be less leveraged. Bauguess, Moeller, Schlingemann and Zutter (2009) show a negative association between target firms' leverage and their abnormal returns.

The mean (median) target *bid-ask spread* is 0.009 (0.007) in my sample. According to Venkatesh and Chiang (1986) and Barclay and Smith (1988) the bid-ask spread measures firm information asymmetry. Highly rated bidders acquire targets with lower levels of information asymmetry. Officer et al. (2009) demonstrate that bidder returns are positively associated with target's information asymmetry when they use stock as a method of payment.

Panel C provides statistics for deal characteristics. The mean (median) *deal value* in my sample is \$3,292.157 million (\$642.800 million). Transactions of investment-grade bidders are significantly larger than those of speculative-grade ones.

The mean (median) *relative size* in my sample is 0.356 (0.142). High debt capacity bidders acquire smaller firms relative to their size than bidders of low debt capacity. Fuller, Netter and Stegemoller (2002) report that bidder stock returns are negatively related with the relative size of the target in public deals. Officer (2003) finds that target stock returns decline with the relative size of the target in public acquisitions.

With respect to the method of payment, around 24% of the deals are *cash*-financed, approximately 38% represent *stock* deals and the remaining 38% include *mixed* means of payment. A significantly higher proportion of stock deals are conducted by highly rated bidders than low rated ones. On the other hand, investment-grade bidders make less mixed payments than speculative-grade ones. Travlos (1987), and Fuller et al. (2002) document a negative effect on bidder announcement returns when they use stock as a method of payment. Huang and Walkling (1987), and Berkovitch and Narayanan (1990) report that target firm returns are lower in stock swap than in cash deals.

Diversifying deals constitute approximately the 63% of the entire sample. This percentage does not differ significantly across the two categories of bidders. Campa and Kedia (2002), and Villalonga (2004) show, that after considering the endogenous choice of firms to diversify, diversification adds value to firm returns.

Only 5.39% of total deals are *hostile*. Additionally, high debt capacity bidders engage in significantly less hostile offers than low debt capacity ones. Servaes (1991) reports a negative association between bidder announcement returns and hostility. On the other hand, Schwert (2000) documents that hostile offers have a positive effect on target announcement returns.

In my sample, 16.86% of the deals comprise *tender offers*. However, I do not find a significant difference between highly rated and low rated bidders. Jensen and Ruback (1983) demonstrate that tender offers have an incremental impact on bidder and target stock returns.

Completed deals represent around the 91% of the total sample. Further, investment-grade bidders appear to go through more successfully with their takeover attempts than speculative-grade ones. Bates and Lemmon (2003), and Billett et al. (2004) both document that completed deals do not affect bidder returns however, they are associated with higher target returns.

The mean *number of bidders* in the total sample is 1.10. High debt capacity bidders face a lower degree of competition for the target firm's control than low debt capacity ones. Bradley, Desai and Kim (1988) demonstrate that competition decreases the returns to bidders, whereas increases the returns to targets. On the other hand, Servaes (1991) reports an insignificant relationship with bidder returns and a positive with target returns.

The mean (median) takeover *premium* in my sample is 40.59% (33.07%). The difference in premiums paid between the two bidder categories does not appear to differ significantly. The value effects of the complementary fit are measured with 5-day (-2, +2) Cumulative Abnormal Returns (*CARs*). The returns are computed using the market model with the market model parameters estimated over the period (-240, -41) days before the announcement. The market returns is the CRSP equally-weighted index return. *Synergy gain* is defined, following Servaes (1991), as the total shareholder gain and it is computed as the weighted-average abnormal return of the bidder and the target in the event window (-2, +2). The returns are weighted by the market values of the respective firms 4 weeks prior to the acquisition announcement. Mean (median) synergy gain is 1.00% (0.80%) for the full sample. Synergy gain for acquisitions of highly rated bidders is lower than low rated ones but still has a positive value (mean of 0.80%). Mean (median) bidder CARs is a negative -1.60% (-

1.10%) for the overall sample. Additionally, high debt capacity bidders experience less negative announcement returns than low debt capacity ones. Mean (median) target CARs is a positive 21.80% (18.00%) for the full sample. The announcement returns of targets that involve investment-grade bidders are significantly higher than those that involve speculative-grade bidders.

[Please Look Table 4.1]

However, I cannot base my inferences solely on the results of the univariate analysis, as it does not take into account of any confounding effects. So far, I have noticed some mixed evidence regarding the impact of debt capacity on synergy, bidder and target firm announcement returns. However, the main hypothesis regarding the financial synergies is derived from the complementary fit of debt capacity and growth opportunities between bidding and target firms, by taking also into consideration the information asymmetry regarding target firm value. Moreover, Moeller et al. (2004) show that bidder firm returns are a decreasing function of their size whereas, Schwert (2000) demonstrate the same pattern for target returns. Additionally, Wang and Xie (2009) provide evidence that synergy gains and target firm returns are higher in tender offers. Therefore, firm and deal characteristics need to be controlled in order to reveal the net effect of the complementary fit on shareholders' wealth. This cross-sectional regression analysis is presented in the next section. The correlation matrix of the above variables is presented in Table 4.2. The main variables of interest – *ComplFit1* and *ComplFit2* - do not exhibit high correlation with the control variables. This should reduce econometric difficulties (such as multicollinearity concerns) in disentangling any effects of the complementary fit variables from synergy gains as well as bidder and target firm announcement returns.

[Please Look Table 4.2]

4.3 Empirical Analysis

4.3.1 *Synergy Gains and the Complementary Fit of Bidding and Target Firms*

I first investigate the relationship between the complementary fit of bidding and target firms and synergy gains in the context of a multivariate OLS regression analysis by controlling for several bidder-, target-, and deal-specific characteristics. All regressions also control for year fixed effects, whose coefficients are suppressed, and heteroskedasticity-robust standard errors adjusted for bidder clustering due to the presence of repeated acquirers in the sample. Table 4.3 provides the results. The dependent variable is the 5-day combined firm CARs. The main variable of interest is the *ComplFit1*, which represents the interaction variable between *investment-grade* and *scaled ΔB/M* as defined above and is the first measure of complementarity. I also include bidder *size*, bidder and target *book-to-market*, bidder and target *run-up,* bidder and target *free cash flow-to-assets,* bidder and target *leverage, relative size*, *premium, stock* dummy, *completed* deals dummy, *diversifying* deals dummy, *hostile* deals dummy, *tender offers* dummy and *multiple bidders* dummy. In specification (1) I find a positive and significant (at the 5% level) effect of *ComplFit1* on synergy returns by reporting a coefficient (1.09%). This result appears to have strong economic significance as it is translated to a 109% increase over the sample average.[54] The signs of the control variables are generally in line with those in the existing M&A literature. Myers and Majluf (1984) theory is based on the fundamental role of information asymmetry on firms' financing decisions and their value implications. In particular, their takeover theory assumes that financial synergies generated by the complementary fit of debt capacity and growth opportunities between the bidder and the target firm, mainly exist when the target firm operates under a high information asymmetry environment. To examine this hypothesis I split

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[54] I calculate the economic significance by taking the fraction of *ComplFit1* coefficient to the average synergy gains on the overall sample.

the sample into high and low information asymmetry targets by using target *bid-ask spread* to measure the degree of information asymmetry, and I expect that the positive relation of *ComplFit1* with synergy returns should be more pronounced for the high *bid-ask spread* targets. Specification (2) contains acquisitions of target firms with higher *bid-ask spread* values than the median *bid-ask spread* of the targets group. The main variable of interest *ComplFit1* continues to carry a positive and significant (at the 1% level) coefficient (2.13%). In economic terms this is translated to a 213% increase over the sample average. Specification (3) contains the low information asymmetry targets. The main variable of interest *ComplFit1* is insignificant at conventional levels and reinforces the hypothesis that the complementary fit of bidding and target firms should be prevalent under a high information asymmetry environment. Overall, the positive association between *ComplFit1* and synergy gains is driven by the group of acquisitions which involve high information asymmetry target firms.

[Please Look Table 4.3]

Table 4.4 presents the same analysis as above however, in this case I am using my second measure of the complementary fit, i.e. *ComplFit2*, which is an interaction variable between *ΔRating* and *scaled ΔB/M.* I also include *Negative* dummy, bidder *size*, bidder and target *book-to-market*, bidder and target *run-up,* bidder and target *free cash flow-to-assets,* bidder and target *leverage, relative size*, *premium, stock* dummy, *completed* deals dummy, *diversifying* deals dummy, *hostile* deals dummy, *tender offers* dummy and *multiple bidders* dummy.[55] In specification (1) the main variable of interest *ComplFit2* is positive (coefficient 0.12%) and significant at the 10% level. In economic terms an increase in *Complfit2* leads to

[55] In all the regressions that include as main control variable *Complfit2*, I bootstrap the standard errors and the coefficients by running 100 replications, in order to avoid any biased inferences associated with an "generated regressor" problem (Wooldridge (2002)). Since, by construction *Complfit2* includes a generated regressor term (i.e., target firm's pseudo-rating) it can be treated like a generated regressor variable.

12% higher synergy returns over the sample average. When I split the sample into high and low information asymmetry targets I get significant results for the high information asymmetry group. In specification (2) the main variable of interest Complfit2 carries a positive coefficient (0.19%) and significant at the 10% level. In economic terms an increase in *Complfit2* leads to 19% higher synergy returns over the sample average. In specification (3) the results for Complfit2 are insignificant at conventional levels. The signs of the control variables are generally in line with those in the existing M&A literature. Collectively, after controlling for numerous variables that are known from the literature to affect synergy returns, these findings support my hypotheses regarding the positive value effect of financial complementarities between bidder and target firms.

[Please Look Table 4.4]

4.3.2 Bidder Firm Returns and the Complementary Fit of Bidding and Target Firms

In a further step to examine the value implications of the complementary fit between the bidding and target firms in acquisitions, this section investigates its relationship with bidder CARs. Table 4.5 presents the cross-sectional regression analysis of 5-day bidder CARs on my measures of complementary fit and other control variables. In specifications (1) through (3) I run the regressions by including the first measure of complementarity, *ComplFit1* whereas in specifications (4) through (6) I use my second measure, *ComplFit2*. In specifications (1) through (3) I also add bidder *size*, bidder and target *book-to-market*, bidder and target *run-up,* bidder and target *free cash flow-to-assets,* bidder and target *leverage, relative size*, *premium, stock* dummy, *completed* deals dummy, *diversifying* deals dummy, *hostile* deals dummy, *tender offers* dummy and *multiple bidders* dummy. In Model (1) the main variable of interest *ComplFit1* exhibits a positive and significant (at 5% level) relationship (coefficient 1.18%) with bidder returns. The impact of *ComplFit1* on bidder returns appears to have a strong economic significance as it is related with a 174% increase relative to the sample average. The signs of the other control variables are generally in line with those in the existing M&A literature. In specifications (2) and (3) I follow the same method as in the analysis of synergy returns above, and split the sample into high and low information asymmetry target groups. In specification (2) the main variable of interest continues to have a positive and significant (at 1% level) relation (coefficient 2.15%) with bidder returns. In economic terms this is translated to a 234% increase relative to the sample average. On the other hand, when I look at the results in specification (3) I am not able to find any significant relationship between complementarity and bidder returns at conventional levels. These results demonstrate that the positive effect of complementarity in the total sample is driven by the high information asymmetry targets, which provides further support to my conjectures about the differential impact of complementarity across the target firm information asymmetry spectrum.

In models (4) through (6) I use *ComplFit2* as my main variable of interest and also include *Negative* dummy, bidder *size*, bidder and target *book-to-market*, bidder and target *run-up,* bidder and target *free cash flow-to-assets,* bidder and target *leverage, relative size*, *premium, stock* dummy, *completed* deals dummy, *diversifying* deals dummy, *hostile* deals dummy, *tender offers* dummy and *multiple bidders* dummy. In specification (4) *Complfit2* carries a positive and significant (at 5%) association (coefficient 0.15%) with bidder returns. In economic terms an increase in *Complfit2* leads to a 109% higher bidder returns than the sample average. When I look at the high and low information asymmetry target groups I observe that in the high information asymmetry group (specification (5)) my main variable of interest carries a positive coefficient (0.21%) that is significant at the 10% level. Economically this is translated as a 113% increase in bidder returns over the sample average. In model (6) I am not able to find any significant relation between my main control variable and bidder returns. Furthermore, in all of the models *ΔRating* carries a positive and significant coefficient with bidder returns, a finding resembling the results in Billett et al. (2004). All the other control variables have generally signs in accordance with the M&A literature. In summary, the findings from both *Complfit1* and *Complfit2* support my main hypotheses about the creation of value in complementary acquisitions where the target operates under a high information asymmetry environment.

[Please Look Table 4.5]

4.3.3 Target Firm Returns and the Complementary Fit of Bidding and Target Firms

Finally, in order to get the whole picture of the value effects created by the complementary fit on acquisition's shareholder returns, in this section I examine their relationship with target firm CARs. Table 4.6 presents these results. As in the analysis of bidder returns, in specifications (1) through (3) I run the regressions by including the first measure of complementarity, *ComplFit1* whereas in specifications (4) through (6) I use my second measure, *ComplFit2*. In none of the models (1) through (3) I am able to find any significant association of *Complfit1* with target returns. In my second set of regressions (models (4) through (6)), I find a negative relation between *ComplFit2* and target returns in models (4) and (6) at the (5%) level respectively.[56] The rational explanation for this result comes when considering the real situation that target firms face. These are firms with high growth opportunities and a strong potential for generation of future income notwithstanding, due to their limited debt capacity, they encounter problems in accessing credit markets when they are in need to fund these future investment projects. Because of this lack on investment capital their investment opportunities might be left unexploited and their growth potentials

[56] In unreported regression results I find that *ComplFit2* is negatively related with the premium paid to target shareholders.

never materialized. Hence, it comes naturally for target firms to start seeking bidding candidates and for target shareholders to exhibit minor reluctance on the bidder's offer, and exchange their stocks without demanding high premiums since, by this way they will be able to participate on the combined firm's future growth wave. Indeed, Myers and Majluf (1984) specifically comment on the choice that targets face, that is; to forgo the investment opportunity or to start seeking for a merger with a cash-rich firm. Collectively, the findings for synergy gains and bidder and target firm returns support Myers and Majluf (1984) theoretical propositions for the financial synergies created by the complementarity in debt capacity and growth opportunities of bidding and target firms.

[Please Look Table 4.6]

4.4 Robustness checks

4.4.1 *Endogeneity Control*

In the main analysis I treated the *ComplFit1* variable as exogenous to my model; that is the level of complementarity is randomly allocated across my sample firms. However, *ComplFit1* is interaction variable with the first term being a credit rating variable. In that respect Liu and Malatesta (2005), and An and Chan (2008) argue that firms determine, at least partially, whether to obtain a higher rating level after considering the benefits against the potential costs. Therefore, it is likely that the decision to have a high credit rating is based on firm specific characteristics and failure to account for that would lead to biased estimates for the effect of *ComplFit1* in my regressions since, it is rational to expect that the interaction variable is also endogenous.

To test this hypothesis in the case of *ComplFit1*, I use an instrumental variables (2SLS) method, with two potential endogenous variables *Investment-Grade* and *ComplFit1;* the *Investment-Grade* and *ComplFit1* choice equations represent the reduced form, and the firms' returns equations represent the structural form. Although, the first stage regressions represent limited dependent variables, the coefficient estimates from the first stage linear probability models that are being used in the 2SLS method are still consistent, and can be used to uncover any endogeneity bias in the data as Heckman (1978), and Heckman and Robb (1985) demonstrate.

In order to determine the probability of a bidder holding a high rating, I follow Liu and Malatesta (2005), Faulkender and Petersen (2006), and An and Chan (2008) and use variables that have been proposed to account for these effects. Specifically, it has been suggested that a firm is more likely to obtain a high rating if it has more tangible assets, is older, and it operates in an industry with low default probabilities. Therefore, I use: the ratio of firm's property, plant and equipment to total assets as a proxy for tangibility; the number of years the firm is covered on COMPUSTAT to capture the age effect; and the average credit rating level of firms in the same 3-digit industry, to control for the existence of low default risk when firms operate in high credit quality industries. Since, I have two potential endogenous variables *investment-grade* and *ComplFit1* that are interrelated by construction, I use the above variables as instruments for *investment-grade*, and the same variables multiplied by *scaled* $\Delta B/M$ as instruments for *ComplFit1*.

Table 4.7 presents the results of this analysis. In specifications (1) and (2) I report the first stage regression estimates for the prediction of *investment-grade* and *ComplFit1*. In model (1) I find that from the included instruments, bidder *age* and bidder *industry level* are significant and carry coefficients with the expected sign. Moreover, the Adjusted-R^2 from the first stage regression indicates that the model can explain up to 52% of the choice in *investment-grade*. In model (2) I find that all the included instruments exhibit a significant association with the main variable of interest *ComplFit1*. Furthermore, the Adjusted-R^2 from the first stage regression indicates that the model can explain up to 79% of the choice in

ComplFit1. In the structural regressions (3) and (5) I am not able to establish any significant relation of the main control variable with the announcement returns. In specification (4) there is a positive and significant relationship of *Complfit1* with bidder CARs. For sensitivity reasons, in the lower part of Table 4.7 I present the Wu-Hausman (WH) (Wu (1974), and Hausman (1978)) test of endogeneity and its *F*-values. However, when I examine the WH test values, the main variable of interest *ComplFit1* seems exogenous in all of the models, and therefore I can base my inferences in the results of the OLS regressions in Tables 4.3, 4.5 and 4.6. Finally, I also report the Sargan (1958) test for instruments validity to disentangle any concerns that my results are biased due to inappropriate instruments. From the examination of the Sargan test values, I am not able to reject the null of instruments validity in any of the structural regressions, and hence I can conclude that my results are not driven by any misspecification, since, the instruments do not appear to be related with the announcement returns in the structural regressions.

[Please Look Table 4.7]

4.4.2 *Other sensitivity Tests*

Tables 4.8, 4.9, 4.10, and 4.11 present the results for synergy gains, bidder CARs, and target CARs using value-weighted CRSP index (instead of equally-weighted) as the market return in the market model estimation. The coefficient estimates and their significance confirm the main results. Particularly, the positive effect of the complementary fit for my measure *Complfit1* hold for synergy gains and bidder CARs, and it appears to be driven by the high information asymmetry target firms group. The positive effect of *Complfit2* holds for the overall sample in synergy gains, and for the overall and high information asymmetry group in bidder CARs. Regarding the target CARs, the negative effect of the *Complfit2* indicate that bidders avoid overpayment for the targets and that are able to capture the whole gain from the synergies created during the complementary acquisitions.

[Please Look Tables 4.8, 4.9, 4.10, and 4.11]

Tables 4.12, 4.13, 4.14, and 4.15 present the results for synergy gains, bidder CARs, and target CARs using a different abnormal returns methodology than the one that has been used so far. Specifically, I employ the market-adjusted abnormal returns (Brown and Warner (1985)), using the value-weighted CRSP index as the market return in the abnormal returns estimation. The coefficient estimates and their significance corroborate once more time my main hypotheses about the value creation during complementary acquisitions.

[Please Look Tables 4.12, 4.13, 4.14, and 4.15]

4.5 Conclusion

This chapter presents an empirical analysis of the Myers and Majluf (1984) theory of takeovers. My findings corroborate their hypotheses regarding the financial synergies created when information for target firms is limited, and combinations between high debt capacity bidders and high growth opportunities targets are formed. The evidence on this chapter demonstrates that mergers reduce underinvestment, with a direct consequence the creation of wealth for the merging parties. I am able to show that the market values favorably the complementary acquisitions during the period surrounding their announcement. Additionally, results of this chapter enhance our understanding on the literature of Q theory of takeovers, by showing that the market reacts favorably on mergers where a bidder with limited growth capacity acquires a high growth capacity target, contrary to the conventional wisdom.

Furthermore, my findings have strong economic significance and are robust even after accounting for endogeneity bias on the decision to obtain a high rating level. Finally, my results, add also further evidence on the role the credit ratings play for the quality of investments, and specifically acquisitions.

Appendix A. Credit Rating Levels and Number of Deals

Credit ratings are from COMPUSTAT and represent the Standard & Poor's (S&P) long-term domestic issuer credit ratings. Number of deals is the number of acquisitions for each bidder and target real credit rating level one month prior to the acquisition announcement.

Credit Rating Level	Number of Deals (Bidders)	Number of Deals (Targets)
D	-	-
C	-	-
CC	-	-
CCC-	-	-
CCC	1	1
CCC+	5	2
B-	18	11
B	27	16
B+	75	52
BB-	99	49
BB	67	43
BB+	64	35
BBB-	119	38
BBB	181	52
BBB+	132	35
A-	149	29
A	174	33
A+	87	19
AA-	43	9
AA	33	5
AA+	5	2
AAA	20	-

Appendix B. Variable Definitions

Variable	Definition
	Panel A: Measures of Abnormal Returns
Synergy Gain (-2, +2)	Synergy gain is defined as the total shareholder gain and it is computed as the weighted-average abnormal return of the bidder and target in the event window (-2, +2). The returns are weighted by the market values of the respective firms 4 weeks prior to the announcement. CARs are computed using daily data with a market model (equally-weighted CRSP index is the benchmark). The market model is estimated over the period starting 240 days to 41 days before the announcement date.
Bidder CARs (-2, +2)	Cumulative abnormal return of bidding firm stock in the 5-day event window (-2, +2) where 0 is the announcement day. The returns are computed using the market model with the market model parameters estimated over the period (-240, -41) days before the announcement. The market returns is the CRSP equally-weighted index return.
Target CARs (-2, +2)	Cumulative abnormal return of target firm stock in the 5-day event window (-2, +2) where 0 is the announcement day. The returns are computed using the market model with the market model parameters estimated over the period (-240, -41) days before the announcement. The market returns is the CRSP equally-weighted index return.
	Panel B: Complementary Fit Variables
ComplFit1	Investment-Grade x Scaled ΔB/M.
ComplFit2	ΔRating x Scaled ΔB/M.
Investment Grade	Dummy variable: 1 for investment grade bidders (above BBB-), 0 for speculative grade bidders for deals that involve unrated targets.
ΔRating	Difference in Credit Rating Levels between the bidder and the target.
Scaled ΔB/M	Difference in Ln(B/M) between the bidder and the target divided by the standard deviation of bidder's industry Ln(B/M) at the fiscal year-end prior to the acquisition announcement. Industries are defined according to the Fama-French 48-industry classification.
	Panel C: Firm Characteristics
Size	Firm market value of equity 4 weeks prior to the acquisition announcement from CRSP in US$ million.
Book-to-Market (B/M)	Book value of equity divided by market value of equity at the fiscal year-end prior to the acquisition announcement. Book and market value of equity is from COMPUSTAT.
Run-Up	Market-adjusted buy-and-hold returns of the firm over the period starting (-205, -6) days prior to the acquisition announcement from CRSP.
Bid-Ask Spread	Average Bid-Ask Spread of the firm daily stock returns measured over the period (-186, -6) days prior to the acquisition announcement from CRSP.

FCF to Assets	Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the total assets at the fiscal year-end immediately prior to the announcement from COMPUSTAT.
Leverage	Firm total financial debt (long-term debt plus debt in current liabilities) divided by the book value of total assets in the fiscal year-end prior to the acquisition announcement from COMPUSTAT.
	Panel D: Deal Characteristics
Relative Size	The ratio of the deal value to bidder market value of equity 4 weeks prior to the acquisition announcement from CRSP in US$ million.
Cash Deals	Dummy variable: 1 for deals entirely financed with cash, 0 otherwise.
Stock Deals	Dummy variable: 1 for deals entirely financed with stock, 0 otherwise.
Mixed Deals	Dummy variable: 1 for deals where consideration is neither all-cash nor all-stock, 0 otherwise.
Diversifying Deals	Dummy variable: 1 for inter-industry transactions, 0 for intra-industry transactions. Industries are defined at the 4-digit SIC level from Thomson Financial SDC.
Hostile Deals	Dummy variable: 1 for deals defined as "hostile" or "unsolicited" by Thomson Financial SDC, 0 otherwise.
Tender Offers	Dummy variable: 1 for tender offers from Thomson Financial SDC, 0 otherwise.
Completed Deals	Dummy variable: 1 for deals that terminate successfully from Thomson Financial SDC, 0 otherwise.
Takeover Premium	The difference between the offer price and the target stock price 4 weeks prior to the takeover announcement divided by the latter from Thomson Financial SDC; values beyond the range of [0,2] are winsorized following Officer (2003).
Number of Bidders	The total number of bidders entering the contest from Thomson Financial SDC.
Multiple Bidders	Dummy variable: 1 if more than one bidders enter the contest, 0 otherwise.
	Panel E: Instrumental Variables
Tangibility	The ratio of firm's property, plant and equipment to total assets at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.
Age	The number of years the firm is covered in COMPUSTAT at the acquisition announcement year.
Industry Rating	The firm's 3-digit SIC industry average credit rating level at the fiscal year-end immediately prior to the acquisition announcement from COMPUSTAT.

Table 4.1

Sample Descriptive Statistics

The table presents descriptive statistics for a sample of US public acquisitions announced over the period between January 1, 1996 and December 31, 2009 drawn from the Thomson Financial SDC Mergers and Acquisitions Database. Panels A, B and C describe the mean, median and number of observations for bidder- target, and deal-specific characteristics, respectively, for the overall sample as well as for investment-grade and speculative-grade bidders. Credit ratings represent the Standard & Poor's (S&P) long-term domestic issuer credit ratings from COMPUSTAT. Stock price data is from CRSP, accounting data is from COMPUSTAT. All variables are defined in Appendix B. Statistical tests for differences in means and equality of medians for each characteristic of investment-grade versus speculative-grade bidders are also presented in parentheses. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels.

	All Sample (1)			Investment-Grade (2)			Speculative-Grade (3)			Difference (2)-(3)	
	Mean	Median	N	Mean	Median	N	Mean	Median	N	(p-value) Mean	(p-value) Median
Panel A: Bidder Characteristics											
Bidder Size	16,209.280	4,639.001	1,299	21,083.840	7,181.664	943	3,297.165	1,356.262	356	(0.000)	(0.000)
Bidder B/M	0.427	0.386	1,287	0.405	0.384	935	0.484	0.392	352	(0.000)	(0.695)
Bidder Run-Up	-0.003	-0.045	1,283	-0.041	-0.054	936	0.102	-0.026	347	(0.000)	(0.278)
Bidder FCF/Assets	0.060	0.057	1,258	0.063	0.055	909	0.052	0.061	349	(0.023)	(0.345)
Bidder Leverage	0.278	0.244	1,281	0.230	0.221	929	0.404	0.388	352	(0.000)	(0.000)
Panel B: Target Characteristics											
Target Size	2,316.771	443.636	1,204	2,764.505	543.195	878	1,110.913	272.105	326	(0.000)	(0.000)
Target B/M	0.549	0.473	1,153	0.533	0.469	844	0.593	0.501	309	(0.037)	(0.378)
Target Run-Up	-0.014	-0.092	1,176	0.003	-0.093	867	-0.060	-0.087	309	(0.365)	(0.643)
Target Bid-Ask Spread	0.009	0.007	1,204	0.008	0.007	879	0.011	0.009	325	(0.000)	(0.000)
Target FCF/Assets	0.033	0.051	1,125	0.037	0.044	821	0.021	0.062	304	(0.142)	(0.001)
Target Leverage	0.248	0.215	1,032	0.234	0.207	753	0.287	0.247	279	(0.000)	(0.141)
Panel C: Deal Characterisitcs											
Deal Value	3,292.157	642.800	1,299	3,868.946	769.303	943	1,764.314	374.401	356	(0.000)	(0.000)
Relative Size	0.356	0.142	1,299	0.272	0.100	943	0.589	0.374	356	(0.000)	(0.000)
% Cash Deals	24.403	-	1,299	24.708	-	943	23.596	-	356	(0.677)	-
% Stock Deals	37.721	-	1,299	39.554	-	943	32.865	-	356	(0.027)	-
% Mixed Deals	37.875	-	1,299	35.737	-	943	43.540	-	356	(0.010)	-
% Diversifying Deals	63.356	-	1,299	66.278	-	943	31.742	-	356	(0.166)	-
% Hostile Deals	5.389	-	1,299	4.348	-	943	8.146	-	356	(0.007)	-
% Tender Offers	16.859	-	1,299	17.285	-	943	15.730	-	356	(0.505)	-
% Completed Deals	90.685	-	1,299	93.320	-	943	83.371	-	356	(0.000)	-
% Takeover Premium	40.594	33.065	1,200	40.350	33.040	878	41.258	33.330	322	(0.675)	(0.896)
Number of Bidders	1.100	-	1,299	1.080	-	943	1.138	-	356	(0.021)	-
Synergy Gain (-2, +2)	0.010***	0.008***	1,203	0.008***	0.006***	878	0.017***	0.017***	325	(0.049)	(0.042)
Bidder CARs (-2, +2)	-0.016***	-0.010***	1,299	-0.014***	-0.009***	943	-0.022***	-0.016***	356	(0.091)	(0.220)
Target CARs (-2, +2)	0.218***	0.180***	1,203	0.230***	0.190***	878	0.188***	0.156***	325	(0.008)	(0.011)

Table 4.2

Variables Correlation Matrix

The table presents pair-wise correlations of the variables. The sample consists of US public acquisitions announced over the period between January 1, 1996 and December 31, 2009. All variables are defined in Appendix B.

	ComplFit1	ComplFit2	Bidder Size	Bidder B/M	Bidder Run-Up	Bidder FCF/Assets	Bidder Leverage	Target B/M	Target Run-up	Target FCF/Assets	Target Leverage	Relative Size
ComplFit1	1.000											
ComplFit2	0.762	1.000										
Bidder Size	-0.018	0.006	1.000									
Bidder B/M	0.229	0.163	-0.092	1.000								
Bidder Run-Up	0.008	0.012	0.021	-0.108	1.000							
Bidder FCF/Assets	-0.064	-0.063	0.058	-0.036	-0.024	1.000						
Bidder Leverage	0.092	0.036	0.012	-0.043	0.003	0.002	1.000					
Target B/M	-0.406	-0.388	-0.114	0.329	-0.113	-0.120	-0.018	1.000				
Target Run-Up	-0.071	-0.027	0.039	-0.040	0.146	0.052	-0.017	-0.041	1.000			
Target FCF/Assets	-0.001	-0.024	0.072	-0.073	0.040	0.323	0.125	-0.035	0.049	1.000		
Target Leverage	0.103	0.165	0.076	0.039	-0.014	0.097	0.400	-0.082	-0.008	0.044	1.000	
Relative Size	0.180	0.123	-0.030	0.196	-0.038	-0.055	0.086	-0.001	-0.013	0.051	0.138	1.000
Stock Deals	-0.067	-0.027	0.033	-0.113	0.084	-0.102	-0.111	-0.041	-0.015	-0.074	-0.160	-0.004
Diversifying	-0.016	-0.022	-0.005	0.009	-0.009	-0.018	-0.008	-0.018	-0.049	-0.009	-0.015	-0.020
Hostile Deals	0.014	0.005	0.039	0.006	-0.017	0.028	0.053	0.032	-0.018	0.053	0.053	0.084
Tender Offers	0.005	-0.038	0.060	0.011	-0.037	0.055	0.020	0.035	0.057	0.005	0.012	0.035
Completed	-0.078	-0.086	-0.016	-0.027	0.042	0.030	-0.062	-0.018	0.003	-0.005	-0.043	-0.137
Premium	-0.097	-0.144	-0.049	-0.023	0.132	-0.010	-0.068	0.141	-0.001	-0.093	-0.050	-0.045
Multiple Bidders	0.083	0.049	0.056	0.009	-0.018	0.024	0.046	0.048	0.092	0.054	0.051	0.081
Synergy Gain	0.072	0.044	-0.066	0.203	-0.134	-0.008	0.046	0.113	-0.026	0.058	0.043	0.142
Bidder CARs	0.033	0.006	-0.048	0.099	-0.052	-0.079	0.014	0.123	0.003	-0.022	0.032	0.075
Target CARs	-0.152	-0.197	0.015	-0.021	-0.015	0.030	-0.079	0.131	-0.062	-0.020	-0.067	-0.139

	Stock Deals	Diversifying	Hostile Deals	Tender Offers	Completed	Premium	Multiple Bidders	Synergy Gain	Bidder CARs	Target CARs
Stock Deals	1.000									
Diversifying	0.002	1.000								
Hostile Deals	-0.035	-0.001	1.000							
Tender Offers	-0.133	0.013	0.175	1.000						
Completed	-0.066	-0.017	-0.402	-0.054	1.000					
Premium	-0.038	0.007	0.022	0.112	0.004	1.000				
Multiple Bidders	-0.024	-0.008	0.358	0.174	-0.305	0.037	1.000			
Synergy Gain	-0.158	-0.044	0.061	0.123	-0.017	0.061	0.023	1.000		
Bidder CARs	-0.032	0.020	-0.027	-0.005	-0.008	-0.043	-0.032	0.854	1.000	
Target CARs	-0.136	0.003	0.011	0.204	0.065	0.592	-0.065	0.307	0.102	1.000

Table 4.3

Cross-Sectional Regression Analysis (OLS) of Synergy Gains on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the synergy gains on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Synergy Gains		
	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)
Constant	0.0550	0.1060**	0.0435
	(1.61)	(2.13)	(0.82)
ComplFit1	0.0109**	0.0213***	-0.0071
	(2.05)	(3.26)	(-0.47)
Investment-Grade	0.0080	0.0124	-0.0039
	(0.91)	(0.96)	(-0.27)
Scaled ΔB/M	-0.0066	-0.0060	0.0023
	(-1.23)	(-1.02)	(0.12)
Ln (Bidder Size)	-0.0055**	-0.0108**	-0.0012
	(-2.08)	(-2.53)	(-0.37)
Bidder B/M	0.0100	-0.0240	0.0255
	(0.63)	(-1.01)	(1.10)
Bidder Run-Up	0.0037	0.0035	0.0250
	(0.50)	(0.36)	(0.88)
Bidder FCF/Assets	-0.0059	-0.0624	0.0907
	(-0.12)	(-0.88)	(1.20)
Bidder Leverage	-0.0170	-0.0428	0.0042
	(-0.74)	(-1.14)	(0.10)
Target B/M	0.0024	0.0087	-0.0005
	(0.21)	(0.66)	(-0.02)
Target Run-Up	0.0018	0.0033	-0.0261*
	(0.82)	(1.55)	(-1.82)
Target FCF/Assets	0.0254	0.0148	0.1246*
	(1.40)	(0.77)	(1.97)
Target Leverage	0.0172	0.0339	-0.0014
	(1.10)	(1.48)	(-0.06)
Premium	0.0002**	0.0003**	0.0001
	(2.02)	(2.18)	(0.52)
Relative Size	0.0221	-0.0077	0.0402**
	(1.38)	(-0.28)	(2.28)
Stock Dummy	-0.0190***	-0.0211**	-0.0083
	(-3.20)	(-2.24)	(-0.95)
Completed	-0.0101	-0.0160	-0.0392
	(-0.53)	(-0.71)	(-1.24)
Diversifying Deals	-0.0026	0.0010	-0.0058
	(-0.45)	(0.10)	(-0.78)
Hostile Deals	0.0056	-0.0115	0.0155
	(0.30)	(-0.61)	(0.39)
Tender Offers	0.0168**	0.0115	0.0114
	(2.44)	(1.11)	(0.99)
Multiple Bidders	-0.0158	-0.0065	-0.0303
	(-1.08)	(-0.33)	(-1.28)
N	560	302	258
Adjusted R^2	0.099	0.095	0.156

Table 4.4

Cross-Sectional Regression Analysis (OLS) of Synergy Gains on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the synergy gains on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are bootstrapped with 100 replications and are adjusted for heteroskedasticity as also bidder clustering. N denotes the number of observations.

	Synergy Gains		
	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)
Constant	0.0420	0.0091	0.0895***
	(1.57)	(0.24)	(2.79)
ComplFit2	0.0012*	0.0019*	0.0004
	(1.73)	(1.79)	(0.37)
ΔRating	0.0005	0.0007	0.0001
	(0.50)	(0.45)	(0.09)
Scaled ΔB/M	-0.0040	-0.0019	-0.0139*
	(-0.80)	(-0.24)	(-1.65)
Negative Dummy	-0.0007	-0.0230	0.0303*
	(-0.06)	(-1.10)	(1.82)
Ln (Bidder Size)	-0.0037*	-0.0025	-0.0070***
	(-1.92)	(-0.80)	(-3.30)
Bidder B/M	0.0123	-0.0059	0.0423***
	(0.79)	(-0.29)	(2.58)
Bidder Run-Up	-0.0052	-0.0103	0.0112
	(-0.66)	(-1.15)	(0.61)
Bidder FCF/Assets	0.0221	-0.0115	0.0878
	(0.54)	(-0.19)	(1.63)
Bidder Leverage	-0.0043	-0.0021	-0.0032
	(-0.23)	(-0.06)	(-0.11)
Target B/M	0.0051	0.0150	-0.0333*
	(0.50)	(1.27)	(-1.67)
Target Run-Up	0.0005	0.0010	-0.0158
	(0.16)	(0.30)	(-1.43)
Target FCF/Assets	0.0392**	0.0283	0.0791
	(2.17)	(1.07)	(1.47)
Target Leverage	0.0059	0.0150	-0.0008
	(0.47)	(0.65)	(-0.04)
Premium	0.0002**	0.0002**	0.0002*
	(2.23)	(2.02)	(1.83)
Relative Size	0.0138*	0.0110	0.0107
	(1.91)	(0.74)	(1.34)
Stock Dummy	-0.0089**	0.0035	-0.0113**
	(-2.05)	(0.43)	(-2.02)
Completed	-0.0114	-0.0041	-0.0234*
	(-1.07)	(-0.25)	(-1.83)
Diversifying Deals	-0.0037	0.0016	-0.0070
	(-0.79)	(0.21)	(-1.21)
Hostile Deals	0.0006	0.0063	-0.0158
	(0.05)	(0.39)	(-1.27)
Tender Offers	0.0264***	0.0283***	0.0227***
	(4.68)	(2.66)	(3.23)
Multiple Bidders	-0.0178**	-0.0119	-0.0277**
	(-2.13)	(-0.64)	(-2.43)
N	885	426	459
Adjusted R^2	0.087	0.044	0.170

Table 4.5

Cross-Sectional Regression Analysis (OLS) of Bidder CARs on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the bidder firm 5-day CARs on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Bidder CARs			Bidder CARs		
	All Sample	High Information Asymmetry	Low Information Asymmetry	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0460	0.1082**	-0.0154	0.0190	0.0136	0.0435
	(1.31)	(2.16)	(-0.24)	(0.70)	(0.36)	(1.14)
ComplFit1	0.0118**	0.0215***	-0.0114			
	(2.28)	(3.27)	(-0.64)			
Investment-Grade	0.0156*	0.0200	0.0035			
	(1.73)	(1.53)	(0.23)			
ComplFit2				0.0015**	0.0021*	0.0005
				(2.19)	(1.91)	(0.34)
ΔRating				0.0041***	0.0034**	0.0044**
				(3.45)	(1.99)	(2.14)
Negative Dummy				-0.0034	-0.0277	0.0302
				(-0.29)	(-1.34)	(1.58)
Scaled ΔB/M	-0.0020	-0.0078	0.0273	-0.0023	-0.0044	-0.0016
	(-0.39)	(-1.42)	(1.10)	(-0.43)	(-0.53)	(-0.13)
Ln (Bidder Size)	-0.0046	-0.0109**	0.0031	-0.0039*	-0.0049	-0.0050*
	(-1.61)	(-2.38)	(0.91)	(-1.74)	(-1.59)	(-1.88)
Bidder B/M	-0.0071	-0.0218	-0.0234	-0.0016	-0.0089	0.0055
	(-0.60)	(-0.87)	(-0.85)	(-0.12)	(-0.42)	(0.19)
Bidder Run-Up	0.0095	0.0077	0.0424	0.0015	-0.0050	0.0149
	(1.23)	(0.89)	(1.18)	(0.18)	(-0.57)	(0.60)
Bidder FCF/Assets	-0.0109	-0.0524	0.0676	-0.0083	-0.0262	0.0409
	(-0.23)	(-0.72)	(0.87)	(-0.19)	(-0.40)	(0.66)
Bidder Leverage	-0.0028	-0.0431	0.0483	0.0251	0.0163	0.0336
	(-0.10)	(-1.10)	(0.96)	(1.09)	(0.48)	(1.00)
Target B/M	0.0158	0.0077	0.0571*	0.0144	0.0133	0.0089
	(1.55)	(0.62)	(1.95)	(1.60)	(1.28)	(0.31)
Target Run-Up	0.0026	0.0044**	-0.0188	0.0026	0.0028	0.0050
	(1.27)	(2.20)	(-1.22)	(0.75)	(0.76)	(0.40)
Target FCF/Assets	0.0049	-0.0006	0.0780	0.0268	0.0223	0.0460
	(0.26)	(-0.03)	(1.18)	(1.39)	(0.88)	(0.78)
Target Leverage	0.0155	0.0488**	-0.0336	-0.0056	0.0119	-0.0269
	(0.98)	(2.09)	(-1.42)	(-0.42)	(0.53)	(-1.52)
Premium	0.0000	0.0001	-0.0003**	-0.0001	0.0000	-0.0003**
	(0.11)	(0.92)	(-2.01)	(-1.25)	(0.00)	(-2.46)
Relative Size	-0.0318**	-0.0538**	-0.0172	-0.0123	-0.0277**	-0.0083
	(-2.18)	(-2.34)	(-1.01)	(-1.53)	(-2.10)	(-0.87)
Stock Dummy	-0.0197***	-0.0278***	-0.0073	-0.0084*	-0.0064	-0.0054
	(-3.27)	(-2.85)	(-0.74)	(-1.82)	(-0.81)	(-0.76)
Completed	-0.0170	-0.0235	-0.0266	-0.0118	-0.0037	-0.0214
	(-0.88)	(-1.03)	(-0.59)	(-1.08)	(-0.23)	(-1.34)
Diversifying Deals	-0.0002	0.0029	-0.0009	-0.0005	0.0023	-0.0014
	(-0.03)	(0.29)	(-0.11)	(-0.11)	(0.29)	(-0.21)
Hostile Deals	-0.0066	-0.0094	-0.0056	-0.0069	-0.0072	-0.0052
	(-0.35)	(-0.43)	(-0.12)	(-0.64)	(-0.47)	(-0.32)
Tender Offers	0.0154**	0.0097	0.0134	0.0201***	0.0185*	0.0181**
	(2.32)	(0.92)	(1.21)	(3.47)	(1.75)	(2.18)
Multiple Bidders	-0.0085	-0.0036	-0.0203	-0.0142	-0.0128	-0.0240*
	(-0.55)	(-0.16)	(-1.03)	(-1.54)	(-0.68)	(-1.87)
N	560	302	258	885	426	459
Adjusted R^2	0.065	0.128	0.004	0.081	0.094	0.055

Table 4.6

Cross-Sectional Regression Analysis (OLS) of Target CARs on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the target firm 5-day CARs on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Target CARs			Target CARs		
	All Sample	High Information Asymmetry	Low Information Asymmetry	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1460	0.1580	0.3970**	0.2090**	0.0836	0.2992***
	(1.01)	(0.78)	(2.52)	(2.37)	(0.63)	(3.17)
ComplFit1	-0.0344	-0.0364	-0.0528			
	(-1.44)	(-1.10)	(-1.15)			
Investment-Grade	0.0305	0.0887	-0.0076			
	(0.87)	(1.61)	(-0.18)			
ComplFit2				-0.0071**	-0.0067	-0.0064**
				(-2.57)	(-1.54)	(-2.56)
ΔRating				0.0158***	0.0191***	0.0132***
				(4.70)	(2.86)	(3.56)
Negative Dummy				0.0784**	0.0634	0.0849***
				(2.27)	(1.21)	(2.91)
Scaled ΔB/M	0.0328	0.0483	-0.0117	0.0409	0.0513	-0.0047
	(0.95)	(1.22)	(-0.22)	(1.60)	(1.36)	(-0.19)
Ln (Bidder Size)	-0.0050	-0.0152	0.0031	-0.0080	-0.0017	-0.0105
	(-0.38)	(-0.71)	(0.25)	(-1.16)	(-0.15)	(-1.44)
Bidder B/M	-0.1084	-0.1819*	0.0483	-0.1011	-0.1474	0.0246
	(-1.48)	(-1.79)	(0.75)	(-1.62)	(-1.60)	(0.47)
Bidder Run-Up	0.0258	0.0397	-0.0135	0.0163	0.0208	0.0215
	(0.97)	(1.30)	(-0.21)	(0.67)	(0.78)	(0.56)
Bidder FCF/Assets	0.0936	-0.0336	0.1692	0.0725	-0.0472	0.1921
	(0.46)	(-0.13)	(0.39)	(0.47)	(-0.26)	(0.79)
Bidder Leverage	-0.0046	0.0851	-0.1509	-0.0306	0.0566	-0.0855
	(-0.05)	(0.59)	(-1.56)	(-0.45)	(0.68)	(-1.33)
Target B/M	0.1580	0.1929	-0.0647	0.1324*	0.1563*	-0.0193
	(1.58)	(1.61)	(-0.70)	(1.91)	(1.66)	(-0.25)
Target Run-Up	-0.0152	-0.0145	-0.0978**	-0.0200	-0.0175	-0.1447***
	(-1.39)	(-1.31)	(-2.09)	(-0.76)	(-0.77)	(-3.82)
Target FCF/Assets	0.0454	0.0683	0.1730	0.1064	0.1681	0.0824
	(0.64)	(0.83)	(1.07)	(1.33)	(1.41)	(0.60)
Target Leverage	0.0075	-0.0252	0.1136	-0.0145	-0.0315	0.0449
	(0.12)	(-0.30)	(1.23)	(-0.29)	(-0.42)	(0.74)
Relative Size	-0.0533	-0.0797	-0.0223	-0.0358***	-0.0348	-0.0265**
	(-1.55)	(-1.34)	(-0.56)	(-2.65)	(-1.06)	(-1.97)
Stock Dummy	-0.0506**	-0.0228	-0.0759**	-0.0233	0.0242	-0.0570***
	(-2.00)	(-0.54)	(-2.39)	(-1.46)	(0.89)	(-2.99)
Completed	0.0535	0.0732	-0.1804**	0.0026	0.0173	-0.0280
	(1.22)	(1.25)	(-2.20)	(0.09)	(0.45)	(-1.06)
Diversifying Deals	-0.0090	-0.0091	-0.0202	-0.0128	0.0016	-0.0222
	(-0.38)	(-0.24)	(-0.79)	(-0.89)	(0.06)	(-1.16)
Hostile Deals	0.1005	0.0587	-0.0631	0.0311	0.0118	-0.0204
	(1.55)	(0.74)	(-0.63)	(1.03)	(0.29)	(-0.61)
Tender Offers	0.0722**	0.0836	0.0703*	0.1043***	0.1530***	0.0744***
	(2.12)	(1.44)	(1.91)	(3.78)	(3.07)	(2.83)
Multiple Bidders	-0.0617	-0.0290	-0.1357***	-0.0664***	-0.0377	-0.0884***
	(-1.58)	(-0.51)	(-3.46)	(-2.77)	(-0.99)	(-3.63)
N	577	312	265	908	438	470
Adjusted R^2	0.090	0.088	0.113	0.157	0.150	0.217

Table 4.7

Endogeneity Control for Credit Rating

The table presents the results of the instrumental variables regression procedure to control for potential endogeneity of ComplFit1 for a sample of US public acquisitions over the period 1996-2009. Specifications (1) and (2) are the reduced regressions. Specification (3) is the structural regression for synergy gains. Specification (4) is the structural regression for bidder CARs. Specification (5) is the structural regression for target CARs. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity. N denotes the number of observations. The lower part of the table shows the F-test of the WH test for endogeneity, and the χ^2 of the Sargan test for instruments validity with their corresponding p-values in parentheses.

	Reduced	Reduced	Structural	Structural	Structural
	Investment-Grade	ComplFit1	Synergy Gains	Bidder CARs	Target CARs
	(1)	(2)	(3)	(4)	(5)
Constant	-0.6359***	0.5478**	0.0667**	0.0605*	0.1185
	(3.20)	(2.40)	(1.99)	(1.73)	(0.80)
ComplFit1			0.0081	0.0108*	-0.0155
			(1.23)	(1.78)	(-0.66)
Investment-Grade			0.0102	0.0280	-0.0790
			(0.46)	(1.32)	(-0.93)
Scaled ΔB/M	0.1513*	-0.3522	-0.0066	-0.0026	0.0170
	(1.66)	(-1.60)	(-1.19)	(-0.50)	(0.59)
Ln (Bidder Size)	0.0996***	-0.0390**	-0.0066*	-0.0071*	0.0084
	(7.77)	(-2.30)	(-1.79)	(-1.81)	(0.46)
Bidder B/M	-0.0340	-0.2726***	0.0115	-0.0064	-0.0972
	(-0.55)	(-2.76)	(0.74)	(-0.54)	(-1.44)
Bidder Run-Up	-0.1352***	0.0208	0.0046	0.0126	0.0060
	(-3.92)	(0.44)	(0.56)	(1.44)	(0.21)
Bidder FCF/Assets	-0.0226	-0.6036**	-0.0145	-0.0110	0.0535
	(-0.10)	(-2.57)	(-0.30)	(-0.23)	(0.27)
Bidder Leverage	-0.5688***	0.3146***	-0.0153	0.0058	-0.0937
	(-5.01)	(2.69)	(-0.54)	(0.18)	(-0.78)
Tar B/M	0.0422	-0.0470	-0.0013	0.0120	0.1581
	(0.92)	(-0.53)	(-0.11)	(1.19)	(1.55)
Target Run-Up	0.0026	-0.0264	0.0019	0.0028	-0.0143
	(0.50)	(-1.63)	(0.91)	(1.47)	(-1.29)
Target FCF/Assets	-0.0127	0.1485	0.0286	0.0080	0.0431
	(-0.13)	(0.89)	(1.62)	(0.44)	(0.63)
Target Leverage	0.0005	0.0385	0.0173	0.0130	0.0363
	(0.44)	(0.37)	(1.14)	(0.84)	(0.59)
Premium	0.0005	-0.0001	0.0002**	0.0000	
	(1.36)	(-0.22)	(2.19)	(0.25)	
Relative Size	-0.1689***	-0.0027	0.0208	-0.0319**	-0.0667*
	(-3.35)	(-0.03)	(1.30)	(-2.21)	(-1.92)
Stock Dummy	-0.0104	0.0659*	-0.0202***	-0.0204***	-0.0467*
	(-0.31)	(1.84)	(-3.42)	(-3.41)	(-1.83)
Completed	-0.0142	0.0212	-0.0143	-0.0220	0.0702*
	(-0.20)	(0.28)	(-0.75)	(-1.13)	(1.72)
Diversifying Deals	0.0112	-0.0286	-0.0019	0.0002	-0.0051
	(0.35)	(-0.87)	(-0.34)	(0.04)	(-0.21)
Hostile Deals	-0.0504	-0.1902	0.0012	-0.0095	0.0975
	(-0.59)	(-0.16)	(0.06)	(-0.52)	(1.55)
Tender Offers	0.0291	-0.0069	0.0174**	0.0163**	0.0842**
	(0.72)	(-0.16)	(2.55)	(2.46)	(2.44)
Multiple Bidders	-0.0809	0.2154***	-0.0166	-0.0089	-0.0729*
	(-1.28)	(2.68)	(-1.16)	(-0.59)	(-1.80)
Bidder Tangibility	-0.0847	-0.3161***			
	(-0.90)	(-3.11)			
Bidder Age	0.0049***	0.0046***			
	(4.45)	(3.42)			
Bidder Industry Rating	0.0469***	-0.0187*			
	(6.21)	(-1.95)			
Bidder Tangibility * Scaled ΔB/M	-0.1165*	-0.6084***			
	(-1.76)	(-4.44)			
Bidder Age *Scaled ΔB/M	-0.0007	0.0141***			
	(-0.86)	(8.15)			
Bidder Industry Rating * Scaled ΔB/M	-0.0078	0.0577**			
	(-1.48)	(2.40)			
N	543	543	543	543	559
Adjusted R^2	0.523	0.790	0.103	0.067	0.067
F-test			0.38	0.29	1.69
WH Test			(0.685)	(0.745)	(0.186)
χ^2			3.98	1.84	2.76
Sargan Test			(0.409)	(0.765)	(0.599)

Table 4.8

Cross-Sectional Regression Analysis (OLS) of Synergy Gains on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the synergy gains on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Synergy Gains		
	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)
Constant	0.0518	0.0797	0.0437
	(1.52)	(1.57)	(0.82)
ComplFit1	0.0117**	0.0202***	0.0007
	(2.22)	(3.05)	(0.05)
Investment-Grade	0.0092	0.0139	-0.0023
	(1.04)	(1.09)	(-0.16)
Scaled ΔB/M	-0.0093	-0.0087	-0.0052
	(-1.62)	(-1.37)	(-0.26)
Ln (Bidder Size)	-0.0055**	-0.0096**	-0.0018
	(-2.06)	(-2.21)	(-0.58)
Bidder B/M	0.0162	0.0016	0.0216
	(1.25)	(0.07)	(0.87)
Bidder Run-Up	0.0041	0.0024	0.0253
	(0.52)	(0.23)	(0.89)
Bidder FCF/Assets	0.0021	-0.0280	0.0781
	(0.04)	(-0.38)	(1.00)
Bidder Leverage	-0.0240	-0.0455	0.0036
	(-1.07)	(-1.20)	(0.09)
Target B/M	0.0019	0.0057	0.0019
	(0.16)	(0.42)	(0.07)
Target Run-Up	0.0034*	0.0049**	-0.0233*
	(1.71)	(2.47)	(-1.66)
Target FCF/Assets	0.0263	0.0183	0.1186*
	(1.45)	(0.91)	(1.89)
Target Leverage	0.0187	0.0355	-0.0025
	(1.21)	(1.53)	(-0.11)
Premium	0.0002**	0.0003**	0.0001
	(2.07)	(2.17)	(0.82)
Relative Size	0.0234	-0.0108	0.0441**
	(1.55)	(-0.43)	(2.59)
Stock Dummy	-0.0169***	-0.0150	-0.0104
	(-2.87)	(-1.61)	(-1.21)
Completed	-0.0130	-0.0173	-0.0373
	(-0.70)	(-0.75)	(-1.15)
Diversifying Deals	-0.0022	0.0026	-0.0044
	(-0.38)	(0.28)	(-0.61)
Hostile Deals	0.0034	-0.0065	0.0179
	(0.19)	(-0.34)	(0.45)
Tender Offers	0.0141**	0.0087	0.0099
	(2.04)	(0.90)	(0.81)
Multiple Bidders	-0.0153	-0.0109	-0.0240
	(-1.01)	(-0.53)	(-0.98)
N	560	302	258
Adjusted R^2	0.098	0.084	0.166

Table 4.9

Cross-Sectional Regression Analysis (OLS) of Synergy Gains on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the synergy gains on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are bootstrapped with 100 replications and are adjusted for heteroskedasticity as also bidder clustering. N denotes the number of observations.

	Synergy Gains		
	All Sample	**High Information Asymmetry**	**Low Information Asymmetry**
	(1)	(2)	(3)
Constant	0.0456*	0.0035	0.0979***
	(1.74)	(0.09)	(3.04)
ComplFit2	0.0012*	0.0016	0.0009
	(1.82)	(1.59)	(0.87)
ΔRating	0.0007	0.0009	0.0001
	(0.67)	(0.62)	(0.07)
Scaled ΔB/M	-0.0068	-0.0045	-0.0169*
	(-1.35)	(-0.55)	(-1.90)
Negative Dummy	-0.0049	-0.0270	0.0250
	(-0.45)	(-1.29)	(1.54)
Ln (Bidder Size)	-0.0042**	-0.0027	-0.0074***
	(-2.22)	(-0.88)	(-3.28)
Bidder B/M	0.0158	0.0056	0.0380**
	(1.19)	(0.28)	(2.15)
Bidder Run-Up	-0.0043	-0.0105	0.0119
	(-0.57)	(-1.15)	(0.66)
Bidder FCF/Assets	0.0143	-0.0139	0.0699
	(0.36)	(-0.23)	(1.27)
Bidder Leverage	-0.0095	-0.0048	-0.0081
	(-0.53)	(-0.15)	(-0.28)
Target B/M	0.0009	0.0085	-0.0325
	(0.10)	(0.73)	(-1.54)
Target Run-Up	0.0020	0.0025	-0.0136
	(0.64)	(0.79)	(-1.24)
Target FCF/Assets	0.0411**	0.0309	0.0825
	(2.24)	(1.22)	(1.57)
Target Leverage	0.0055	0.0163	-0.0041
	(0.46)	(0.73)	(-0.23)
Premium	0.0002**	0.0003**	0.0003**
	(2.55)	(2.27)	(2.04)
Relative Size	0.0155**	0.0132	0.0112
	(2.16)	(0.86)	(1.37)
Stock Dummy	-0.0077*	0.0068	-0.0135**
	(-1.76)	(0.87)	(-2.21)
Completed	-0.0136	-0.0045	-0.0262*
	(-1.30)	(-0.27)	(-1.92)
Diversifying Deals	-0.0026	0.0034	-0.0061
	(-0.61)	(0.45)	(-1.06)
Hostile Deals	0.0013	0.0097	-0.0146
	(0.11)	(0.60)	(-1.17)
Tender Offers	0.0246***	0.0263***	0.0211***
	(4.26)	(2.58)	(2.80)
Multiple Bidders	-0.0200**	-0.0171	-0.0284**
	(-2.35)	(-0.90)	(-2.46)
N	885	426	459
Adjusted R^2	0.084	0.042	0.169

Table 4.10

Cross-Sectional Regression Analysis (OLS) of Bidder CARs on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the bidder firm 5-day CARs on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Bidder CARs			Bidder CARs		
	All Sample	High Information Asymmetry	Low Information Asymmetry	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0446	0.0837	-0.0137	0.0239	0.0094	0.0529
	(1.22)	(1.61)	(-0.21)	(0.87)	(0.24)	(1.36)
ComplFit1	0.0126**	0.0203***	-0.0032			
	(2.41)	(3.06)	(-0.17)			
Investment-Grade	0.0167*	0.0215	0.0047			
	(1.80)	(1.63)	(0.31)			
ComplFit2				0.0015**	0.0018*	0.0010
				(2.26)	(1.74)	(0.71)
ΔRating				0.0043***	0.0036**	0.0044**
				(3.58)	(2.15)	(2.22)
Negative Dummy				-0.0077	-0.0316	0.0245
				(-0.64)	(-1.49)	(1.31)
Scaled ΔB/M	-0.0048	-0.0106*	0.0194	-0.0055	-0.0071	-0.0049
	(-0.86)	(-1.76)	(0.75)	(-1.00)	(-0.86)	(-0.37)
Ln (Bidder Size)	-0.0047	-0.0098**	0.0025	-0.0044**	-0.0052*	-0.0054**
	(-1.61)	(-2.11)	(0.74)	(-2.02)	(-1.67)	(-1.97)
Bidder B/M	-0.0014	0.0036	-0.0277	0.0018	0.0024	0.0011
	(-0.11)	(0.14)	(-0.95)	(0.14)	(0.11)	(0.03)
Bidder Run-Up	0.0098	0.0064	0.0433	0.0025	-0.0052	0.0161
	(1.20)	(0.68)	(1.21)	(0.31)	(-0.59)	(0.66)
Bidder FCF/Assets	-0.0052	-0.0192	0.0503	-0.0172	-0.0292	0.0213
	(-0.10)	(-0.25)	(0.64)	(-0.40)	(-0.44)	(0.33)
Bidder Leverage	-0.0112	-0.0468	0.0458	0.0186	0.0123	0.0274
	(-0.42)	(-1.16)	(0.93)	(0.82)	(0.36)	(0.80)
Target B/M	0.0152	0.0046	0.0598*	0.0101	0.0067	0.0097
	(1.44)	(0.35)	(1.93)	(1.16)	(0.64)	(0.32)
Target Run-Up	0.0043**	0.0060***	-0.0164	0.0041	0.0043	0.0073
	(2.29)	(3.17)	(-1.11)	(1.30)	(1.22)	(0.58)
Target FCF/Assets	0.0051	0.0021	0.0719	0.0280	0.0237	0.0498
	(0.27)	(0.10)	(1.10)	(1.42)	(0.98)	(0.84)
Target Leverage	0.0176	0.0510**	-0.0340	-0.0052	0.0140	-0.0294
	(1.11)	(2.16)	(-1.45)	(-0.39)	(0.63)	(-1.62)
Premium	0.0000	0.0001	-0.0002	-0.0001	0.0000	-0.0003**
	(0.20)	(0.90)	(-1.62)	(-0.97)	(0.22)	(-2.16)
Relative Size	-0.0304**	-0.0572**	-0.0129	-0.0107	-0.0258*	-0.0078
	(-2.14)	(-2.55)	(-0.80)	(-1.37)	(-1.85)	(-0.84)
Stock Dummy	-0.0176***	-0.0213**	-0.0096	-0.0072	-0.0028	-0.0076
	(-2.97)	(-2.25)	(-1.00)	(-1.50)	(-0.36)	(-1.01)
Completed	-0.0199	-0.0245	-0.0256	-0.0139	-0.0038	-0.0243
	(-1.05)	(-1.05)	(-0.55)	(-1.28)	(-0.23)	(-1.44)
Diversifying Deals	0.0003	0.0044	0.0006	0.0005	0.0039	-0.0005
	(0.04)	(0.45)	(0.08)	(0.10)	(0.52)	(-0.07)
Hostile Deals	-0.0098	-0.0055	-0.0042	-0.0067	-0.0045	-0.0040
	(-0.53)	(-0.25)	(-0.09)	(-0.62)	(-0.30)	(-0.24)
Tender Offers	0.0128*	0.0072	0.0120	0.0183***	0.0165*	0.0165*
	(1.89)	(0.72)	(1.01)	(3.11)	(1.66)	(1.88)
Multiple Bidders	-0.0078	-0.0075	-0.0140	-0.0163*	-0.0178	-0.0248*
	(-0.47)	(-0.31)	(-0.66)	(-1.69)	(-0.91)	(-1.88)
					(-0.17)	(-0.50)
N	560	302	258	885	426	459
Adjusted R^2	0.061	0.121	0.002	0.076	0.089	0.057

Table 4.11

Cross-Sectional Regression Analysis (OLS) of Target CARs on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the target firm 5-day CARs on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Target CARs			Target CARs		
	All Sample	High Information Asymmetry	Low Information Asymmetry	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1382	0.1198	0.4047**	0.2095**	0.0718	0.3101***
	(0.97)	(0.59)	(2.58)	(2.40)	(0.54)	(3.27)
ComplFit1	-0.0354	-0.0392	-0.0480			
	(-1.48)	(-1.19)	(-1.05)			
Investment-Grade	0.0312	0.0884	-0.0061			
	(0.89)	(1.60)	(-0.14)			
ComplFit2				-0.0072***	-0.0071	-0.0061**
				(-2.64)	(-1.62)	(-2.51)
ΔRating				0.0159***	0.0194***	0.0131***
				(4.64)	(2.89)	(3.57)
Negative Dummy				0.0740**	0.0588	0.0804***
				(2.18)	(1.11)	(2.79)
Scaled ΔB/M	0.0333	0.0486	-0.0162	0.0396	0.0500	-0.0062
	(0.96)	(1.22)	(-0.31)	(1.55)	(1.33)	(-0.25)
Ln (Bidder Size)	-0.0048	-0.0131	0.0022	-0.0082	-0.0016	-0.0108
	(-0.36)	(-0.61)	(0.18)	(-1.19)	(-0.14)	(-1.50)
Bidder B/M	-0.1036	-0.1569	0.0454	-0.0976	-0.1350	0.0212
	(-1.47)	(-1.57)	(0.70)	(-1.61)	(-1.45)	(0.41)
Bidder Run-Up	0.0274	0.0401	-0.0141	0.0181	0.0225	0.0217
	(1.03)	(1.30)	(-0.23)	(0.73)	(0.83)	(0.57)
Bidder FCF/Assets	0.1131	0.0123	0.1811	0.0750	-0.0385	0.1884
	(0.55)	(0.05)	(0.42)	(0.48)	(-0.22)	(0.77)
Bidder Leverage	-0.0081	0.0861	-0.1494	-0.0305	0.0618	-0.0876
	(-0.09)	(0.60)	(-1.54)	(-0.45)	(0.74)	(-1.35)
Target B/M	0.1619	0.1948	-0.0626	0.1320*	0.1535	-0.0189
	(1.62)	(1.63)	(-0.68)	(1.91)	(1.62)	(-0.25)
Target Run-Up	-0.0140	-0.0133	-0.0955**	-0.0190	-0.0163	-0.1427***
	(-1.29)	(-1.19)	(-2.05)	(-0.70)	(-0.71)	(-3.80)
Target FCF/Assets	0.0585	0.0846	0.1675	0.1178	0.1830	0.0834
	(0.82)	(1.02)	(1.04)	(1.47)	(1.53)	(0.61)
Target Leverage	0.0073	-0.0259	0.1109	-0.0170	-0.0328	0.0397
	(0.11)	(-0.31)	(1.21)	(-0.34)	(-0.43)	(0.66)
Relative Size	-0.0541	-0.0839	-0.0209	-0.0347***	-0.0327	-0.0265**
	(-1.59)	(-1.46)	(-0.52)	(-2.59)	(-1.03)	(-1.98)
Stock Dummy	-0.0481*	-0.0175	-0.0762**	-0.0220	0.0265	-0.0580***
	(-1.90)	(-0.41)	(-2.41)	(-1.36)	(0.95)	(-3.06)
Completed	0.0509	0.0727	-0.1816**	-0.0009	0.0154	-0.0323
	(1.17)	(1.24)	(-2.19)	(-0.03)	(0.40)	(-1.22)
Diversifying Deals	-0.0095	-0.0079	-0.0205	-0.0121	0.0031	-0.0220
	(-0.40)	(-0.20)	(-0.80)	(-0.84)	(0.11)	(-1.14)
Hostile Deals	0.1011	0.0667	-0.0640	0.0326	0.0164	-0.0206
	(1.58)	(0.82)	(-0.63)	(1.06)	(0.39)	(-0.61)
Tender Offers	0.0708**	0.0826	0.0696*	0.1037***	0.1531***	0.0729***
	(2.08)	(1.42)	(1.89)	(3.72)	(3.04)	(2.79)
Multiple Bidders	-0.0618	-0.0321	-0.1325***	-0.0690***	-0.0421	-0.0896***
	(-1.59)	(-0.56)	(-3.32)	(-2.88)	(-1.08)	(-3.77)
N	577	312	265	908	438	470
Adjusted R^2	0.092	0.089	0.112	0.158	0.150	0.216

Table 4.12

Cross-Sectional Regression Analysis (OLS) of Synergy Gains on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the synergy gains on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Synergy Gains		
	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)
Constant	0.0402	0.0648	0.0456
	(1.17)	(1.27)	(0.85)
ComplFit1	0.0119**	0.0225***	-0.0042
	(2.09)	(3.17)	(-0.27)
Investment-Grade	0.0079	0.0142	-0.0056
	(0.87)	(1.05)	(-0.39)
Scaled AB/M	-0.0083	-0.0077	-0.0018
	(-1.34)	(-1.10)	(-0.09)
Ln (Bidder Size)	-0.0047*	-0.0083*	-0.0020
	(-1.75)	(-1.87)	(-0.64)
Bidder B/M	0.0164	-0.0003	0.0196
	(1.10)	(-0.01)	(0.77)
Bidder Run-Up	0.0178**	0.0172	0.0345
	(2.17)	(1.57)	(1.20)
Bidder FCF/Assets	0.0110	-0.0175	0.0708
	(0.21)	(-0.24)	(0.94)
Bidder Leverage	-0.0256	-0.0456	-0.0020
	(-1.18)	(-1.24)	(-0.05)
Target B/M	0.0042	0.0101	-0.0001
	(0.36)	(0.74)	(-0.00)
Target Run-Up	0.0037**	0.0051***	-0.0240*
	(2.15)	(2.99)	(-1.70)
Target FCF/Assets	0.0326*	0.0240	0.1273**
	(1.76)	(1.19)	(2.05)
Target Leverage	0.0166	0.0334	-0.0066
	(1.07)	(1.43)	(-0.30)
Premium	0.0002**	0.0003**	0.0001
	(2.09)	(2.13)	(0.76)
Relative Size	0.0276*	-0.0030	0.0448**
	(1.79)	(-0.11)	(2.51)
Stock Dummy	-0.0137**	-0.0114	-0.0094
	(-2.31)	(-1.20)	(-1.10)
Completed	-0.0072	-0.0122	-0.0290
	(-0.37)	(-0.51)	(-0.87)
Diversifying Deals	-0.0013	0.0039	-0.0052
	(-0.22)	(0.42)	(-0.70)
Hostile Deals	0.0058	-0.0061	0.0251
	(0.31)	(-0.29)	(0.62)
Tender Offers	0.0126*	0.0057	0.0102
	(1.78)	(0.56)	(0.85)
Multiple Bidders	-0.0111	-0.0082	-0.0170
	(-0.74)	(-0.41)	(-0.71)
N	560	302	258
Adjusted R^2	0.106	0.085	0.187

Table 4.13

Cross-Sectional Regression Analysis (OLS) of Synergy Gains on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the synergy gains on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are bootstrapped with 100 replications and are adjusted for heteroskedasticity as also bidder clustering. N denotes the number of observations.

	Synergy Gains		
	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)
Constant	0.0408	-0.0008	0.0985***
	(1.50)	(-0.02)	(3.03)
ComplFit2	0.0013*	0.0019*	0.0008
	(1.89)	(1.79)	(0.82)
ΔRating	0.0007	0.0004	0.0004
	(0.65)	(0.29)	(0.24)
Scaled ΔB/M	-0.0028	-0.0245	0.0257
	(-0.26)	(-1.22)	(1.60)
Negative Dummy	-0.0070	-0.0047	-0.0179**
	(-1.28)	(-0.56)	(-2.05)
Ln (Bidder Size)	-0.0040**	-0.0022	-0.0076***
	(-2.19)	(-0.72)	(-3.46)
Bidder B/M	0.0157	0.0039	0.0405**
	(1.01)	(0.19)	(2.09)
Bidder Run-Up	0.0098	0.0053	0.0216
	(1.25)	(0.54)	(1.19)
Bidder FCF/Assets	0.0283	0.0108	0.0665
	(0.66)	(0.17)	(1.24)
Bidder Leverage	-0.0101	-0.0078	-0.0067
	(-0.57)	(-0.24)	(-0.22)
Target B/M	0.0018	0.0109	-0.0368*
	(0.18)	(0.91)	(-1.77)
Target Run-Up	0.0023	0.0028	-0.0139
	(0.81)	(0.85)	(-1.23)
Target FCF/Assets	0.0462**	0.0314	0.0883*
	(2.51)	(1.22)	(1.68)
Target Leverage	0.0046	0.0186	-0.0078
	(0.37)	(0.83)	(-0.45)
Premium	0.0002***	0.0003**	0.0003**
	(2.77)	(2.47)	(2.05)
Relative Size	0.0157**	0.0131	0.0116
	(2.15)	(0.85)	(1.37)
Stock Dummy	-0.0066	0.0081	-0.0135**
	(-1.48)	(1.00)	(-2.19)
Completed	-0.0101	-0.0020	-0.0219
	(-0.92)	(-0.12)	(-1.60)
Diversifying Deals	-0.0021	0.0049	-0.0069
	(-0.47)	(0.65)	(-1.16)
Hostile Deals	0.0042	0.0131	-0.0125
	(0.36)	(0.78)	(-0.95)
Tender Offers	0.0228***	0.0224**	0.0213***
	(3.79)	(2.16)	(2.85)
Multiple Bidders	-0.0195**	-0.0161	-0.0273**
	(-2.29)	(-0.85)	(-2.34)
N	885	426	459
Adjusted R^2	0.081	0.032	0.178

Table 4.14

Cross-Sectional Regression Analysis (OLS) of Bidder CARs on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the bidder firm 5-day CARs on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. I also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Bidder CARs			Bidder CARs		
	All Sample	High Information Asymmetry	Low Information Asymmetry	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0372	0.0733	-0.0079	0.0208	0.0061	0.0546
	(1.02)	(1.37)	(-0.12)	(0.74)	(0.15)	(1.44)
ComplFit1	0.0124**	0.0222***	-0.0088			
	(2.26)	(3.16)	(-0.48)			
Investment-Grade	0.0150	0.0207	0.0019			
	(1.60)	(1.48)	(0.13)			
ComplFit2				0.0016**	0.0021*	0.0010
				(2.32)	(1.92)	(0.68)
ΔRating				0.0042***	0.0030*	0.0047**
				(3.48)	(1.81)	(2.32)
Negative Dummy				-0.0050	-0.0273	0.0244
				(-0.44)	(-1.31)	(1.34)
Scaled ΔB/M	-0.0038	-0.0097	0.0237	-0.0058	-0.0076	-0.0057
	(-0.65)	(-1.47)	(0.92)	(-0.98)	(-0.88)	(-0.46)
Ln (Bidder Size)	-0.0042	-0.0088*	0.0020	-0.0043**	-0.0048	-0.0057**
	(-1.45)	(-1.84)	(0.61)	(-2.03)	(-1.52)	(-2.10)
Bidder B/M	-0.0019	0.0010	-0.0301	0.0012	0.0003	0.0029
	(-0.15)	(0.04)	(-1.02)	(0.09)	(0.02)	(0.10)
Bidder Run-Up	0.0246***	0.0220**	0.0553	0.0179**	0.0110	0.0296
	(2.92)	(2.22)	(1.53)	(2.20)	(1.16)	(1.21)
Bidder FCF/Assets	0.0017	-0.0123	0.0449	-0.0058	-0.0077	0.0165
	(0.03)	(-0.16)	(0.59)	(-0.13)	(-0.11)	(0.26)
Bidder Leverage	-0.0133	-0.0477	0.0401	0.0171	0.0077	0.0291
	(-0.51)	(-1.21)	(0.82)	(0.77)	(0.23)	(0.84)
Target B/M	0.0165	0.0078	0.0580*	0.0103	0.0082	0.0057
	(1.60)	(0.60)	(1.87)	(1.15)	(0.76)	(0.20)
Target Run-Up	0.0043***	0.0061***	-0.0193	0.0042	0.0044	0.0047
	(2.78)	(3.69)	(-1.30)	(1.34)	(1.14)	(0.37)
Target FCF/Assets	0.0131	0.0096	0.0829	0.0341*	0.0247	0.0579
	(0.68)	(0.46)	(1.27)	(1.71)	(1.01)	(0.98)
Target Leverage	0.0165	0.0505**	-0.0379	-0.0043	0.0188	-0.0319*
	(1.03)	(2.11)	(-1.62)	(-0.32)	(0.83)	(-1.77)
Premium	0.0000	0.0001	-0.0002*	-0.0001	0.0001	-0.0003**
	(0.25)	(0.91)	(-1.72)	(-0.72)	(0.46)	(-2.02)
Relative Size	-0.0282**	-0.0524**	-0.0137	-0.0112	-0.0267*	-0.0080
	(-1.97)	(-2.18)	(-0.86)	(-1.41)	(-1.85)	(-0.86)
Stock Dummy	-0.0145**	-0.0182*	-0.0083	-0.0062	-0.0019	-0.0073
	(-2.44)	(-1.89)	(-0.87)	(-1.28)	(-0.23)	(-0.98)
Completed	-0.0139	-0.0192	-0.0191	-0.0104	-0.0008	-0.0207
	(-0.70)	(-0.78)	(-0.40)	(-0.92)	(-0.05)	(-1.24)
Diversifying Deals	0.0009	0.0055	-0.0005	0.0008	0.0055	-0.0015
	(0.15)	(0.57)	(-0.07)	(0.17)	(0.72)	(-0.23)
Hostile Deals	-0.0084	-0.0051	-0.0013	-0.0039	-0.0003	-0.0032
	(-0.43)	(-0.21)	(-0.03)	(-0.35)	(-0.02)	(-0.19)
Tender Offers	0.0115*	0.0041	0.0128	0.0167***	0.0126	0.0169**
	(1.68)	(0.40)	(1.10)	(2.75)	(1.25)	(1.96)
Multiple Bidders	-0.0032	-0.0049	-0.0061	-0.0154	-0.0171	-0.0229*
	(-0.20)	(-0.20)	(-0.30)	(-1.62)	(-0.88)	(-1.69)
N	560	302	258	885	426	459
Adjusted R^2	0.069	0.115	0.034	0.075	0.071	0.075

Table 4.15

Cross-Sectional Regression Analysis (OLS) of Target CARs on the Complementary Fit of Bidding and Target Firms

The table presents the results of the cross-sectional OLS regression analysis of the target firm 5-day CARs on the complementary fit of debt capacity and growth opportunities between bidding and target firms and other bidder, target-, and deal- characteristics for a sample of US public acquisitions over the period 1996-2009. IF also split the overall sample of acquisitions into deals that involve high and low information asymmetry targets. High (Low) information asymmetry target firms are the ones with higher (lower) *bid-ask spread* values than the median *bid-ask spread* of the target firms in the sample. See Appendix B for definitions of the variables. All regressions control for year fixed effects whose coefficients are suppressed. The symbols ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics reported in parentheses are adjusted for heteroskedasticity and bidder clustering. N denotes the number of observations.

	Target CARs			Target CARs		
	All Sample	High Information Asymmetry	Low Information Asymmetry	All Sample	High Information Asymmetry	Low Information Asymmetry
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1212	0.1022	0.4011**	0.2072**	0.0770	0.3100***
	(0.85)	(0.51)	(2.54)	(2.36)	(0.58)	(3.23)
ComplFit1	-0.0361	-0.0390	-0.0519			
	(-1.51)	(-1.20)	(-1.13)			
Investment-Grade	0.0286	0.0878	-0.0096			
	(0.81)	(1.58)	(-0.22)			
ComplFit2				-0.0071***	-0.0067	-0.0063**
				(-2.62)	(-1.56)	(-2.55)
ΔRating				0.0158***	0.0186***	0.0133***
				(4.63)	(2.78)	(3.59)
Negative Dummy				0.0752**	0.0569	0.0830***
				(2.22)	(1.09)	(2.85)
Scaled ΔB/M	0.0352	0.0507	-0.0122	0.0402	0.0503	-0.0055
	(1.03)	(1.30)	(-0.23)	(1.62)	(1.35)	(-0.21)
Ln (Bidder Size)	-0.0031	-0.0110	0.0020	-0.0080	-0.0016	-0.0111
	(-0.23)	(-0.52)	(0.17)	(-1.18)	(-0.15)	(-1.49)
Bidder B/M	-0.1070	-0.1646*	0.0353	-0.0996	-0.1399	0.0186
	(-1.50)	(-1.68)	(0.54)	(-1.62)	(-1.53)	(0.32)
Bidder Run-Up	0.0299	0.0440	-0.0208	0.0222	0.0288	0.0167
	(1.14)	(1.46)	(-0.33)	(0.91)	(1.09)	(0.43)
Bidder FCF/Assets	0.1188	0.0238	0.1482	0.0951	-0.0012	0.1716
	(0.58)	(0.09)	(0.34)	(0.61)	(-0.01)	(0.70)
Bidder Leverage	-0.0087	0.0892	-0.1546	-0.0307	0.0609	-0.0903
	(-0.09)	(0.62)	(-1.60)	(-0.46)	(0.72)	(-1.38)
Target B/M	0.1648*	0.1990*	-0.0577	0.1323**	0.1548*	-0.0172
	(1.69)	(1.71)	(-0.62)	(1.96)	(1.67)	(-0.22)
Target Run-Up	-0.0102	-0.0099	-0.0764	-0.0146	-0.0123	-0.1288***
	(-0.98)	(-0.93)	(-1.64)	(-0.62)	(-0.62)	(-3.38)
Target FCF/Assets	0.0594	0.0840	0.1861	0.1167	0.1764	0.0930
	(0.84)	(1.02)	(1.16)	(1.45)	(1.46)	(0.68)
Target Leverage	0.0031	-0.0312	0.1122	-0.0214	-0.0393	0.0397
	(0.05)	(-0.37)	(1.22)	(-0.43)	(-0.52)	(0.66)
Relative Size	-0.0462	-0.0720	-0.0184	-0.0338**	-0.0321	-0.0260*
	(-1.37)	(-1.28)	(-0.45)	(-2.50)	(-1.02)	(-1.93)
Stock Dummy	-0.0457*	-0.0132	-0.0776**	-0.0221	0.0268	-0.0594***
	(-1.80)	(-0.31)	(-2.46)	(-1.35)	(0.95)	(-3.07)
Completed	0.0558	0.0754	-0.1691**	0.0023	0.0175	-0.0280
	(1.29)	(1.29)	(-2.04)	(0.08)	(0.45)	(-1.06)
Diversifying Deals	-0.0064	-0.0059	-0.0178	-0.0106	0.0046	-0.0210
	(-0.27)	(-0.15)	(-0.70)	(-0.73)	(0.17)	(-1.11)
Hostile Deals	0.1062*	0.0649	-0.0394	0.0366	0.0194	-0.0140
	(1.65)	(0.80)	(-0.39)	(1.21)	(0.45)	(-0.41)
Tender Offers	0.0695**	0.0822	0.0663*	0.1007***	0.1487***	0.0703***
	(2.04)	(1.41)	(1.80)	(3.64)	(2.98)	(2.65)
Multiple Bidders	-0.0611	-0.0352	-0.1270***	-0.0698***	-0.0444	-0.0892***
	(-1.57)	(-0.63)	(-3.23)	(-2.91)	(-1.14)	(-3.73)
N	577	312	265	908	438	470
Adjusted R^2	0.091	0.091	0.106	0.157	0.150	0.210

Chapter 5
Conclusion

The primary aim of this thesis was to examine the impact of CRAs' actions and decisions on the process and outcomes of M&As. Specifically, it has investigated the effect of credit ratings on the choice of payment method in acquisitions, the influence of credit rating changes expectations on the bidding firm's decision to acquire another firm, and the shareholder value creation of complementary acquisitions.

To summarize the results, Chapter 2 has examined one of the most important aspects of the M&As process; that is the choice of payment method for the consummation of the deal. Given the evidence that cash acquisitions are to a great extent funded by debt while on the same time recognizing that, the bidders' ability to tap the public credit markets as it is measured by their credit ratings must exert a huge influence on that decision, I have tried to investigate the impact of credit ratings on the payment choice. It has been demonstrated that bidding firms holding a high credit rating (high credit quality), are more likely to use cash as a payment method in M&As deals. This finding was attributed to the high debt capacity and low financial constraints which these firms possess, a fact that facilitates substantially their access to the credit markets, and makes them less reluctant to use cash for the consummation of the deals. Consistent with the importance which high credit ratings and debt capacity have in the choice of payment method, I also found that unused debt capacity from the bidder or the target side plays a significant role in this decision.

The findings of this chapter have important implications for financial practitioners and academic researchers. On the practical side, the results regarding the impact of high credit ratings on the choice of cash as payment method in M&As, imply that bidding firms can expropriate benefits related with that form of payment. The literature on shareholder wealth effects around acquisition announcements documents that cash acquisitions create non-negative returns for both public and private deals a fact which entails, that holding a high credit rating pays off both to the creditors and to the shareholders of the firm. In a more general mindset, it can be reasonably argued that having a high credit quality can mitigate some aspects of the bondholder-shareholder conflicts. Additionally, it is known that the usage of cash during takeover contests enjoys low target managerial resistance, and impedes competition from rival bidders, an implication of paramount importance for the management of both bidder and target firms when the deal is considered highly synergetic. On the academic side, my results offer a new determinant on the M&As' method of payment literature that was so far unexplored. Therefore, future research on this topic should take into consideration among other factors, the credit rating levels which the bidders might hold.

Chapter 3 has investigated another important topic of the M&As' literature which is the decision to initiate an acquisition of another firm. Given the evidence on the credit ratings' significance for various capital structure and investment decisions, and the literature which relates M&As with an increase in default risk, I have tried to explore the effect of credit ratings' on the largest investment that a firm might ever undertake. Anecdotal evidence has indicated that firms' management consider future credit rating levels as one of the most important factors when deciding their corporate policies and accordingly, adjust these policies to credit rating targets. In support of this evidence, I have shown that bidding firms' credit rating changes considerations have a considerable impact on the decision to acquire. In particular, firms near the Investment-grade cutoff follow a conservative policy, and abstain from acquisitions with the expectation of avoiding a downgrade to the Speculative-grade or achieving an upgrade to Investment-grade status. Moreover, I used other proxies to capture the imminence to a credit rating change, and find that firms close to an upgrade (downgrade) are more (less) likely to undertake acquisitions. These findings are attributed to the fact that a large number of business, regulatory, and contractual agreements are tied to various credit rating levels that render credit ratings a major component of corporate policies.

The conclusions of this chapter offer valuable insights for both academics and practitioners. On a practical level, the results imply that different expected credit rating actions (upgrades/downgrades) signal a material change in firms' fundamentals and lead their management to decide their corporate policies conditional on these credit rating actions. Overall, they entail that credit ratings considerations have a real impact on firms' management decisions and they should not be treated from practitioners and regulators as "mere" opinions of firms' creditworthiness, but as consequential factors influencing corporate policies. This empirical reality is of a paramount importance especially, after the severe criticism and discussions about the function of CRAs that was taking place during the recent financial crisis. In particular, the Dodd-Frank Act moved towards the right direction, as CRAs are now subject to so-called expert liability. This means that CRAs are no longer exempt on First Amendment grounds from private rights of action, and they are subject to similar standards of liability and accountability as are investment bankers, auditors, and security analysts. On an academic level, the results with respect to the non-linear relationship between credit rating levels and acquisition investments entail that the traditional finance theory, which portrays a linear association between cost of capital and investments cannot explain satisfactorily the above relationship. This is a challenging task for academics who want to examine in more detail the impact of credit ratings on corporate investments, since it can be seen from the results in this chapter and other recent evidence that credit ratings display discrete costs and benefits for firms which do not follow a linear logic; in other words it can be said that "*credit ratings have a merit on their own*".

Chapter 4 has examined the shareholder value creation from complementary acquisitions in levels of debt capacity and growth opportunities. Prior theoretical literature

(Myers and Majluf (1984)) has demonstrated that in states where high information asymmetries about the target firms' values prevail, this type of acquisitions create wealth for the shareholders. Nonetheless, the empirical evidence supporting this theoretical argument is scarce and in this chapter I have tried to fill this void. In particular, by measuring firms' debt capacity with their credit rating level and growth opportunities with the book-to-market ratio, it has been established that mergers between bidders and targets that complement each other on the levels of debt capacity, and growth opportunities generate higher synergistic gains. These incremental gains are captured by the bidding firms, as bidding firms avoid overpayment. These effects are more pronounced when the target operates under a high information asymmetry environment, a setting which is perfectly aligned with the theoretical propositions that form my main assumptions.

The results of this chapter have critical implications for both academic and practitioner worlds. For example, hedge funds and other types of arbitrageurs that are seeking profitable investment strategies through M&As deals, should look for transactions that exhibit these complementarity characteristics. My results have shown that complementary acquisitions generate on average 2.13% abnormal returns over the 5-day window surrounding the acquisition date. For academics the findings concerning the complementary acquisitions indicate that, to the extent that a complementary fit of debt capacity and growth opportunities between bidding and target firms leads to value creation in M&As, credit ratings can help to reduce underinvestment problems. Additionally, the evidence on the wealth effects of the combination where a low valuation bidder buys a high valuation target, suggests that it is against the conventional wisdom of the Q theories of takeovers, where the typical merger involves a high valuation bidder purchasing a low valuation target.

While the specific way which credit ratings influence the process and outcomes of M&As varies across the three studies, the general findings broadly support a consequential role of CRAs actions and decisions in the M&As, that has been overlooked from the hitherto relevant literature.

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