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Essays in Corporate Finance

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ESSAYS IN CORPORATE FINANCE

by

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ABSTRACT OF THE DISSERTATION

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Doctor of Philosophy in Finance

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Professor Todd Milbourn, Chairperson

This dissertation studies the effects of information asymmetry, financial constraints and stock market valuation on the behavior of firms. The first essay explores the role of deal initiation and bidder asymmetry in determining the use of auction and target premia in merges and acquisitions. The second essay examines the behavior of the segments of conglomerates and single segment firms in the distressed industries. The third essay investigates the incentive of takeover arising from the temporary disparity of stock valuation.

While half of all acquisition targets are sold in negotiated deals with only one buyer rather than by auction, the wealth effects for target shareholders are surprisingly similar in both auctions and negotiations. This begs the following questions: why do companies frequently avoid auctions and instead negotiate with just one buyer, and how can targets achieve comparable premia in negotiations? Drawing on Fishman's (1988) model of preemptive bidding and Povel and Singh's (2006) model of asymmetric bidders, I hypothesize that the sales procedure (i.e., auction or negotiation) is most likely determined by the party that initiates the deal. When an acquirer initiates a deal, it prefers a negotiated

deal and hence agrees to pay a high premium to preempt the target and other potential bidders from running an auction. I document detailed information on the private bargaining process for 598 deals. I find that most negotiation deals are in fact initiated by the acquirers and that most of the target-initiated deals use an auction, which indicates that targets are using an auction as a mechanism to discover the highest bidder. Moreover, I provide evidence that the targets receive higher excess returns in the deals initiated by the acquirers than in the deals initiated by the targets. I also provide further evidence of preemptive bidding and bidder asymmetry by studying the indicative bids and the business relations between the targets and the acquirers. Hence, target firms are willing to forgo the potential benefits of an auction and agree to a negotiated deal because they are already facing a bidder with a high valuation and are able to get a high price.

The second essay uses economic distress in an industry as a natural experiment and tests the alternate theories of conglomeration. We find that segments of conglomerates in distressed industries experience better performance than single segment firms. The distressed segments have higher sales growth, higher R&D expenditure and greater cash flows than single segment firms. Indicating greater financial constraints for single segment firms, the superior performance of segments of conglomerates is confined to the subsample of firms without credit ratings and for firms in competitive industries. Single-segment firms reduce their investment in non-cash current assets and significantly increase their cash holdings during periods of industry distress. There is some evidence that the single segment firms that accumulate cash also reduce their R&D expenditure. The diversification discount almost disappears in the years when one of the conglomerate segments is in distress. Overall, our evidence highlights the benefits of conglomerates in enabling segments to avoid financial constraints during periods of industry distress.

The third essay studies the effect of valuation difference on merger incentives. There is widespread evidence that bidders are more highly valued than their targets, and that both parties tend to be in temporarily high-valued industries. We find that valuation differences are also extremely important in predicting who will be acquired and when. Our evidence also suggests that the driving force is more a desire to increase earnings per share the (the bootstrap game" in the classic text of Brealey and Myers) than to exploit market mis-valuation. We find that a firm is more likely to be a target when others in the industry could acquire them in a stock-swap merger that appears accretive to the buyer while paying the target a substantial premium. The resulting measure is similar to the dispersion of valuation multiples within an industry, but is grounded in a specific model of managerial behavior and is empirically much stronger than dispersion. Indeed, it is stronger than any measure in the existing literature, including recent industry merger activity.

Chapter 1

The Deal Process, Asymmetric Bidders and Target Premia

1.1 Introduction

The decision to engage in an acquisition is a strategic choice for a corporation. One major task for the target's board of directors is to decide whether to run an auction to sell the firm or to negotiate privately with a potential buyer. While the cost of an auction may be a deterrent to running one (Hansen 2001), negotiation deals can often put the target's board at risk of a lawsuit for breaching the fiduciary duty by not actively seeking bidders or favoring some particular bidder. Since the Revlon case, Delaware courts have required the board of directors to act as "auctioneers charged with getting the best price for the stockholders at a sale of the company."[1] Such a requirement can also find support in the study of auction theory. In the discussion of auctions and takeovers, Cramton (1998) concludes that "Auctions generally dominate negotiation in terms of revenues" (see also Bulow and Klemperer (1996, 2009)) and "ascending auctions are especially desirable when the target's board is unfaithful". However, empirical work on this subject is not so one sided. Boone and Mulherin (2007) document that half of the targets negotiated with only

[1]In the Revlon case (1985), the company was first approached by Pantry Pride for a friendly deal, but it later rejected any offer by Pantry Pride. Pantry Pride then started the tender offer. However, the Revlon board chose to negotiate a deal with Forstmann to fund a management leveraged buyout (MLBO). This deal included deal protection clauses such as the lock-up option, the no-shop provision and cancellation fee. Pantry Pride sued the Revlon board for breach of fiduciary duty. The court barred all of the deal protection clauses and required a fair auction.

one buyer and there was no material difference in the target premia between auction and negotiation deals. The purpose of my study is to shed light on the question, raised by Dasgupta and Hansen (2008), of why companies frequently avoid auctions and instead negotiate with just one buyer. An additional contribution of my work is to explain why targets achieve similar premia in negotiation deals and auction deals.

There is some recent theory to guide us in this exercise. Povel and Singh (2006) predict that negotiation deals are more likely to happen when bidders have asymmetric valuations of the target. They propose a sequential sales procedure as a solution to this problem. When the target is facing asymmetric bidders, it is optimal for the target to negotiate exclusively with the better-informed bidder first. If such a bidder is willing to pay a high premium, the target can sign a merger agreement with this bidder. If negotiation fails, the target can then choose to run an auction. However, a bidder's valuation of the target is usually unknown to the target in practice. The open questions that arise from Povel and Singh (2006) are related to the assumptions of their model. How can the target identify the better-informed bidder before it runs an auction? Why will the bidder reveal its valuation to the target? If we can empirically identify situations where the target is facing asymmetric bidders and where the target can pick out the better-informed bidder, then we can apply the model to explain the empirical puzzle inherent in the findings of Boone and Mulherin (2007).

I document that there is significant information revealed during the early stage of the deal process. Sometimes the target can tell which buyers are better informed even before it runs an auction. One such situation occurs when the deals are initiated by the final buyers. I find that the buyers tend to reveal their valuations in the early stage in such deals. By reading the proxy statements of mergers and acquisitions deals, I am able to identify the deal initiation between the target and the final buyer in most cases. Specifically, if the buyer approaches the seller first and makes inquiries regarding a potential acquisition, then the buyer is the Initiator in the deal. On the other hand, if the seller approaches the buyer first about a potential deal, then the seller is the Initiator in the deal. I have a total of 598 deals in which I can clearly identify the deal initiator in a sample covering the period from 2000 to 2004.

Based on my data and the existing theories in the literature, I formalize several hypotheses. The first hypothesis is that *negotiation deals are more likely to be initiated by* *the acquirer and auction deals are more likely to be initiated by the target.* There are two reasons for this. First, when the buyer discovers a high valuation signal and approaches the target, it doesn't want the target to use an auction because an auction can cause information leakage and attract other potential bidders. From the target's point of view, if the better-informed bidder is willing to pay a high premium, it's optimal to negotiate exclusively with such bidder (Povel and Singh 2006, Hansen 2001). It can run an auction later if the negotiation fails. Thus, those who indeed have a sufficiently high valuation will be able to pay a premium high enough to induce the target to conduct an exclusive deal and will end up being the final buyers in a negotiated deal. The second reason is that when the targets start to contact any potential bidder, it is hard for them to identify the better-informed bidders. Even if they can, such bidders will naturally hide their information. Therefore, the targets are more likely to face symmetric bidders, and the targets are most likely to use an auction in the first place. By using auctions, the target increases its chance of finding serious bidders and of getting the best offer by evoking competition among the bidders. I find that 84.8% of target-initiated deals are done through an auction, while most negotiated deals are initiated by the acquirers. When a deal is initiated by the acquirer, the chance of using an auction drops by 41% in comparison with a deal initiated by the target.

The second hypothesis is that *the merger deal initiated by the acquirer will have a higher premium than the merger deal initiated by the seller.* First, since an acquisition is a risky project and the process is costly, if the acquirer doesn't have a high valuation of the target firm, it will not approach the target first. Once the acquirer initiates the deal, it has an incentive to keep the target from soliciting other bidders. It will pay a high premium in order to prevent the target and other potential bidders from running an auction (Fishman 1988). Second, when the deal is initiated by the target, the target is in weak bargaining position. Any buyer will wonder why the target firm wants to sell if it is doing well. The informed bidder will hide itself among the uninformed bidders. Also, whereas the acquirer is ready to move forward in an acquirer-initiated deal, timing may not be the best for the bidder in a target-initiated deal. To compensate for the inconvenience, the targets have to lower the price to induce the buyers to make a deal. Third, the targets in acquirer-initiated deals can use resistance as a bargaining strategy. The initiating bidders need to pay high premium to overcome the targets from resisting the offer to merger. Hence, the targets in the acquirer-initiated deals will be able to get higher excess returns than those in the target-initiated deals due to the higher possibility of a high valuation bidder and more bargaining power. In my empirical test, I find that the targets receive on average 8.2% higher excess returns and the result is significant at the 1% level.

I provide further evidence of bidder asymmetry by exploring two new variables from the deal process. During the early stage, the bidders will make proposals to the targets which may contain indicative offer prices. I hand-collect those prices from the indicative offers by the acquirers. I then calculate the indicative offer premium based on the target's stock price one day before the indicative offer. I find that the indicative premium is a strong predictor of the final target excess return and such a prediction is mainly driven by those acquirers who make high premium indicative bids. Thus, the targets are able to identify the better-informed bidder based on the indicative bids. The bidders can use high premium indicative offers to persuade the targets into exclusive negotiated deals. I also hand-collect a variable based on whether the target has business relationship with the acquier. When the acquirer has a business relationship with the target, it is more likely to be better informed than other bidders. I find that having a business relationship indeed makes the acquirer more likely to initiate the deal and leads to a higher probability of a negotiated deal.

To test the robustness of these results, I first use alternative measures of target premium including target excess return of longer window periods and offer premium based on initial offer price. The positive effect of the Initiator variable on target premium is consistent. Another concern is that the higher premium received by the targets in the acquirer-initiated deals can be due to the better quality of the targets. To control for this possibility, I include the targets' financial information in the regression. The Initiator effect survives in all regressions with more control variables. The initiator effect is therefore unlikely to be caused by the targets' quality.

I also conduct a robustness test with some changes of my Initiator variable. Before the contact between the target and the final buyer, the target may have contacted or been contacted by third parties and may have signed confidential agreements with them. So, one could thus argue that the target may be the initiator of the sale process in the acquirer-initiated deal and that a third party may be the initiator of the sale process in the target-initiated deal. I exclude these cases and find that the Initiator effects on sales procedure and target premium are almost the same as in early tests.

Related Literature

The paper is related to the research of Boone and Mulherin (2007 and 2008). They find that both auctions and negotiations provide similar excess returns for the targets. I show that this result hold in a larger sample consisting of deals larger than $10 million (they only consider deals larger than $100 million) and in a different period (my sample begins at 2000 and theirs covers 1989-1999). Importantly, I establish some new facts and patterns in the process of merger deals. First, I show that auction is the favored mechanism to sell a firm when the targets want to sell their firms initially. In fact, 84.8% of target-initiated deals were done through auction. Second, I introduce the deal Initiator variable and hence is able to test auction theory more precisely. I show the deal initiation is an important factor in determining the sales procedure and target premium. [2] Third, I collect the business relation between the target and the acquirer and the indicative offer prices, which can help us to understand further the deal process.

This paper provides direct evidence for the sequential auction model proposed by Povel and Singh (2006). To test their theory, I use deal initiation as a proxy for bidder asymmetry. I argue that the target is more likely to be in asymmetric bidder scenario when the deal is initiated by the acquirer since this initiating acquirer is quite likely to a better-informed bidder. I find exclusive negotiations happen more often in the acquirer-initiated deals than in the target-initiated deals.

The result that the targets receives a lower premium in the target initiated deal is also related to the findings in Stulz et al. (1990) and Gaspar et al. (2005). They find that when the target has more institutional shareholders, especially short -term institutional shareholders, it is more likely to be sold and receive a lower premium. They argue that it is because short-term investors have weaker bargaining power in merger deals. I show directly that when the target initiates the deal, it is in weak position and hence gets a lower premium. Thus, my Initiator variable can be accepted as a measure of the "impatience"

[2] There is some ,but not complete overlap between the "Initiator" variable in this paper and the "Unsolicited" variable in Boone and Mulherin's papers (2007,2008). I leave the detailed discussion of the difference between the "unsolicited" variable and my "Initiator" variable in the Appendix.

of the player in the merge deals.

The result that the buyers pay higher premium to the targets in the buyer-initiated deals can be explained to some extent by the models of Fishman (1988) and Hansen (2001). In Fishman's model, the bidder who discovers a signal of high valuation will make a pre-emptive bid to keep other potential bidders from entering the bidding process. Though the model is cast in a public bidding setting, the situation of private auction can be similar. When the first buyer makes a high offer, the target can still shop around to see whether there is potential for other bidders to make a higher offer. If other bidders think it's unlikely for them to make a higher price, they will be not interested in participating the bidding process. Since running an auction is costly and if it is unlikely to find a higher offer price, it's not necessary to run an auction (Hansen (2001)). So, the first buyer can still play the pre-emptive bidding strategy and the target accepts such bids in some cases. Also, since Betton and Eckbo (2000) shows that rival bids may arrive quickly and make jump bids once a tender offer is announced, it may be optimal for the initiating acquirer to make a high premium to deter the potential competition after the announcement.

Besides, in the acquirer-initiated deals, the target management can use resistance as a bargaining strategy while the targets are less likely to use resistance in target-initiated deals since they want to sell in the first place. Hence, the initiating bidders want to bid high to overcome the potential resistance from the target management. Jennings and Mazzeo (1993) find that a high bid premium appears to deter competing offers and is also associated with a lower likelihood of resistance. While their result is based on events after the public merger announcement, I show that high premium offer also leads to higher probability of negotiation deal in the private sales process.

In Bulow and Klemperer (1996), it is argued that it is better for the seller to run an auction with two serious bidders than to negotiate with a single serious bidder. My data provide mixed evidence. First, the auction deals don't provide higher excess return for the target than negotiated deals. Second, I document that among all auctions, the targets receive, on average, three written offers in target-initiated deals and only two written offers in acquirer-initiated deals and yet they receive greater excess returns in the latter case. However, it can be argued that making a written offer doesn't mean that the bidder is a serious bidder in that the offer is too low relative to the seller's reserve price. On the other hand, I can argue that even though the target has less written offers in the auctions of the acquirer-initiated deals, they are potentially facing more serious bidders since at least the initiator is one of serious bidders. Thus, we need to be cautious in interpreting the results. But, the results at least show that when bidders are asymmetrically informed, simply having more bidders is not always an optimal strategy for the seller.

There are several other contemporaneous papers which also collect the Initiator variable with varying sample selection criteria. Simsir (2008) also finds the initiator effect on target premium I document here, but his purpose is to explain the effect from the standpoint of information asymmetry between the target and the buyer about the potential synergy. Also he doesn't collect the auction variable. Though both my hypothesis and his predict a higher target premium in the buyer-initiated deals, my hypothesis is driven by two assumptions: 1.) targets are more likely to face bidders with higher valuation in the buyer-initiated deals than in the target-initiated deals; 2.) targets have less bargaining power in the target-initiated deals because they are making the first move.

Aktas et al. (2008) try to explain the result in Boone and Mulherin (2007) as arising because of the target's threat of auction. But their initiator variable is not as precisely defined as the one in my paper. As they note, "when it is not possible to infer the parties initiating the deal between the winning bidder and the target from the available SEC filings, I assume that the winning bidder is the initiator". Thus, their initiator variable may be noisy. The important distinction in their work from mine is that they don't put the initiator variable in the regression on target premium and hence don't find the Initiator effect. They do find in the regression that target-initiated deals are more likely to be auctions, which confirms my result.

Anilowski et al. (2009) also collect information on sales procedure and deal initiation. They find that auction helps to reduce the adverse effect of target earnings management and hence improve the target premium. Thus, they provide one scenario where auction may work for the target. The different result from my paper can be attributed to the different criteria and identification on sales procedure and deal initiation. Since the percentage of auction deals in their paper is lower than Boone and Mulherin (2007) and mine, they probably identify more formal auctions in terms of the time span and the rules due to the question they investigate. It may be also due to the different sample selection on the target size.

The rest of the paper proceeds as follows. Section 1 develops the hypotheses and derives their main testable predictions. Section 2 both describes my data and sample selection and outlines my empirical specification and presents the summary statistics. Section 3 reports and discusses the results of my empirical tests. Section 4 provides further evidence of asymmetric bidders. Section 5 presents the robustness tests. Section 6 provides potential extension and Section 7 concludes.

1.2 Hypotheses

In this section, I discuss the existing theories on how to sell a firm and draw my hypotheses based on the analysis of the cost and benefit of the sales procedure and the strategic interaction between the seller and the bidder.

Bulow and Klemperer (1996) argue that auction is generally better than negotiation for the seller of the firm, but they assume that the seller can find at least two serious bidders and bidders are symmetric. In Povel and Singh (2005), they also implicitly assume that the seller can identify two serious bidders and further assume that the seller knows one of the bidders is better informed. By introducing bidder asymmetry into the model, they show that auction is no longer the optimal sales procedure. In this case, the target can negotiate exclusively with the better-informed bidder first. If such a bidder is willing to pay a high premium, the target can sign a merger agreement with this bidder. If negotiation fails, the target can then choose to run an auction or sell the firm to the less infomed bidder directly. But, in reality, before running an auction, it's hard for the seller to know whether there are more than two serious bidders. From the data, I observe that sometimes the sellers could not obtain a bid price above their reserve price from the auctions and gave up the intention to sell.

Besides the issue of serious bidders, running an auction has various costs in reality. Hansen (2001) suggests that there exists "competitive information cost" from running an auction. Such cost arises when the target releases its confidential information to the potential bidders who may take advantage of such information later as some of the bidders are its competitors, suppliers and customers. So, if the competitive information cost is very high, running an auction will hurt the value of the firm.

On the other hand, the buyer faces choices as well. If the buyer identifies the target before the target runs an auction, it would prefer a negotiated deal for several reasons.

First, if the target runs an auction, there may emerge another buyer with a higher valuation, then it will lose the deal. Second, even if another buyer does not have a higher valuation, the competition may still drive the price up. Third, if the target runs an auction, then some of the targets' confidential information will be revealed to other bidders who may use it later, thus it will reduce the value of the target to the first buyer. Facing these potential costs, the buyer will have incentive to get a negotiated deal.

In order to persuade the target to negotiate the deal exclusively, the first buyer with high valuation has incentive to offer the seller a high price to preempt the target from running an auction (Fishman (1988)). The price can be high enough that the additional benefit of an auction for the seller will be less than the cost of running an auction. The first buyer has another strategy. If the target is not strategically important, the first buyer can use the threat of withdrawal to prevent the target from running an auction. Because the first buyer will not participate the auction, the target has to judge whether it can attract enough bidders and sell itself successfully. If it cannot, then running an auction purely imposes cost to the target firm.

The above discussion highlights that the decision to use auction can be influenced by both the target and the buyer with high valuation. Whether an auction will help the seller to get a higher price depends on whether it can find the buyer with highest valuation and force it to pay a high price with competition in the bidding process.

One way to quickly know a potential buyer of high valuation is to see who approaches whom. If it is the buyer who approaches the target, then the buyer must believe that it has a high valuation on the target and it is willing to make an acquisition. Since acquisition is a risky project and the process is very costly, if the buyer doesn't have a high valuation on the target firm, it will not approach the target in the first place.

Once a potential buyer approaches the target, the target can first identify whether the initial bidder has high enough valuation compared with its reserve price and then use negotiation or auction to extract the highest price from it. As we argue above, the initial bidder will prefer the target not using auction. But, the resulted sales procedure depends on whether this bidder has high enough valuation. If the buyer does have a very high valuation and agrees to make an offer with high premium , then it is an optimal strategy for the target to negotiate with this buyer first because other bidders are likely to be less informed and running an auction is costly to the target. It can also threaten to use auction to get a higher offer (Povel and Singh 2006). If they finally reach a deal, then we observe an acquirer-initiated negotiation deal. If the target is not satisfied with the offer by the first approached buyer in the end, it can either neglect the offer or run an auction to seek other offers. If it neglects the offer, we don't' observe this initial offer and bidder in the data. (We usually only observe the offers and deal initiation relation between the target and the final buyer from proxy documents). If it runs an auction, there is some chance that it can be sold to another bidder, but then it is an auction deal initiated by the target.

However, when it is the target firm who wants to sell first, it's hard to immediately identify a buyer with high valuation. It can be that the target thinks a buyer may have a high valuation, but the buyer actually doesn't. Even if it happens to find a buyer with a high valuation, the buyer will hide its valuation and take advantage of the target's impatience to sell. (If the target is sold in negotiated deal in some cases, it is most likely to get a low price.) Hence, the targets are more likely to face symmetric bidders and could not use the sequential sales procedure suggested in Povel and Singh (2006). So, its best strategy is to use auction to find the highest valuation bidder and enhance its negotiation power through competition. The target will approach many potential buyers through an investment banker or through management who know the key players in the industry simultaneously. However, even if the target holds an auction, it is still less likely for it to find more serious bidders than the auctions of acquirer-initiated deals where the approaching acquirer is already a serious bidder. So, there are less chances for the target to find very high valuation buyer or extract high price from such buyer than the case when the buyer approaches the target.

Overall, the above analysis generates the following two hypotheses

Hypothesis 1: *The negotiated deals are more likely to be initiated by the acquirer and auction deals are more likely to be initiated by the target.*

Hypothesis 2: *Merger deal initiated by the acquirer will have higher premia than merger deals initiated by the target.*

1.3 Data Description and Summary Statistics

1.3.1 Data and Sample Selection

To test these predictions, I first obtain the source of M&A announcements from SDC. I focus on the US targets and the public firms. To insure the availability of SEC filings, I also requires the acquirers be public firms. I exclude the merger and acquisition deals with effective transaction value less than 10 million dollars. I then merge the announcement data with CRSP and Compustat to get stock price and firm financial data. The final sample also excludes firms for which I don't have sufficient data to calculate the excess return on target firms. I then hand-collect the initiator and auction variables by reading the filings from EDGAR system of the U.S. Securities and Exchange Commission. Information on the details of the process of firm sale can be found from the background section 14A and S-4 filings and 14D filings.

Following the definition of Boone and Mulherin (2007), I identify a merger deal as an auction deal if the target firm contacts and signs confidential agreements with more than one potential buyers. If the target only deals with a single bidder, I classify the deal as a negotiation deal. For tender offers, some deals are classified as tender offers (which are treated as unknown in Table 1.1) if I can not identify whether the tender offers were the result of an auction or a negotiation. Still some deals cannot be identified and are coded as unknown. There are many cases where I could not calculate the actual number of confidential agreements, but I can see that the targets were running an auction and the number of confidential agreements were greater than two and hence I still code them as auction deals. Also, there are cases where the targets didn't mention confidential agreements but were actively in talk with other potential bidders and received more than two offer prices. I code such deals as auction deals too. Thus, my definition of Auction tends to identify more auction deals. In the robustness test, I will address this issue.

As for *Initiator*, if it is the acquirer who approaches the target first, then the initiator is the acquirer. If it is the target who approaches the acquirer first, then the initiator is the target. However, there are some cases in which the acquirer and the target happen to be mutually interested in a deal, then the initiator is the mutual parties. Finally, there are some deals which I can not identify the initiator and are coded as unknown.

1.3.2 Summary Statistics

Table 1.1 provides the year-wise distribution of my sample for regression. My original sample has 846 observations, but I drop deals which I can not identify the Initiator or the sales procedure or target excess return. From Panel A, we can see that about 52.7% of the deals were initiated by the final acquirers, 47.3% of deals were initiated by the target. The pattern is quite similar in each year. As for sales procedure, we can see that about 64% percent of deals were conducted through auctions, 36% of deals were done through negotiation. Again the pattern is stable for each year. This result is close to what Boone and Mulherin (2007) document in their finding while my data has higher percentage of auction deals. Since I also include deals with size bet \$ 10 million and \$100 million while they only consider deals greater than \$100 million, the difference can be attributed to the fact that deal size negatively affects the probability of using auction (shown in the regression in Table 1.4). It is also intuitive because as it's more difficult to find many bidders for larger firms. Panel B is the table of the Initiator and the sale procedure. we can see clearly that negotiated deals concentrate in the group of acquirer-initiated deals. Panel C and D show the distribution of the raw data before regression.

Table 1.2 provides the summary statistics for the key variables related to firm size and deal characteristics in the regression. The mean size for the target is \$0.89 billion. The average target size in the acquirer initiator sample is \$1.23 billion, while the average target size in the target initiator sample is only \$0.5 billion. The difference is significant at the 1% level. Similarly, the size of acquirers in the deals initiated by the acquirers is significantly bigger than the size of acquirers in the deals initiated by the targets. So, it's more likely for the large firms to approach the target initially. The relative size is bigger in the acquirer-initiated deals, but the difference is not significant.

In Panel B, we can see that about 34% of the deals were paid with cash only. More acquirer-initiated deals were paid in cash only than target-initiated deals and the difference is close at the 10% level with p-value at 0.11. About 20% of deals were made in the form of tender offer and there is no difference in both sub samples. About 64% of the target firms in the whole sample are sold through auction, so auction is used more frequently as the sales procedure. However, there is a dramatic difference between the two sub samples. In the target-initiated deals, 85% of deals are in auction. But in the acquirer-initiated deals, it's a little less likely to be auction deals with only 45% deals in auction, that is, negotiation is more likely to be used in the acquirer-initiated deals. The difference is significant at the 1% level. So, it gives the first support the first hypothesis.

In Panel C, I compare the effectiveness of auction in the target-initiated deals and the acquirer-initiated deals with hand-collected data on contacts and offers. I find that the targets contact on average 18 more potential buyers when they initiate the deal than when the acquirers initiate the deal. Though they also receive a slightly more written offer, the ratio of written offer over the number of contacts show that the targets are more effective in obtaining offers when the deals are initiated by the acquirers. So, it indicates the difficulty for the target to obtain written offers. One role of auction is for the target to find a serious buyer who will make an offer.

Table 1.3 compares the mean target excess return of the deals. The targets receive on average 25.6% excess return in the full sample. Panel A documents the mean target excess return according to the initiator. The target excess return is 6.6 percentage points higher in the acquirer-initiated deals than in the target-initiated deals and the difference is significant at the 1% level. So, it supports the second hypothesis. As for sale procedure, auctions deals generate similar excess return as negotiated deals and the difference is not significant at 10% level.

1.4 Empirical Tests and Results

In this section, I run multivariate regressions to test my hypotheses. The dependent variable will be either the target excess return or the sale procedure or the initiator. Following Boone and Mulherin (2007) and the literature and, I use the deal size (the log of effective transaction value),cash dummy, tender offer dummy,relative size, regulated and unsolcited as control variables.

1.4.1 Probability of Using Auction

I run probit regressions to test whether the use of auction or negotiation is related to the initiator and report results in Table 1.4. The dependent variable is auction, which equals to one if the deal is an auction deal and zero if it is an negotiated deal. The Initiator variable is also a dummy variable, which equals to one if the deal is initiated by the acquirer and zero if it is initiated by the target. Column (1) reports the regression without the Initiator variable. We can see that larger deals are less likely to use auction. Also the use of auction is more likely when the deal is paid in cash and being unsolicited variable. I add the Initiator variable in the second regression. I find that acquirer-initiated deals are more likely to be negotiated deals. The effect is significant at 1% level. I then calculate the marginal effect of initiator. When a deal is initiated by the acquirer, it is 41% less likely to be an auction than a deal initiated by the target. The cash dummy has a positive coefficient, which means if the deal is paid through cash, it's more likely to be an auction deal. The marginal effect of being cash will increase the probability of being an auction deal by 21.6%. I still find the effect of Unsolicited variable in Boone and Mulherin (2007) even when I include the Initiator variable. The results support the claim in my first hypothesis.

In column (3) I look at the deals greater than $100 million to match the size of deals in the sample of Boone and Mulherin (2006). In column (4) I look at the deals less than or equal to $100 million. The coefficients of the Initiator variable are almost the same as in the whole sample and both are significant at 1% level. The unsolicited variable predicts an even higher probability of auction in the sub sample of deals greater than $100 million than in the whole sample. This again shows that my unsolicited variable is similar to the one in Boone and Mulherin (2007). It also predicts more likely of auction in the group of small size deals though the coefficient is not significant with p-value of 0.14.

1.4.2 Target Excess Return

Table 1.4 provides the multivariate regression results for target excess return. I calculate the target excess return based on the market model. I first estimate the beta of target stocks using stock prices 64 days before the merger announcement. I then calculate the cumulative abnormal return of the targets during the (-1,1) window. In column (1), I run the regression without the control of Initiator variable. Similar to the result of Boone and Mulherin(2006), the coefficient for auction is slightly negative and is not significant. Hence sales procedure doesn't affect target excess return.

In column (2), I include the Initiator variable to test the second hypothesis. I find that for firms initiated by the acquirer, the targets'excess return will increase by 8.2% and it's significant at 1% level. Ideally, with the control of Initiator variable, I will expect to find net effect of Auction be positive. The coefficient of auction now becomes positive but is still not significant. I find that the deal size is negatively related to the target excess return, which is in accordance with the literature. The use of cash in the payment will improve the target excess return by 11.9 % at 1% significant level. The sign for relative size is negative, but not significant. But I don't find the positive effect of unsolicited variable as in Boone and Mulherin (2006).

In column (3) I look at the deals greater than \$100 million to match the size of deals in the sample of Boone and Mulherin (2006). The sign of the coefficient for auction changes to negative and is still not significant. The Initiator's positive effect remain the same while the coefficient of initiator drops slightly to 8% and significant level drops to 5%. In column (4) I test for the deals less or equal to \$100 millions. The coefficient of initiator rises to 9.5% at 10% significant level, which can be attributed to the reduced sample size. Thus, the Initiator effect appears to be stronger in the small size deals. Also, the coefficient of Auction becomes positive at 0.062 though it's still not significant. Overall, as I have seen in the univariate test in Table 1.3, the multivariate regressions show that the acquirer-initiated deals on average generate about eight percentage higher excess return for the targets. This supports the second hypothesis.

1.4.3 Sub sample Test

I first divide the sample into two groups of auction deals and negotiaton deals because I want to know how the Intiator effect works in those sub samples. The first regression is in the group of auction deals. I regress the target excess return on initiator and other control variables. I find that acquirer-initiated auction deals will improve the target excess return by 6.6% (see Table 1.6). The coefficient is significant at 5% level. This can be interpreted as that the targets which are approached by the acquirers may have an inherently higher value or they are in a better position to use competition to force the initial buyer to pay a higher price. The second regression use the sub sample of negotiated deals. The coefficient on initiator is 12.3% and is significant at 5% level. The result thus can support the argument that the targets in the acquirer-initiated deals are in a better bargaining position than those in the target-initiated deals. It may be also possible that the total synergies or quality of the targets are different between the two groups.

While I could not find the effect of auction after the control of deal initiation, the linear control of Initiator variable may be not enough. I then divide the sample according to the initiator, but I still do not find any significant effect of auction in either group. However, the coefficient of Auction in the target-initiated deals is positive at 0.049 with p value of 0.2. It raises a question to us that why some targets use negotiation when they initiate the deal. When the targets initiate the deal talk to sell the firms, they are mostly likely in a weak bargaining position and yet are still able to achieve a similar return as auction. Since only 41 out of 268 target-initiated deals in the regression are done by negotiation, it is possible that the targets can use top investment banks to help it precisely identify the high valuation buyer and then negotiate with the buyer. I obtain the information of target advisor from SDC for most of the deals and collect the rest of them by reading the SEC filing. I use the result of Ma (2005) to identify top investment banks. Basically, I then classify the target advisor as a top investment bank if it is one of following investment banks: Goldman Sachs & Co, Credit Suisse First Boston ,Morgan Stanley, Salomon Brothers,Merrill Lynch,Lazard Freres, and Lehman Brothers. 23.3% of negotiated deals are done with top investment banks while only 17l7% of auction deals use top investment banks (Table 1.7). However, the t test show that the difference is not significant at 10% level. The p-value is 0.19. (The t-test for the sub sample from 2001 to 2004 is significant at 10% level.)

I also look at the time that the deals took from initial contact to signing the merger agreement (Table 1.8). I find that in the acquirer-initiated deals, the auction deals took average 161 days while the negotiation only took average 135 days and the difference is significant at the 5% level. I don't find any significant differences in comparisons of any other groups. This may suggest that in the acquirer-initiated deals, the acquirers were willing to offer a high premium in order to get an exclusive negotiated deal and close the deal quickly.

1.5 Further Evidence of Bidder Asymmetry

1.5.1 Indicative Bids and Pre-emptive Bids

According to Fishman(1989)'s theory, the target's expected gain will be lower if the initial bidder uses pre-emptive bid. So, the target has incentive to reduce the information cost to the other potential bidders. When the initial bidder approaches the target in private, it's even harder to prevent the target from running a private auction. A high bid may only convey a high potential value to the target while it fails to preempt other potential bidders because the other potential bidders cannot observe it. The initial bidder will be reluctant to reveal its private valuation to the target. On the other hand, if the initial bidder wants to prevent the target from soliciting other bidders, it has to show that it has high valuation on the target. So, one empirical question is: is there pre-emptive bid in the private bidding process? [3]

In order to test it, I hand-collect the indicative prices from the SEC documents. Usually during the early stage of deal process, the bidders will make indicative offers. However, it's not common for the target or the buyer to report the details of indicative prices in the SEC filings. I only get 198 indicative offer prices. I then calculate the indicative premium relative to the target stock price one day before the date of indicative offer. I generate a dummy variable called High Premium if the indicative premium is in the upper quartile of the sample, specifically if it is higher than 49%. Such high premium can be regarded as a pre-emptive bid in the public bidding environment. Out of 198 indicative bids, 49 bids can be regarded as pre-emptive bids. I also created a dummy variable called Low Premium if the indicative premium is in the lower quartile of the sample, specifically if it is lower than 17.9%.

I then investigate how these indicative offers in the early stage of the deal process are related to the ultimate premium the targets obtain and how they affect the use of auction. The first regression of the Table 1.9 shows that indeed the indicative bids reveal the bidder's valuation to the targets. Those who bid high will provide higher premium to the target in the final agreement. Also, the High Premium dummy variable has additional predicting power on the ultimate premium. So, those whose indicative offers are among the top quartile will also give the target an 15.6 % higher excess return than average in the final deal. Note that the Initiator variable now doesn't predict a higher target excess return. So, the initiator effect on target premium is most likely from those acquirers who bid high in the early stage. But, we don't know which buyers make high premium indicative offers. They could be the buyers who initiated the deal or the buyers whom were contacted by the targets.

[3] I would like to thank professor Michael Fishman for the discussion on the possibility of such pre-emptive bids.

The next regression of indicative premium in Column 2 then shows that the indicative premium will be 28% higher when a deal is initiated by the acquirer. So, it is the initiator-acquirer who has more incentive to bid high in the indicative offer. In column 3, I further find evidence that the high premium indicative offers are more likely from the initiator-acquirers. When the deal is initiated by the acquirer, the indicative bid is 15% more likely to be a high premium bid. Thus, the targets indeed have information to tell bidders of high valuation from their initial bids and can decide on whether to use exclusive negotiation.

In the regressions in column 4 and column 5, I test whether indicative premium or high premium will cause the deal to be more likely a negotiated deal. While Indicative Premium has no predicting power, the High Premium indeed can predict a higher chance of negotiated deal. So, the effect of indicative offer on the target's use of auction is non linear. It has to be high enough to induce the target to an exclusive deal. When I add the Initiator in column 6, the coefficient of high premium is no longer significant while the Initiator has more predicting power. So, it is likely that the effect of High Premium is from the acquirers who initiated the deals. So, when the initiator-acquirers indeed have very high valuation of the targets, they can use high premium in the indicative offer as part of strategy to persuade the targets into a negotiation deal. Given such high indicative premium and the potential bidder asymmetry, the targets will consider a negotiated deal as optimal. Thus, this finding provides further for the sequential sales procedure in Povel and Singh's (2006) paper.

1.5.2 Informed Bidders

Povel and Singh's (2006) model has an assumption that the seller knows which bidder has more precise information. Besides indicative bids, is there other way the target can identify better-informed bidder directly? Higgins and Rodriguez (2006) find in a sample of pharmaceutical acquisitions that acquriers' returns are positively correlated with prior acquirer access to information about the research and development activities at target firms and such information gives the acquirers a superior negotiating position. During the data collection process, I find that some bidders had either ongoing or recent business relationship with the targets. The bidder and the target may have customer-supplier relation or they may serve a common client or they have some joint project. Such business relationship will provide the bidder a reliable channel to understand and analyze the target's business. Also, being a business partner gives the acquirer much more insider information about the situation of the target through business interaction. So, those who have business relationship with the targets are more likely to be better informed. Besides, the recent papers by Schmidt (2009) and Cai and Sevilir (2009) show that board connection is related to M&A transaction. In a few cases, I also record a business relation when the management or the board of directors of the acquirers and the targets were connected and were involved in the initiation of a deal talk.

I hand-collect a dummy variable "Business Relation" based on whether the target has a ongoing or recent business relationship with the acquirer. I have 94 cases in which the acquirers have business relationship with the targets. To supplement it, I create a dummy variable "Same Ind" which equals to 1 if the target and the acquirer are in the same 4 digit SIC industry and 0 otherwise. Being in the same business line with the target, the bidder is more likely to be better informed (at least about the industry). I report the result in Table 1.10. In the first column I regress the Initiator variable on these two dummy variables. I find that having a business relation indeed causes the buyer more likely to initiate a deal talk with the target. The negative coefficient of "Same Ind" indicates that a firm is less likely to initiate a deal to buy its competitor, but when a firm wants to sell itself, it will regard its competitor as a potential buyer and initiates the contact.

I next test a proposition in Povel and Singh (2006) (Proposition 3, p1416). They predict that when the bidder asymmetry increases, an exclusive deal is more likely. I regress the Auction variable on these two dummy variables. In column 2, I find that the probability of negotiated deal indeed increases when the acquirer has a business relationship with the target. Such business relationship results in 20% higher chance of being a negotiation deal. I do not find such effect of the "Same Ind" variable. In column 3, I find that among the acquirer-initiated deals, when the acquirer also has business relationship with the target, the deal is more likely to be a negotiation deal. Interestingly, when the acquirer is in the same business line of the target, the target prefers to running an auction when approached by the acquirer. In column 4, I run the regression within the group of the target-initiated deals. I find that the target is not more likely to have a negotiation deal with its business partners when it wants to sell itself first. However, it is willing to have a negotiation deal with its competitor. Potentially it may be hard for them to find a buyer when it wants to sell. So when its competitor (who is presumably an informed bidder) agrees to pay a descent premium, the target will accept it for an negotiation deal.

1.6 Robustness Test

1.6.1 Alternative measure of target premium

I also test the hypotheses on longer event window periods and use the offer premium based on initial prices from SDC. My main results hold in both cases (table Table 1.11). In the first two columns, I calculate the target excess return based on the longer windows. Column 1 reports the result of the regression with target accumulated excess return calculated from 63 days before the announcement to 126 days after the announcement. The initiator dummy predicts a 12.4% higher excess return while p value is 0.051. I also use the window period from 20 days before the announcement to 20 days after the announcement in the second regression. The initiator predicts a 9% higher excess return and is significant at 5%. In the last regression, I use offer premium to measure target return. I calculate the offer premium based on the estimated offer price (the term "initialprsh" in SDC) relative to the target's stock price 64 days prior to the announcement and set it to missing if the calculated offer premium is greater than 2 following Officer (2003). The regression shows that when the deal is initiated by the acquirer, the offer premium is 7.7% higher than when the deal is initiated by the target and the p-value is 0.067.

It is possible that the higher premium received by the targets in the acquirer-initiated deals can be attributed to the better quality of the targets in the acquirer-initiated deals. To control this possibility, I include the targets' financial information into the regression. I add the target's return on asset (ROA), market to book ratio (M/B), q, price earning ratio (P/E) and leverage. I also include the "Same Ind" variable which measures whether the target and the acquirer are from the same 4 digit SIC industry. I then run regression with target excess return of 3 day window and the above alternative measures of target premium. The Initiator effect survives in all these regressions. The size of the coefficients drops a little but the significant levels remain the same. So, my initiator effect is not likely to be caused by the quality of targets, at least from what can be observed publicly.

In an unreported regression, I find that the liquidity is positive related to the Initiator variable, which implies that the targets of lower liquidity are more likely to initiate the deal. As Officer (2007) finds that firms sell assets at a discount due to the need of liquidity, it is possible that the targets in target-initiated deals suffered liquidity constraints and sold the firms in discount. So, I include the liquidity of the target firms in the last column. I measure the liquidity using the net working capital normalized by total assets. However, due to the missing data on current assets and current liabilities on Compustat (especially for year 2000), my data points drop to 361. The Initiator variable now predicts 11.3% higher offer premium and significant at 5% level. The liquidity is positively related to the offer premium with a p-value of 0.142. I also use target excess return of various window periods as dependent variable and other measures of liquidity as in Officer (2007) such as the the abnormal cash asset ratio and abnormal net working capital asset ratio. Some of the measures are positive and significant in some regressions, but the effect of Initiator variable remains the same and hence the results are not reported here to save space.

1.6.2 Excluding the "In auction" deals

One concern about the results is that the Initiator variable does not capture the entire sales process. Among the acquirer-initiated deals, there are cases that the targets were already in the process of selling the firm. In the data collection process, I define the number of contacts and confidential agreements that the target has signed at the same period or after the time when the acquirer and the target had first contact on the issue of merger. This does not raise issue when the target is the initiator. However, when the acquirer is the initiator, the target may already have had contacts with other firms and signed confidential agreements. Thus, the "auction" variable may not reflect the acquirer's effort to stop the target from soliciting other buyers in this case. To precisely test my hypotheses, I read again those auction deals among the acquirer initiated sample and require that the auction happened strictly after the acquirer approached the target. I identify 46 cases where the target were already in auction at the time when the acquirer approached the targets.

I run the tests in the first three columns after excluding those "in auction" deals in Table Table 1.12. My results show that the initiator effect on target excess return is slightly stronger (in column 1) while the initiator effect on sales procedure is much stronger (in column2). The acquirer initiator now predicts 50.7% less likely to be an auction deal compared to the 41% in the original regression in Table 1.5. In column 2, I restrict the sample with the acquirer-initiated deals and still do not find any effect of auction on target premium after excluding the "In auction" deals. At the same time, one may argue that among the target initiated auction deals, the entire sales process may be driven by a third party who initiated the deal talk with the target. That is, when the target started to contact the final buyer, it was already in auction due to the deal initiation from a third party. I further identify 27 cases where the entire sales process can be regarded as started by a third party. Further excluding those deals reduces the number of records in the regression to 507. The initiator effect on target premium is almost the same as the original sample, and the acquirer initiator still predicts 50.1% less likely to be an auction deal.

1.6.3 Alternative Definitions of Auction

I mention early that I also recognize a deal as an auction deal even if I could not identify the exact number of confidential agreements the targets signed during the deal process. One may argue that my result may be affected by such a broader definition of Auction. To address this issue, I run robustness tests with two alternative definitions of auction variable. I start with the originally recognized auction deals. Among those auction deals, the dummy variable Auction2 will be equal to one only when I can identify the exact number of confidential agreements signed by the targets with bidders and when this number is greater than or equal to two. Thus, if the number of confidential agreement of an auction deal is missing, then the variable Auction2 for such deals is set to missing too. The definition of negotiation is the same as before. By this definition, only 103 deals are recognized as sold through auction and 216 deals are sold through negotiation. Thus, Auction2 is a very strict definition of auction and it tends to underestimate the number of auction deals. Auction3 modifies from Auction2 by recognizing some deals as auction ones if the number of written offers is greater than or equal to two while the number of confidential agreement of an auction deal is missing. I use this definition because the purpose of an auction is to discover prices and evoke competition. When a target can obtain two written offers, even if I could not find the exact number of confidential agreements, I still regard the targets had an auction. Auction3 now identifies 255 auction deals. Still some originally recognized auction deals are missing by this definition. So, Auction3 is still quite strict in comparison to the original definition.

I then repeat regression in Table 1.4, V and X with these two alternative auction variables. The results are reported in Table Table 1.13. In column 1 and column 5, the probit regressions show that the Initiator variable still predicts a negative likelihood of use of auction. The coefficients are similar to that in Table 1.4 and are both significant at 1%. The effect of Initiator on target excess return on three day window are also similar to that in Table 1.5. But the Initiator now predicts a stronger effect on target excess return of (-63,126) window period and on the offer premium compared with the results in Table 1.10. Also the significance levels of coefficients increase to 5%. The coefficient of Auction3 in the regression of offer premium (column 8) is 0.075 and the p-value is 0.111. So, my original broader recognition of auction deals actually weakens the effect of the Initiator and Auction variables.

1.6.4 Other Robustnesst Tests

I also conduct other robust tests. First, I control the year fixed effect. The Initiator still predicts 8.2% higher excess return at 1% significant level. Second, I also include the industry fixed effect together with year fixed effect. I use the first two digit of target's primary SIC code as proxy for industry. The coefficient of Initiator drops to 0.072 but is still at 1% significant level. Third, since Delaware and Nebraska are subject to the enhanced fiduciary duties (the Revlon case and the cases of Unocal and Blasius), it is possible that firms incorporated in such states choose to run auction due to legal concern. Hence, I create a dummy variable legal_state which equals to 1 if a firm is incorporated in either Delaware or Nebraska and 0 otherwise. I then add the legal_state dummy variable in the original probit regression on auction, but the coefficient of the legal_state dummy variable is slightly negative and not significant. I also split sample of targets according to where a firm is incorporated in Delaware and Nebraska or other states. The coefficients of Initiator in both sub-samples are almost the same. Hence, our Initiator effect on auction is not likely caused by state of incorporation.

Fourth, it is more likely to have information leakage in the target-initiated deals since most of targets use auction. Hence, the lower target excess return in target-initiated deals may be due to the information linkage. One way to identify the information leakage and its effect on target premium is to exam the price run-up for the target firms (Schwert

(1996),Betton et al. (2008)). To test the possibility of information leakage, I run the regression of the target price run-up on the Initiator variable. If there is more information linkage in the target-initiated deals, then run-up will be more likely for such deals and we will see negative coefficient of Initiator. The results show that the coefficient is positive and is not significant. So, the Initiator effect on target premium is not likely to be caused by information linkage in target-initiated deals.

1.7 Extension

1.7.1 Testing target's relative gain

It is possible is that the initiator effect on target premium may be purely driven by the high synergies. Acquirers with high synergies are more likely to initiate the deal. So, the higher target premium is just due to the higher synergies in those deal. Though this doesn't totally work against my story, I would like to see whether the Initiator variable also captures the relative bargaining power and see whether the initiator effect is due to the fact that the targets have more bargaining power in the acquirer-initiated deals.

To test this, I use target's relative gain as a measure of their bargaining power. I first multiply the target's market value two days before the announcement by the three-day abnormal return to obtain the target's gain. Similarly, I multiply the acquirer's market value two days before the announcement by the three-day abnormal return to obtain the acquirer's gain. I then obtain the total gain from the deal by adding the targets'gain and acquirers' gain. I then calculate the target's relative gain by dividing targets' gain by total gain. Here I require that both the target's gain and acquirer's gain be positive because the negative gain is hard to interpret. The average target's relative gain is 40% among these deals. I then run regression of target's relative gain on the Initiator variable and other control variable (Table Table 1.14). The coefficient of Initiator is negative in the first regression of whole sample, but it is not significant. I also restrict the regression on the sample of cash only deals because the acquirers' stock in the stock deals may be under pressure due to the arbitrage activities or signalling effect of overvalued stock. The coefficient of Initiator becomes positive but is not significant. In column 3 and column 4, I then run separate regressions within the group of acquirer-initiated deals and target-initiated deals. The auction has not effect on the target's relative gain in the acquirer-initiated deals. However, auction predicts a higher target's relative gain in the target-initiated deals. So, when the targets want to sell themselves, they can use auction to improve their bargaining position. For those targets who didn't use auction, while they could still obtain comparable premium, it seems that they had disadvantage in the bargaining process.

1.7.2 Deal initiation, sales procedure and deal protection

One implication of Povel and Singh (2006) is that deal protection devices can be used by the target board as a commitment to the close of contract in order to extract a higher price in the optimal sequential sales procedure. Since the winning bidders in the first stage (i.e., the exclusive negotiation stage) are more likely to be subject to topping up from unknown bidders once the deal is announced, they would need more protection from the deal. Hence, I would expect that deal protection will be used more often in the negotiated deals.

I use termination fee as a proxy for deal protection. The SDC dataset documents whether the targets are liable to pay a termination fee. Out of 598 deals in regression, 468 deals have a target termination fee. From Table Table 1.15, we can see that target termination fee is more likely to be used in the negotiation deals. A negotiation deal is 7.9% more likely to use a target termination fee than an auction deal. Interestingly, I find the result is mainly driven by the negotiation deals in the target initiated sample. One potential explanation is that the acquirers in the target initiated negotiation deals play a key role of "price discovery". In order to provide incentive for them to make a reasonable offer, the targets have to provide more deal protection. This result combining the finding of target relative gain in table Table 1.14 further suggests that the targets were in a weak bargaining position in the target-initiated negotiation deals. However, since only 43 deals are target-initiated negotiated deals, I need to be cautious in drawing further implication from this finding.

1.7.3 Further Investigation of Auction in Target-Initiated Deals

Since the analysis in section 6.1 and 6.2 suggests that there may be a role for auction in the target-initiated deals, this section further investigate the issues. Following the robustness test of Table 1.10, I use target excess return on longer window period of (-63,126) and offer premium as dependent variable and restrict the regression within the sample of target-initiated deals. The regression in column 1 (Table Table 1.16) shows that the Auction variable predicts a 28% higher excess return for the targets and it is significant at 1% level. The regression of offer premium also have an coefficient of 0.124 for the Auction but it is not significant (p-value at 0.123). With more control variable, the Auction variable still predicts 19.1% higher excess return for the targets in column 3. This result indicates that Auction may play a role in helping the target get higher premium as found in the case of target earning management in Anilowski et al. (2009).

This raises a question: why I don't find the effect of Auction in the sub sample test of three day target excess return in Table 1.6? From regression of target runup in column 5, I find that the auction deals predicts a 15.6 % higher runup than negotiation deals. So, it is possible that the targets in auction already experienced a fair amount of price runup due to the leakage of information before the announcement. The runup in auction deals reflects part of the final premium. Hence the three day target excess return is not bigger in auction deals than that in the negotiation deals. Or it is possible that the targets in negotiation experienced a decline of price and hence becomes more feasible for the acquirers to pay a descent amount of premium. Hence the three day target excess return in negotiation deals appear to be similar to that in auction deals. I find that the mean of runup is -0.028 in the negotiation deals and is 0.149 in the auction deals. So it can be due to either case or both.

1.8 Conclusion

M&A is a very important decision for many firms. Researchers have begun to investigate whether and how the deal process affects the success of an M&A deal. The finding in Boone and Mulherin (2007,2008) raise a puzzling question: why do companies frequently avoid auctions and instead negotiate with just one buyer?

To answer this question, I hypothesize that negotiation deals are likely to happen when the targets are facing asymmetric bidders, as predicted by Povel and Sighn's (2006) model. I document the deal initiation relation between the target and the final buyer and use it as a proxy for bidder asymmetry. I argue that the targets are most likely facing better-informed bidders in the acquirer-initiated deals and hence will negotiate exclusively with such bidders first. I find that most negotiation deals are indeed acquirer-initiated while most target-initiated deals are auction deals. I then show that the targets receive on average 8.2% higher excess return in acquirer-initiated deals than in target-initiated deals. Hence, target firms are willing to forgo the potential benefits of an auction and agree to a negotiated deal because they are already facing a bidder with a high valuation and are able to get a high price. Thus, my findings show the importance of bidder asymmetry in the study and practice of auctions in corporate takeovers.

My findings also provide some guidelines for the targets' board as they decide whether to run an auction. First, when the target is approached by a bidder, a rational strategy is to talk with this bidder to identify its valuation range. The existing literature describes some ways to identify a high valuation bidder. The bidder is likely to have a high valuation if it wants to pay cash,if it wants to make a tender offer or if it is much larger than the target. Second, once the target knows that the bidder has a high valuation, it can try to negotiate with the bidder to get a high premium by threatening to use an auction. If the negotiation fails, it can then consider a small scale auction to increase its bargaining power with the initial bidder. Third, when the target wants to sell itself first, it should still use a large scale auction to find a high valuation bidder and enhance its bargaining power unless it can precisely identify a buyer who is willing to pay a sufficient premium for an exclusive negotiated deal.

Many questions remain open. For example, I haven't investigated exactly what causes the parties to initiate a deal. The underlying reason for deal initiation may have a long term effect on the acquisition. For example, can deal initiation be driven by the acquirer's true synergies or the empire-building incentive of the acquirer's CEO? There are cases where deal initiations are related to board connections. Will such deals hurt or benefit the target and the acquirer? Also, I document the indicative offers. What determines the indicative offer premium and the bidder's bidding strategy? Even though I don't find that auction generates a higher premium for the target, are there situations in which auction can help targets get higher premia? Finally, how does the business relationship affect the deal dynamics between the target and the acquirer?

Appendix the Difference between the Unsolicited variable and the Initiator variable

There is potential overlap between the "Initiator" variable in this paper and the "Unsolicited" variable in Boone and Mulherin's papers (2007,2008). In their 2007 paper there is a variable named "Unsolicited", which is "defined as takeovers that were initiated by the bidder or a third party, either privately or publicly". According to the definition, I should observe more "Unsolicited" deals than acquirer-initiated deals because the "Unsolicited" dummy will be equal to one even when the deal was not initiated by the ultimate winning bidder but by a third party instead. So, it seems that their "Unsolicited" variable should subsume my "Initiator" variable. Since their "unsolicited" variable also predicts a higher target excess return, it seems that my finding is redundant. But, there is major difference between the "Initiator" variable and the "Unsolicited" variable. First, in my sample, about 50% of deals were initiated by the acquirers while in their sample, only "15% of the takeovers are unsolicited". So, apparently I am collecting two different variables. Second,they mention "this rate of unsolicited deals is higher than the 4% figure reported by Andrade et al. (2001) for the 1990s". But there is not an explicit "unsolicited" variable in Andrade et al (2001)'s paper, while they (2001, p 106) "define a bid as 'hostile' if the target company publicly rejects it, or if the acquire describes it as unsolicited and unfriendly" and they find that "4 percent of transaction in the 1990s involved a hostile bid at any point." So, I guess that they code a deal as "unsolicited" based on whether a deal is hostile as in Andrade et al (2001). Further, in Boone and Mulherin (2008) , when they want to measure factors affecting takeover competition, they also use the "unsolicited" variable. According to the paper, " a final deal characteristic that we study is whether the takeover was initially unsolicited". Also, citing the result of Schwert (2000) that hostile deals are more likely to have multiple public bidders, they say "This suggests that unsolicited offerings are likely to induce the target firm to conduct an auction". When they discuss the regression results, they conclude,"Hence, a natural response of a target faced by an unsolicited bid is to see other buyers". So, I guess that they collect the "Unsolicited" variable based on whether the target received an unsolicited bid initially and whether the deal is hostile. [4] Based on my understanding of their variable, I collect the "Unsolicited" variable for the sample. About 13% of the deals in my sample are identified as "Unsolicited", which quite resemble the 15% number in their sample. My regression results also show that when a deal is unsolicited, it's more likely to be an auction deal. However, my "unsolicited" variable doesn't predict a higher target excess return. This remains a puzzle to us.

[4] I would like to thank professor Audra Boone for the discussion on the data collection process.

Table 1.1: Year-wise Distribution of Deals

This table reports the year-wise distribution of my sample. The variable Initiator identifies who initiates the merger deal. Auction is where the target firm contacts and signs confidential agreement with at least two bidders. Negotiation is where the target firm only deals with one bidder. In panel A, I split the sample according to the Initiator and the sale procedure for each year. In panel B, I present the table of the Initiator and the sale procedure. Panel C and D provide raw data including deals in which I read but could not clearly identify Initiator or sales procedure.

Panel A

Year	Year Total	Acquirer Initiator	Target Initiator	Auction	Negotiation
2000	175	93	82	112	63
2001	132	65	67	95	37
2002	87	48	39	50	37
2003	103	53	50	70	33
2004	101	56	45	56	45
Total	598	315	283	383	215

Panel B

	Auction	Negotiation	Total
Acquirer Initiator	143	172	315
Target Initiator	240	43	283
Total	383	215	598

Panel C

Year	Acquirer Initiator	Target Initiator	Mutual Initiator	Unknown
2000	111	94	31	34
2001	70	74	21	18
2002	56	43	12	5
2003	59	53	29	2
2004	62	45	19	8

Panel D

Year	Auction	Negotiation	Unknown
2000	129	94	46
2001	114	55	15
2002	62	48	6
2003	74	60	9
2004	67	62	6

Table 1.2: Summary Statistics

This table reports the summary statistics of the key variables used in my analysis. Panel A summarizes firm size while Panel B summarizes deal characteristics and Panel C summarizes the deal process. I provide the number of deals, the mean and the median for the full sample and also the subsamples according to who initiates the deal. Following Boone and Mulherin (2007), I measure target size as the equity value of the target firm 64 days before the merger announcement and same for the bidder size. Relative size is the ratio of target size to the bidder size. Cash refers to the deals with payments in cash only. Tender refers to the deals of tender offer. Auction refers to the deals which were sold through auction. The means for Cash, Tender Offer and Auction are the percentages of using one of those methods among each group. *number of contact* is the number of contact the target made during the sales process. *number of written offer* includes the number of written interests or preliminary proposal or formal proposal that the target received during the sales process (the offers made by the same bidder is only counted once) . *offer ratio* is the ration between *number of contact* and *number of written offer*. The p-value is the p value of the one way t test on the mean difference for those variables between the acquirer initiator sample and the target initiator sample.

Panel A. Firm Size

Variable	Full Sample			Acquirer Initiator			Target Initiator			p-value
	#obs.	Mean	Median	#obs.	Mean	Median	#obs.	Mean	Median	
Target size ($bil)	597	0.89	0.11	314	1.23	0.20	283	0.50	0.08	0.0065
Bidder size ($bil)	581	15.79	1.76	313	21.28	2.31	268	9.46	1.44	0.0023
relative size	579	1.32	0.09	311	1.59	0.10	268	1.01	0.08	0.3132

Panel B. Deal Characteristics

Variable	Full Sample		Acquirer Initiator		Target Initiator		p-value
	#obs.	Mean	#obs.	Mean	#obs.	Mean	
Cash	598	0.34	315	0.37	283	0.32	0.1134
Tender Offer	598	0.20	315	0.20	283	0.20	0.4786
Auction	598	0.64	315	0.45	283	0.85	0.0000

Panel C. Effectiveness of Auction

Variable	Full Sample		Acquirer Initiator		Target Initiator		p-value
	#obs.	Mean	#obs.	Mean	#obs.	Mean	
number of contact	178	23.93	62	11.94	116	30.34	0.0094
number of written offer	231	3.00	80	2.59	151	3.23	0.0025
offer ratio	120	0.36	40	0.48	80	0.30	0.0007

Table 1.3: Event Study Analysis:(-1,+1) Window

This table reports even study returns for the full sample and sub samples. Panel A tests the difference in mean target excess return for acquirer-initiated deals and target-initiated deals. Panel B tests the difference in mean target excess return for auction deals and negotiated deals. p-value is the p-value of one way t test of the mean differences between each subsample.

Panel A. Analysis by Initiator

Variable	Full Sample		Acquirer Initiator		Target Initiator		p-value
	#obs.	mean	#obs.	mean	#obs.	mean	
Target execess return (%)	598	0.2563	315	0.2877	283	0.2214	0.0025

Panel B. Analysis by Sale Procedure

Variable	Full Sample		Auction		Negotiation		p-value
	#obs.	mean	#obs.	mean	#obs.	mean	
Target execess return (%)	598	0.2563	383	0.2577	215	0.2539	0.4383

Table 1.4: Probit Regression of Auction

This table reports the results of Probit regressions of sale procedure on variables for the initiator, deal size, relative target to acquirer size, the payment method, and acquisition form. The dependent variable *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation. *Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were unsolicited by the final buyer or a third party. Column 1 is the regression without the Initiator variable. Column 2 adds the Initiator variable. Column 3 is the regression for deals with deal size greater than $100 million and Column 4 is the regression for deals with deal size less than or equal to $100 million.

	(1)	(2)	(3)	(4)
Initiator		-1.215	-1.213	-1.241
		(.129)***	(.158)***	(.228)***
Deal size	-.139	-.066	-.042	-.095
	(.033)***	(.035)*	(.053)	(.208)
Tender Dummy	.012	-.116	.032	-.552
	(.158)	(.170)	(.200)	(.340)
Cash Dummy	.497	.639	.578	.873
	(.137)***	(.148)***	(.177)***	(.288)***
Relative Size	-.002	-.003	-.004	-.172
	(.004)	(.004)	(.004)	(.161)
Unsolicited	.682	.946	1.097	.569
	(.193)***	(.209)***	(.250)***	(.385)
Regulated	.404	.216	.268	.072
	(.127)***	(.137)	(.165)	(.264)
Obs.	579	579	385	194
R^2				

Table 1.5: Multivariate Regression of Target Excess Return

This table reports the results of regressions of target excess returns on variables for the sales procedure (auction), initiator, deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation.*Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition is a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 is the regression without the Initiator variable. Column 2 adds the Initiator variable. Column 3 is the regression for deals with deal size greater than $100 million and Column 4 is the regression for deals with deal size less than or equal to $100 million.

	(1)	(2)	(3)	(4)
Auction	-.028	.006	-.023	.062
	(.025)	(.028)	(.031)	(.054)
Initiator		.082	.080	.095
		(.027)***	(.031)**	(.049)*
Deal Size	-.013	-.017	-.025	-.0009
	(.007)*	(.007)**	(.010)**	(.038)
Tender Dummy	.058	.067	.135	-.082
	(.033)*	(.033)**	(.037)***	(.063)
Cash Dummy	.128	.118	.065	.210
	(.028)***	(.028)***	(.033)*	(.050)***
Relative Size	-.0003	-.0002	-.0001	-.114
	(.0008)	(.0008)	(.0008)	(.037)***
Unsolicited	-.004	-.022	-.035	.024
	(.037)	(.037)	(.043)	(.071)
Regulated	-.014	-.002	-.035	.043
	(.027)	(.027)	(.031)	(.050)
Obs.	579	579	385	194
R^2	.077	.092	.118	.168

Table 1.6: Sub sample regression

This table reports the results of regressions of target excess returns for the subsamples of auction deals and negotiated deals on variables for initiator, deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation.*Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value.*Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition is a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 is the regression within the sample of auction deals, Column 2 is within the sample of negotiated deals, Column 3 is within the sample of acquiere-initiated deals, and Column 4 is within the sample of target-initiated deals.

	(1)	(2)	(3)	(4)
Initiator	.066	.123		
	(.032)**	(.051)**		
Auction			-.009	.049
			(.034)	(.048)
Deal Size	-.021	-.010	-.018	-.011
	(.009)**	(.011)	(.009)*	(.011)
Tender Dummy	.045	.112	.123	.007
	(.040)	(.061)*	(.045)***	(.049)
Cash Dummy	.118	.121	.100	.140
	(.033)***	(.056)**	(.040)**	(.040)***
Relative Size	-.0001	-.00004	-.0002	7.69e-07
	(.001)	(.001)	(.001)	(.001)
Unsolicited	-.020	-.064	-.050	.012
	(.040)	(.087)	(.047)	(.059)
Regulated	-.008	-.002	-.061	.041
	(.033)	(.046)	(.040)	(.037)
Obs.	367	212	311	268
R^2	.09	.111	.116	.074

Table 1.7: The Use of top investment banks among target-initiated deals

This table reports the distribution of the use of top investment bank as target advisor between the auction deals and negotiated deals among the target-initiated deals. An investment bank is identified as a top investment bank in M&A if it is one of the following: Goldman Sachs & Co, Credit Suisse First Boston, Morgan Stanley, Salomon Brothers, Merrill Lynch,Lazard Freres and Lehman Brothers.

	Top Investment Bank	Non-Top IB
Negotiation	10	33
Auction	42	196

Table 1.8: How long to make a deal

This table reports the number of days to make a deal. I measure he number of days to make a deal from the date of initial contact to the date of signing the merger agreement. I then conduct t test by deal initiator and by sales procedure. In panel A, I first run t test between target-initiated deals and acquirer-initiated deals. I then run the same t test on deal initiator within groups of auction deals and of negotiation deals. In panel B, I first run t test between auction deals and negotiation deals. I then run the same t test on sales procedure within groups of acquirer-initiated deals and of target-initiated deals.

Panel A: Analysis by Deal Initiator

	Full Sample		Auction		Negotiation	
	observations	Mean	observations	Mean	observations	Mean
Target Initiated	201	145	170	147	31	130
Acquirer Initiated	269	146	118	161	151	135
P-value		0.4515		0.1816		0.4136

Panel B: Analysis by Sales Procedure

	Full Sample		Acquirer Initiated		Target Initiated	
	observations	Mean	observations	Mean	observations	Mean
Auction	288	153	118	161	170	147
Negotiation	182	134	151	135	31	130
P-value		0.0408		0.0242		0.2405

Table 1.9: Can the target tell high valuation bidder from Indicative Offers?

This table reports the results of regressions of target excess returns (column 1), indicative premium (column 2) and high premium(column 3) and auction (column 4 to column 6) for the deals on variables for auction, initiator, indicative premium, high premium, deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation. *Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Indi Premium* is the offer premium based on the indicative offer and target share price 1 day prior to the offer. *High Premium* is a dummy variable which equals to one if the indicative offer premium is in the upper quartile (premium of 49 percent) of the sample. *Low Premium* is a dummy variable which equals to one if the indicative premium is in the lower quartile (premium of 17.9 percent) of the sample. *Deal Size* is the log value of effective transaction value.*Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *Regulated* is a dummy variable equal to one for targets in the regulated industries. *Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. The first two regressions are OLS regressions and the last four regressions are probit regressions.

	(Target Excess Return)	Indi Premium	High Premium	Auction	Auction	Auction
	(1)	(2)	(3)	(4)	(5)	(6)
Auction	-.062	-.049	-.310			
	(.051)	(.123)	(.256)			
Initiator	.015	.280	.549			-1.348
	(.049)	(.116)**	(.253)**			(.262)***
Indi Premium	.074			-.278		
	(.037)**			(.182)		
High Premium	.156				-.475	-.218
	(.059)***				(.237)**	(.256)
Low Premium	-.018					
	(.054)					
Deal Size	-.012	-.017	-.398	-.159	-.197	-.078
	(.016)	(.035)	(.088)***	(.071)**	(.075)***	(.083)
Tender Dummy	-.002	.148	.233	-.365	-.378	-.587
	(.051)	(.124)	(.258)	(.239)	(.240)	(.258)**
Cash Dummy	.080	.053	.101	.245	.259	.473
	(.050)	(.120)	(.256)	(.233)	(.234)	(.255)*
Relative Size	-.0006	-.0002	.012	.031	.036	.036
	(.001)	(.003)	(.017)	(.059)	(.065)	(.072)
Unsolicited	.0006	.007	.098	.061	.071	.073
	(.008)	(.019)	(.043)**	(.038)	(.038)*	(.042)*
Regulated	-.039	-.135	-.031	.122	.160	.062
	(.054)	(.132)	(.291)	(.270)	(.268)	(.294)
Obs.	194	194	194	194	194	194
R^2	.201	.08				

Table 1.10: Test on Informed Bidder

This table reports the results of regressions of Initiator (colummn 1) and auction (column 2 to column4) on variables for auction, initiator, Business Relation, Same Ind, deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation. *Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Business Relation* is a variable based on whether the target has a ongoing business relationship with the acquirer. *Same Ind* is dummy variable which equals to 1 if the target and the acquirer are in the same 4 digit Sic industry and 0 otherwise. *Deal Size* is the log value of effective transaction value.*Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 and 2 are for the whole sample. Column 3 and column 4 are for acquirer-initiated deals and target-initiated deals respectively

	Initiator	Auction	Auction	Auction
	(1)	(2)	(3)	(4)
Initiator		-1.178		
		(.130)***		
Business Relation	.445	-.444	-.458	-.409
	(.159)***	(.164)***	(.197)**	(.325)
Same Ind	-.233	.057	.372	-.448
	(.116)**	(.126)	(.164)**	(.212)**
Deal Size	.203	-.069	-.044	-.117
	(.034)***	(.036)*	(.044)	(.064)*
Tender Dummy	-.308	-.138	-.369	.312
	(.153)**	(.172)	(.210)*	(.349)
Cash Dummy	.096	.677	.750	.449
	(.132)	(.151)***	(.182)***	(.292)
Relative Size	-.0007	-.004	.0004	-.352
	(.004)	(.004)	(.006)	(.175)**
Unsolicited	.415	.893	.843	
	(.177)**	(.211)***	(.226)***	
Regulated	-.496	.151	.055	.157
	(.128)***	(.142)	(.189)	(.228)
Obs.	579	579	311	246
R^2				

Table 1.11: Robustness Test with alternative measures of premium

This table reports the results of regressions of alternative measure of premium on variables for the sales procedure (auction), initiator,deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation.*Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. *ROA* is the return on asset which equals to net income divided by total assets. *M/B* is the market value of equity divided by the book value of equity. *q* is the market value of assets divided by the book value of assets. *P/E* is the price earning ratio. *Leverage* is the total debt divided by total assets. *Sales Growth* is the current year's sales value divided by last year's sales value. *Liquidity* is the net current assets (current assets minus current liabilities) divided by total assets. *Same Ind* is dummy variable which equals to 1 if the target and the acquirer are in the same 4 digit Sic industry and 0 otherwise. Column 1 is the regression for the target excess return on the window period (-63,126), Column 2 is the regression for the target excess return on the window period (-20,20), Column 3 uses offer premium calculated based on the offer value or price relative to the target's stock price 64 days prior to the announcement date. Column 4 to column 7 include more control variables.

	(-63,126)	(-20,20)	Offer Premium	(-1,1)	(-63,126)	(-20,20)	Offer Premium	Offer Premium
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Auction	.095	.050	.029	-.002	.079	.046	.012	.045
	(.065)	(.036)	(.043)	(.028)	(.062)	(.036)	(.044)	(.054)
Initiator	.125	.087	.080	.079	.104	.077	.088	.113
	(.064)**	(.035)**	(.042)*	(.028)***	(.060)*	(.035)**	(.042)**	(.054)**
Deal Size	-.056	-.029	-.0001	-.015	.0001	-.012	-.012	.010
	(.017)***	(.009)***	(.011)	(.008)*	(.018)	(.011)	(.013)	(.017)
Tender Dummy	.152	.126	.035	.081	.142	.128	.027	.045
	(.078)*	(.042)***	(.051)	(.034)**	(.074)*	(.043)***	(.051)	(.059)
Cash Dummy	.021	.061	.095	.111	.029	.068	.109	.137
	(.067)	(.036)*	(.044)**	(.029)***	(.064)	(.037)*	(.045)**	(.056)**
Relative Size	-.001	-.0006	-.0005	-.0002	-.002	-.0007	-.0004	-.0005
	(.002)	(.001)	(.001)	(.0008)	(.002)	(.001)	(.001)	(.001)
Unsolicited	-.034	-.061	.013	-.030	-.036	-.057	.025	.061
	(.089)	(.049)	(.059)	(.038)	(.083)	(.049)	(.058)	(.067)
Regulated	-.126	-.056	-.078	-.028	-.176	-.073	-.114	-.229
	(.064)**	(.035)	(.043)*	(.030)	(.064)***	(.037)**	(.046)**	(.113)**
ROA				.033	-.389	-.085	.239	.191
				(.045)	(.097)***	(.057)	(.074)***	(.083)**
M/B				.004	.022	.005	.011	.013
				(.004)	(.009)**	(.005)	(.006)*	(.007)*
q				-.023	-.150	-.044	-.021	-.033
				(.010)**	(.022)***	(.013)***	(.016)	(.018)*
P/E				.0002	.0008	.0003	.001	.001
				(.0002)	(.0005)*	(.0003)	(.0004)***	(.0004)***
Leverage				-.048	-.060	-.080	-.045	.051
				(.066)	(.143)	(.083)	(.102)	(.143)
Same Ind				.006	.072	.025	.073	.079
				(.026)	(.056)	(.032)	(.040)*	(.050)
Liquidity								.169
								(.115)
Obs.	582	582	543	543	543	543	507	361
R^2	.052	.079	.041	.114	.166	.114	.099	.124

Table 1.12: Robustness Test excluding "in auction" deals

This table repeats the regressions in Table 1.4 and V after excluding the deals where the acquirers initiated the deal but the targets were already auction. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation.*Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 is the regression for the target excess return after excluding the auction deals from the acquirer initiated sample if the targets were already in deal talk with a third party before the final acquirer initiated the deal talk between them, Column 2 is the regression of the target excess return in the sample of acquirer initiated deals after excluding those in-auction deals , Column 3 is the regression of auction in the sample after excluding those in-auction deals, Column 4 is the regression of the target excess return after further excluding the auction deals from the target initiated sample in which a third party has initiated deal talk with the target before the target contacted the final acquirer, and Column 5 is the regression of auction on this further reduced sample.

	Target Excess Return	Target Excess Return	Auction	Target Excess Return	Auction
	(1)	(2)	(3)	(4)	(5)
Auction	.014 (.029)	.0007 (.038)		.013 (.030)	
Initiator	.091 (.029)***		-1.459 (.136)***	.083 (.030)***	-1.416 (.138)***
Deal Size	-.014 (.007)*	-.015 (.010)	-.059 (.039)	-.015 (.008)*	-.057 (.039)
Tender Dummy	.055 (.034)	.106 (.049)**	-.250 (.187)	.068 (.036)*	-.240 (.189)
Cash Dummy	.131 (.029)***	.119 (.042)***	.733 (.158)***	.122 (.031)***	.725 (.161)***
Relative Size	-.0003 (.001)	-.00005 (.002)	-.013 (.013)	-.0003 (.001)	-.013 (.013)
Unsolicited	-.029 (.039)	-.052 (.051)	.950 (.221)***	-.001 (.045)	.903 (.229)***
Regulated	.005 (.027)	-.053 (.042)	.204 (.146)	-.002 (.028)	.210 (.147)
Obs.	533	266	533	507	507
R^2	.093	.112		.093	

Table 1.13: Robustness Test with Alternative Definitions of Auction

This table repeats the regressions in Table 1.4 and 1.5 and table 10 using alternative definitions of auction. *Auction2* is a dummy variable equal to zero when the sales procedure is a negotiation and equal to one when the sales procedure is an auction and the recorded number of confidential agreements is greater or equal to two. (Thus, the dummy variable will be missing if the number of confidential agreements is unknown or equal to one). *Auction3* reset some missing value *Auction2* to one if the targets received more than or equal to two written offers. *Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries. *Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 and Column 5 are the probit regression with *Auction2* and *Auction3* as dependent variable respectively. Column 2, 3 and 4 use target excess returns for window periods of (-1,1), (-63,126) and offer premium as dependent variables and *Auction2* in the regression. Column 6, 7 and 8 repeat the regressions with *Auction3*.

	Auction2	(-1,1)	(-63,126)	Offer Premium	Auction3	(-1,1)	(-63,126)	(Offer Premium)
Auction2		-.003	.032	.034				
		(.040)	(.099)	(.059)				
Auction3						.011	.084	.075
						(.030)	(.073)	(.047)
Initiator	-1.220	.098	.208	.175	-1.220	.082	.188	.098
	(.182)***	(.039)**	(.099)**	(.058)***	(.142)***	(.030)***	(.073)**	(.047)**
Deal Size	.028	-.018	-.067	-.009	-.064	-.026	-.077	-.012
	(.050)	(.010)*	(.024)***	(.014)	(.040)	(.008)***	(.019)***	(.012)
Tender Dummy	-.230	.117	.254	.074	-.178	.063	.159	.010
	(.239)	(.047)**	(.118)**	(.070)	(.196)	(.037)*	(.091)*	(.058)
Cash Dummy	1.013	.091	-.003	.016	.728	.098	-.042	.013
	(.210)***	(.042)**	(.106)	(.063)	(.168)***	(.032)***	(.078)	(.050)
Relative Size	-.008	-.00004	-.003	.0005	-.001	-.00005	-.001	-.0005
	(.011)	(.001)	(.003)	(.002)	(.004)	(.0008)	(.002)	(.001)
Unsolicited	.334	-.035	-.021	-.023	.790	-.038	-.037	.087
	(.341)	(.068)	(.169)	(.100)	(.243)***	(.046)	(.111)	(.071)
Regulated	.355	-.006	-.028	-.035	.377	-.030	-.127	-.114
	(.196)*	(.038)	(.095)	(.057)	(.151)**	(.030)	(.072)*	(.047)**
Obs.	309	309	309	291	454	454	454	424
R^2		.103	.066	.047		.1	.065	.045

Table 1.14: Test on Target Relative Gain in the Deals

This table reports the results of tobit regressions of the target's relative gain on variables for the sales procedure (auction), initiator,deal size, relative target to acquirer size, the payment method, and acquisition form. The dependent variable is the target's relative gain in market valuation against the total gain of the target and the acquirer during the three day period around the announcement day. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation.*Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 is the regression of target's relative gain on the whole sample, Column 2 is the regression of target's relative gain on the sub sample of cash only deals, Column 3 only includes acquier-initiated deals and Column 4 only include target-initiated deals.

	(1)	(2)	(3)	(4)
Auction	-.018	-.023	-.058	.178
	(.048)	(.062)	(.053)	(.089)**
Initiator	-.013	.015		
	(.047)	(.061)		
Deal Size	-.001	-.005	.009	-.007
	(.014)	(.019)	(.018)	(.019)
Tender Dummy	.036	.076	.058	.012
	(.052)	(.059)	(.066)	(.073)
Cash Dummy	-.002		.024	.002
	(.043)		(.058)	(.057)
Relative Size	.003	.002	.002	.350
	(.001)**	(.001)**	(.001)**	(.071)***
Unsolicited	.038	.061	.049	.007
	(.061)	(.072)	(.070)	(.100)
Regulated	.117	.144	.147	.073
	(.050)**	(.079)*	(.079)*	(.062)
Obs.	209	105	108	101
R^2				

Table 1.15: Target Termination Fee

This table reports the results of regressions of the use of target termination fee on variables for the sales procedure (auction), initiator,deal size, relative target to acquirer size, the payment method, and acquisition form. The dependent dummy variable equals to one if target termination fee is used in the deal. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation.*Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries.*Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. Column 1 is the regression of target termination fee on the whole sample, Column 2 is the regression of target termination fee on the sub sample of negotiation deals, Column 3 is the regression of target termination fee on sample of acquirer initiated deals, and Column 4 is the regression of target termination fee on the sample of target initiated deal.

	(1)	(2)	(3)	(4)
Auction	-.311		-.122	-.483
	(.157)**		(.200)	(.268)*
Initiator	.075	-.050		
	(.146)	(.297)		
Deal Size	.233	.232	.269	.199
	(.043)***	(.079)***	(.063)***	(.062)***
tender Dummy	.620	.652	.678	.529
	(.195)***	(.432)	(.279)**	(.283)*
Cash Dummy	-.327	-.487	-.572	-.092
	(.148)**	(.329)	(.218)***	(.210)
Relative Size	.005	.011	.005	.006
	(.016)	(.046)	(.020)	(.031)
Unsolicited	.122	.271	-.337	1.148
	(.205)	(.612)	(.250)	(.481)**
Regulated	-.482	-.839	-.508	-.447
	(.139)***	(.262)***	(.221)**	(.186)**
Obs.	579	212	309	269
R^2				

Table 1.16: Auction in the Target-Initiated Deals

This table reports the results of regressions of target premium on variables for the sales procedure (auction), initiator,deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries. *Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. *ROA* is the return on asset which equals to net income divided by total assets. *M/B* is the market value of equity divided by the book value of equity. *q* is the market value of assets divided by the book value of assets. *P/E* is the price earning ratio. *Leverage* is the total debt divided by total assets. *Sales Growth* is the current year's sales value divided by last year's sales value. *Liquidity* is the net current assets (current assets minus current liabilities) divided by total assets. *Same Ind* is dummy variable which equals to 1 if the target and the acquirer are in the same 4 digit Sic industry and 0 otherwise. Column 1 is the regression for the target excess return on the window period (-63,126), Column 2 uses offer premium calculated based on the offer value or price relative to the target's stock price 64 days prior to the announcement date. Column 5 is the regression for the target excess return on the window period (-63,-1), which is the runup for the target. Column 3, Column 4 and Column 6 include more control variables.

	(-63,126)	(Offer Premium)	(-63,126)	(Offer Premium)	Runup	Runup
	(1)	(2)	(3)	(4)	(5)	(6)
Auction	.280	.124	.191	.067	.156	.109
	(.102)***	(.080)	(.096)**	(.080)	(.064)**	(.061)*
Deal Size	-.026	.008	.009	-.012	-.0008	.015
	(.024)	(.019)	(.024)	(.020)	(.015)	(.015)
Tender Dummy	.194	-.004	.140	-.001	.125	.088
	(.103)*	(.080)	(.097)	(.080)	(.065)*	(.062)
Cash Dummy	.002	.100	.008	.074	-.027	-.037
	(.086)	(.067)	(.081)	(.067)	(.054)	(.052)
Relative Size	-.005	.0008	-.006	.0004	-.002	-.002
	(.003)*	(.002)	(.003)**	(.002)	(.002)	(.002)
Unsolicited	-.079	.116	-.130	.130	-.017	-.015
	(.132)	(.102)	(.121)	(.099)	(.083)	(.078)
Regulated	-.011	-.008	-.135	-.125	-.009	-.081
	(.079)	(.064)	(.080)*	(.069)*	(.050)	(.052)
ROA			-.294	.344		-.104
			(.130)**	(.111)***		(.084)
M/B			.070	.047		.031
			(.018)***	(.015)***		(.012)***
q			-.327	-.149		-.154
			(.050)***	(.040)***		(.032)***
P/E			.00004	.0002		.0003
			(.0008)	(.0007)		(.0005)
Leverage			-.051	-.188		.048
			(.199)	(.167)		(.128)
Same Ind			.068	.082		.019
			(.072)	(.060)		(.046)
Obs.	269	246	251	229	269	251
R^2	.079	.034	.264	.15	.05	.177

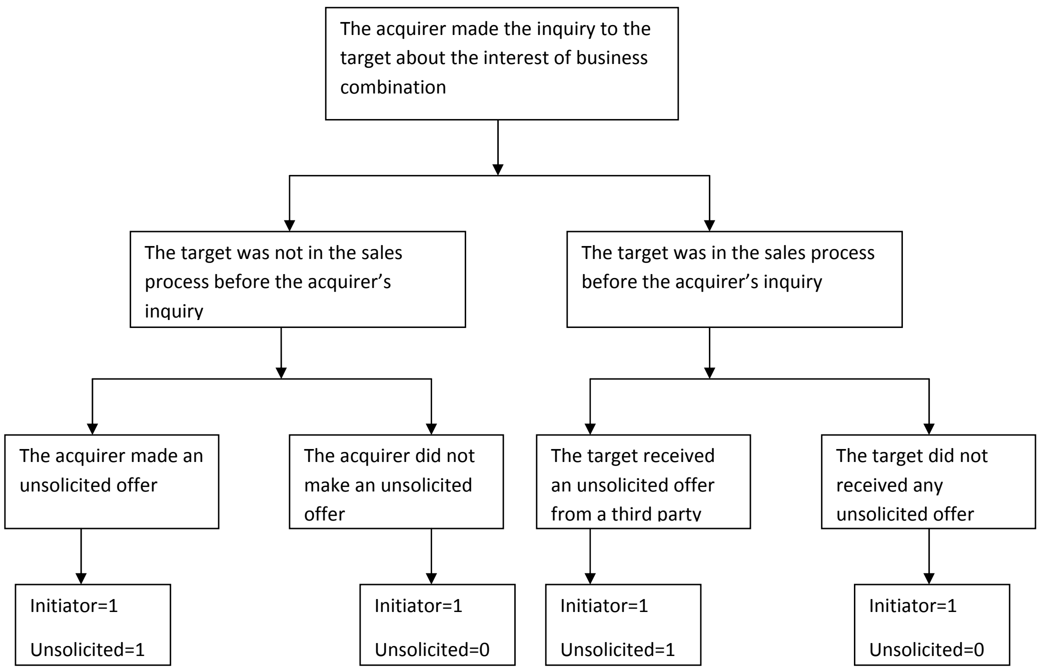
Table 1.17: The Unsolicited Variable

This table reports the results of regressions of target excess returns on variables for the sales procedure (auction), deal size, relative target to acquirer size, the payment method, and acquisition form. *Auction* is a dummy variable equal to one when the sales procedure is an auction and equal to zero when the sales procedure is a negotiation. *Initiator* is a dummy variable equal to one when it is the acquirer that first approaches the target and equal to zero when the target first approaches the acquirer. *Deal Size* is the log value of effective transaction value. *Cash* refers to the deals with payments in cash only. *Tender* is a dummy variable equal to one when the form of acquisition os a tender offer. *Relative size* is the ratio of target size to the bidder size. *regulated* is a dummy variable equal to one for targets in the regulated industries. *Unsolicited* is a dummy variable equal to one for deals that were initiated by the bidder or a third party. The last three columns are regressions after deleting the deals in which the acquirier made unsolicited offer to the targets after the targets announced merger agreements with third parties.

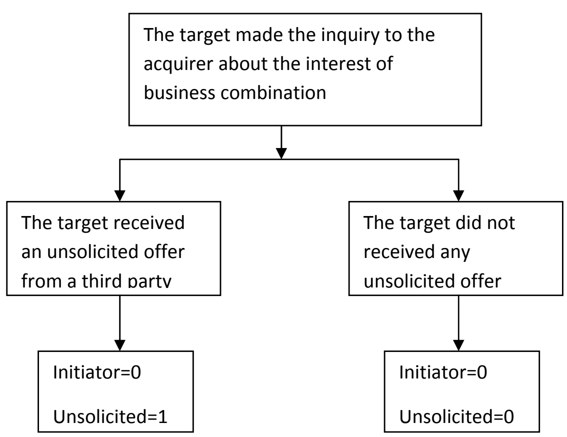
	(-1,1)	(-63,126)	(Offer premium)	(-1,1)	(-63,126)	(Offer Premium)
	(1)	(2)	(3)	(4)	(5)	(6)
Auction	-.028	.029	-.005	-.028	.033	.001
	(.025)	(.060)	(.040)	(.026)	(.061)	(.040)
Deal Size	-.013	-.052	.003	-.013	-.053	.007
	(.007)*	(.017)***	(.011)	(.007)*	(.017)***	(.011)
Tender dummy	.058	.146	.031	.057	.142	.039
	(.033)*	(.077)*	(.051)	(.034)*	(.080)*	(.052)
Cash Dummy	.128	.043	.099	.131	.041	.089
	(.028)***	(.067)	(.044)**	(.029)***	(.068)	(.045)**
Relative size	-.0003	-.001	-.0006	-.0003	-.002	-.0007
	(.0008)	(.002)	(.001)	(.0008)	(.002)	(.001)
Unsolicited	-.004	.003	.033	.006	.033	.078
	(.037)	(.088)	(.058)	(.040)	(.094)	(.062)
Regulated	-.014	-.131	-.087	-.014	-.135	-.078
	(.027)	(.063)**	(.043)**	(.027)	(.064)**	(.043)*
Obs.	579	579	542	569	569	532
R^2	.077	.047	.034	.08	.047	.034

The difference between the Initiator variable and the Unsolicited variable

Acquirer Initiated Deals



Target Initiated Deals



Chapter 2

Conglomerates and Industry Distress

*

2.1 Introduction

Understanding the costs and benefits of conglomeration is an area of significant research interest. Conglomerates are known to operate an internal capital market (ICM) that distributes cash to the different segments in response to investment opportunities. By comparing the performance of conglomerate segments and single segment firms – that depend on external financial markets to a greater extent – we can understand the investment efficiency of the ICM vis-a-vis the external financial markets.[2] This comparison is also relevant for understanding the boundaries of the firm as it lets us understand the situations in which firms or markets are better at coordinating economic activity (Coase (1937)). Despite its importance, answering this question has proved a difficult empirical

* This chapter is a joint work with Radhakrishnan Gopalan.

[2]See Stein (2003) and Maksimovic and Phillips (2007) for important summaries of the current research in this area.

task because observed organizational forms are endogenous and conglomerate segments and single segment firms may differ in systematic unobserved ways (see Maksimovic and Phillips (2002)). Identifying an instrumental variable for the population of conglomerates has also proved difficult. In this paper we try to overcome this problem by doing an event study around periods of *unexpected* economic distress in an industry. We identify periods of economic distress using the methodology in Opler and Titman (1994) and compare the behavior of conglomerate segments and single segment firms during such periods to shed light on the costs and benefits of conglomeration.

Our study offers a number of unique advantages. Since the distress episodes we study are *unexpected*, firms are less likely to change their organizational form and behavior in anticipation. We also employ segment fixed effects in our tests and base our conclusions on within segment changes in behavior. Industry distress is likely to depress segment cash flows and increase the differences in investment opportunities across conglomerate segments. This in turn will enhance our ability to test the theories of conglomeration. Our experimental setting allows us to study multiple outcome variables and perform a number of Difference-in-Difference estimates which allow us to better distinguish between the theories of conglomeration.

To identify industries in economic distress, we follow Opler and Titman (1994). We classify an industry as distressed if the median sales growth of single segment firms in the industry is negative and the median stock return is less than -30%. A definition of distress based on stock return ensures that it is at least partly unanticipated by the market and firm managers. This procedure results in identifying 214 episodes of distress in 3-digit SIC code industries spread uniformly over our sample period of 1986-2008 (See Table 2.1.). While the number of industries in distress is higher during recession years (1989, 1990-91, 2001 and 2007-08), we also have a number of idiosyncratic episodes of industry distress in our sample. Searching news reports, we find the common causes for industry distress include a fall in demand or an increase in input prices.

We obtain data for our analysis from standard sources. Our stock return data is from CRSP and financial data on conglomerates and single segment firms is from the Compustat business segment files. We classify firms as conglomerates if they report positive assets and sales in segments in more than one three-digit SIC code industry. Prior research has identified problems with the Compustat identification of segment industry affiliation (Hyland (1997) and Villalonga (2004)). Since our tests are based on within segment changes in behavior, they are likely to be less biased due to data errors. We discuss a number of additional robustness tests that we perform to control for industry misclassification in Section 3.

We start our empirical analysis by comparing the sales growth, cash flows and R&D expenditure of conglomerate segments and single segment firms in distressed industries.[3] We find that conglomerate segments in distress have higher sales growth, cash flows and R&D expenditure as compared to distressed single segment firms. While an average distressed segment experiences a 13.8% (4.7%) decline in sales growth (cash flows), conglomerate segments in distress experience 6.3% (2.1%) higher sales growth (cash flows) as compared to single segment firms. Similarly while single segment firms in distress reduce R&D ex-

[3]Hereafter for brevity, we refer to single segment firms and conglomerates segments in distressed industries as being in distress.

penditure by 0.6%, distressed conglomerate segments do not reduce R&D expenditure. On the other hand, we do not find any significant difference between distressed conglomerate segments and single segment firms in the extent of capital expenditure. Thus our evidence indicates that conglomerate ICMs treat short term capital expenditure and long term R&D expenditures differently during industry distress. When we differentiate segments based on prior ability – using lagged abnormal cash flows– we find that the higher sales growth and cash flows of conglomerate segments in distress is confined to those with high ability. This is consistent with conglomerate ICMs differentiating segments based on ability when deciding on capital allocation.

We distinguish between temporary and prolonged distress by classifying distress periods that last for one year as temporary and those that last for two or more successive years as prolonged. We find that the higher sales growth and higher cash flows of more able conglomerate segments is confined to temporary distress periods. The higher R&D expenditure of conglomerate segments is present both during temporary and prolonged distress periods.

The better performance of distressed conglomerate segments in comparison to single segment firms is consistent with both the *Cross subsidization* and the *Financial constraints* hypotheses of conglomeration. The *Cross subsidization* hypothesis as formulated by Scharfstein and Stein (2000) and Rajan et al. (2000) argues that conglomerate ICMs inefficiently transfer resources from the productive to the non-productive segments – in our case, the distressed segments. The fact that the better performance of conglomerate segments is confined to those with high ability is less consistent with inefficient cross subsidization. The *Financial constraints* hypothesis stresses the presence of information frictions in the external financial markets which are likely to worsen during periods of industry distress and disproportionately affect the performance of single segment firms.

The *Financial constraints* hypothesis predicts that the difference between distressed conglomerate segments and single segment firms should be greater in the subsample of firms ex ante more likely to face financial constrains. Following existing literature (see Dimitrov and Tice (2006)), we identify firms without credit ratings as likely to face more financial constraints and consistent with the *Financial constraints* hypothesis, find that the higher sales growth and cash flows of the distressed conglomerate segments is confined to the subsample of unrated firms. Thus our evidence is consistent with conglomerates enabling segments overcome financial constraints during periods of industry distress (see also Billett and Mauer (2003), Hubbard and Palia (1999), Khanna and Palepu (2000), and Lins and Servaes (1999))

Following Ali et al. (2009) we use the census data to measure industry concentration and individually compare distressed conglomerate segments and single segment firms in concentrated and competitive manufacturing industries. We find that the higher sales growth and R&D expenditure of conglomerate segments in distressed industries is greater in competitive industries. This is consistent with firms in competitive industries facing greater financial constraints during industry downturns. Our results also highlight an interesting manner in which industry concentration interacts with organizational form to affect a firm's response to industry distress.

To test the *Cross subsidization* hypothesis we follow Rajan et al. (2000) and classify conglomerates with greater asset size diversity as more prone to cross-subsidize. We do not find any systematic evidence that the difference between distressed conglomerate segments and single segment firms is greater among conglomerates with greater asset size diversity.

When we estimate the effect of industry distress on firm investment in working capital, we find that distressed single segment firms disproportionately reduce their investment in receivables and the level of payables in comparison to conglomerates. This may highlight one possible channel linking firm financial constraints and performance. We also find that distressed single segment firms significantly increase the amount of cash balance they retain. This is consistent with such firms having greater precautionary savings motive during periods of industry distress – another sign of facing financial constraints (see Almeida et al. (2004)).

We also find that the better performance of conglomerate segments during industry distress is value enhancing. The diversification discount, which we measure as the difference between the Tobin's Q of the conglomerate and the asset weighted Industry Tobin's Q of all the segments of the conglomerate goes down significantly around periods of industry distress. The discount reduces on average by 8.9% in the year of industry distress.

We find that periods of industry distress are active periods of industry consolidation. While we do not find any significant difference between conglomerates and single segment firms in their acquisition activity during periods of industry distress, we do find that firms with high ability are more likely to acquire other distressed firms in their industry. This is consistent with the neoclassical view of firm behavior in the market for corporate assets (Maksimovic and Phillips (2001)). We also find this effect to be more pronounced in the subsample of rated firms. Finally, when we study firm exits during industry distress we find that conglomerates are more likely to sell low ability distressed segments through mergers while low ability single segment firms are more likely to delist during periods of distress either through bankruptcy, liquidation or a merger. Overall our evidence is consistent with high ability segments expanding and low ability segments exiting the distressed industry. The lack of evidence for less constrained conglomerates to expand in the distressed industry is partly consistent with the *Flexibility* hypothesis that highlights the ability of conglomerates – as compared to single segment firms – to divert resources towards the more productive segments (Matsusaka and Nanda (2002), Mathews and Robinson (2006), and Guedj and Scharfstein (2004)).

Summarizing, our results highlight the "bright" side of conglomeration that comes to fore during periods of industry distress. Segments of conglomerates in distress appear less financially constrained than comparable single segment firms. The lower financial constraints improves performance and significantly enhances the value of conglomerates in comparison to single segment firms. Our results also highlight the important role of industry distress in promoting industry consolidation. While high ability firms acquire their distressed counterparts, low ability conglomerate segments and low ability single segment firms exit the industry in response to industry distress. We find very little evidence for inefficient cross-subsidization by conglomerates during industry distress.

The rest of the paper proceeds as follows. Section 1 outlines our hypothesis and derives the main testable predictions. Section 2 describes the data, lays out the empirical methodology, and provides the main results stemming from the tests of our predictions. Section 3 presents additional robustness tests and Section 4 concludes.

2.2 Hypotheses

We group the hypotheses that are relevant for our setting into three: The *Financial constraints*, *Cross subsidization*, and the *Flexibility* hypotheses. We now outline their main predictions.

The *Financial constraints* hypothesis arises from the presence of frictions such as information problems in the external financial markets. Such frictions are likely to worsen during periods of industry distress and disproportionately affect single-segment firms that depend on the external financial markets to a greater extent. Conglomerate segments, on the other hand, can rely on the firm's ICM for their financing needs. Due to its diversified nature, the conglomerate's ICM may be able to continue accessing either internal or external finance and fund profitable investment opportunities. Thus the financial constraints hypothesis predicts a higher sales growth, cash flow, and investment for the distressed conglomerate segments in comparison to single segment firms. Since financial constraints are less likely to discriminate between high and low ability segments and to the extent that conglomerate ICMs do discriminate, we expect the differences to be present in segments with high ability and also expect an increase in the valuation of conglomerates in comparison to single segment firms during periods of industry distress. These effects are likely to be more pronounced in the subsample of firms that are ex ante more likely to face external financial constraints. The *Financial constraints* hypothesis also predicts constrained single segment firms to exit the industry at a greater frequency.

The *Cross subsidization* hypothesis as formulated in Scharfstein and Stein (2000) and Rajan et al. (2000) argues that conglomerate ICMs inefficiently transfer resources from the productive segments to the less-productive segments. Such transfers occur either to reduce inefficient rent seeking by division managers (Scharfstein and Stein (2000)) or to ensure sufficient investment by division managers in efficient joint technologies (Rajan et al. (2000)). Segments in distressed industries are likely to have lower productivity in comparison to those in non-distressed industries. In light of this, the *Cross subsidization* hypothesis predicts a transfer of resources by conglomerates *into* the distressed segments and away from the non-distressed segments. Such transfers are likely to boost the sales growth, investment and cash flow of the distressed segments above that of single segment firms. Since cross-subsidization by definition is inefficient, this hypothesis predicts the better performance to be present both for high- and low ability segments as well as a reduction in the valuation of conglomerates in comparison to single segment firms. All these effects are likely to be greater among conglomerates more prone to cross-subsidize. The *Cross subsidization* hypothesis also predicts the single segment firms to exit distressed industries at a greater frequency.

Finally, the *Flexibility* hypothesis highlights the ability of conglomerates to redistribute resources internally into the most productive segments. If industry distress reduces the investment opportunities of a segment, then the conglomerate's ICM may engage in "winner picking" and redirect resources towards the more productive non-distressed segments

(Stein (1997), Matsusaka and Nanda (2002) Mathews and Robinson (2006), and Guedj and Scharfstein (2004)). Single-segment firms, on the other hand, lack such alternate investment opportunities and may hence continue investing in the distressed industry. Hence the *Flexibility* hypothesis predicts that distressed segments of conglomerates will have lower sales growth rates, investments levels, and cash flows than comparable single segment firms. Since the redirection of resources by conglomerates is likely ex post efficient, the *Flexibility* hypothesis predicts a higher value for conglomerates in comparison to single segment firms during periods of industry distress. Unlike the other two hypothesis, the *Flexibility* hypothesis predicts conglomerate segments to exit distressed industries at a greater frequency.

2.3 Empirical analysis

In this section, we describe the data, lay out the empirical methodology, and provide the main results stemming from the tests of our predictions.

2.3.1 Data and descriptive statistics

We obtain our data from three standard sources. Stock returns and firm financials are from CRSP-Compustat merged database, financial data on conglomerate segments is from the Compustat business segment files and data on mergers and acquisitions is from SDC Platinum. Our sample period extends from 1986 to 2008, and we include all segments with non-missing positive values for sales and assets in our sample. We exclude financial firms

(SIC codes 6000-6999), regulated firms (SIC codes 4900-4941), and industries with less than four segments. We identify firms as conglomerates if the Compustat business segment files report positive assets and sales in more than one three-digit SIC code industry for the firm. For robustness, we repeat all our tests with a conglomerate identification based on four-digit SIC code industry and the Fama-French industry classification (see Fama and French (1997)).

Table 2.1 provides the year-wise distribution of our sample. We identify distressed industries using the methodology outlined in Opler and Titman (1994). Specifically, for every year, we calculate the stock return and sales growth for the two-year period starting from the beginning of the year for all single segment firms. We define a firm's industry using the three-digit SIC code and classify an industry as distressed during a year if the median two-year sales growth in that industry is negative and the median two-year stock return is less than -30%. For robustness, we repeat all our regressions defining industry at the level of four-digit SIC codes and get comparable results. A definition of distress based on stock returns ensures that the distress is at least partly unanticipated by the market and firm insiders. This makes it less likely that firms will have adjusted their organization and behavior in anticipation. We identify 214 distressed industry-years during our sample period. We classify approximately 5.1% of the industries in our sample as distressed (214 out of 4212). This is slightly higher than the fraction in Opler and Titman (1994) mainly because of the larger fraction of distressed industries during the second half of our sample period.

During our sample period, NBER classifies parts of 1989, 1990-91, 2001, and 2007-08 as recessionary. The number of industries in distress increases during recession years. But apart from recession years, there are also a number of idiosyncratic episodes of industry distress. About 3.9% (2401 out of 60,949) of the segments in our sample are in distressed industries which is comparable to the 3.0% firms in distressed industries in Opler and Titman (1994). We have a total of 60,949 segment-year observations in our sample composed of 20,386 conglomerate segment-year observations and 40,563 single segment-year observations. The number of observations for tests that differentiate segments based on prior ability will be less because of more stringent data requirements. As can be seen, the number of conglomerate segments goes down from 1291 in 1986 to 204 in 2007.[4] We now outline our empirical methodology.

2.3.2 Empirical specification and key variables

We are interested in comparing the performance of segments of conglomerates to that of single segment firms during periods of industry distress. We do this by estimating variants of the following model:

$$\begin{aligned} y_{i,j,t} &= \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Distress}_{j,t} + \beta_3 \text{Conglomerate}_{i,t} \times \text{Distress}_{j,t} \\ &\quad + \gamma \text{Controls} + \mu_t + \mu_{i,j}, \qquad (2.1) \end{aligned}$$

where subscript i refers to the firm, subscript j refers to the industry, and subscript t refers to time in years, μ_t refers to time fixed effects and $\mu_{i,j}$ refers to segment fixed

[4]We do not have data on all firms for 2008. Our results are robust to excluding 2008 from our sample.

effects. The dependent variable y is a measure of segment performance and in the first set of tests, we model *Segment sales growth*, *Segment cash flow* and *Segment R&D*.[5] *Segment cash flow* is the ratio of segment cash flow to lagged book value of segment total assets where cash flow is the sum of segment operating profit and segment depreciation. *Segment R&D* is the ratio of segment research and development expenditure to the lagged book value of segment total assets. We use *Segment R&D* as a measure of investment by conglomerates and single segment firms.[6] *Conglomerate* is a dummy variable that takes a value one for segments of conglomerates. *Distress* is a dummy variable that takes a value one if the industry is in distress during a particular year. In the above specification, β_3 is a measure of the difference in performance between conglomerate segments and single segment firms in distress. X refers to a set of segment level control variables. The specific control variables vary with the dependent variable being modeled and include one or more of, lagged values of *Segment sales growth*, *Segment cash flow*, *Industry Tobin's Q* and *Segment investment*. All variables are defined in Appendix A. The standard errors in all the specifications are clustered at the level of three-digit SIC code industry and are robust for heteroscedasticity.

The research design in our paper is similar to that in Lamont (1997), Campello (2002), and Khanna and Tice (2000). Unlike Lamont (1997) we compare the performance of segments of conglomerates and single segment firms in the distressed industry. The main difference between our paper and Campello (2002) and Khanna and Tice (2000), is our ability

[5]Following the criticism in Whited (2001) we do not rely on the differential response of conglomerate and single segment firm investments to Tobin's Q for our conclusions.

[6]In unreported tests we also model *Segment investment*. We discuss this in greater detail in footnote 7.

to study shocks to multiple industries. This enables us to do cross-sectional Difference-in-Difference tests to better distinguish between the existing theories. We can also highlight how industry characteristics such as the level of competition interacts with organizational form to affect a firm's response to industry distress.

Following Maksimovic and Phillips (2002), in some of our tests, we differentiate across segments (and single segment firms) with high and low ability. We classify segments as having high ability if their abnormal cash flows over the previous two years is above the sample median. We measure abnormal cash flows as the difference between *Segment cash flow* and the median cash flows of all segments in the same three-digit SIC industry during the year. We then estimate (2.1) after including interaction terms between *High ability*, a dummy variable that identifies segments with high ability and *Conglomerate*, *Distress* and *Conglomerate* $\times$ *Distress*.

We also estimate the effect of industry distress on a number of firm-level variables. The first set of firm-level variables we model include measures of working capital such as *Receivable/Assets*, *Inventory/Assets*, *Payable/Assets* and *Cash/Assets*. These are the ratio of the book value of receivables, inventory, payables and cash and marketable securities respectively over lagged book value of total assets. To compare these variables across conglomerates and single segment firms, we use a model similar to (2.1) with a few important changes. The sample for these regressions includes one observation per firm-year and we replace *Distress* with *Firm distress*, a dummy variable that takes a value one if *any* of the segments of the conglomerate are in distress. In the case of single segment firms, *Firm distress* takes a value one if the firm's industry is in distress. In our firm level regressions we include firm fixed effects and the standard errors are clustered at the industry level and are robust for heteroscedasticity. We also use a similar model to compare the level of acquisition activity of conglomerates and single segment firms in distress. To do that, we create a dummy variable, *Distress acquisition*, that identifies distressed firms that acquire another firm or segment in their industry. Finally, we use the model to study the propensity of firms to exit industries during distress. We do that by modeling *Distress segment sold* and *Firm delisted*. *Distress segment sold* is a dummy variable that takes a value one for distressed firms and conglomerates with distressed segments that are sold during the year. Similarly, *Firm delisted* is a dummy variable that takes a value one if the firm is delisted from the stock exchange because of bankruptcy, liquidation or a merger during the year.

Finally, we test how the diversification discount, *Q-Difference*, varies during periods of industry distress. *Q-Difference* is the difference between the conglomerate's Tobin's Q and an asset-weighted average industry-Q. We use the fraction of book value of assets of the conglomerate's segments as the weights for measuring average industry-Q. We offer further discussion of the specification we use to model *Q-Difference* in Section 2.4.4.

2.3.3 Summary statistics

Table 2.2 provides the summary statistics for the key variables used in our analysis. Panel A summarizes the data for conglomerates, while Panel B summarizes the data for single segment firms. From the table we find that segments of conglomerates are comparable to single segment firms in terms of book value of total assets, $798 million as compared to

$877 million. While conglomerate segments have lower average sales growth as compared to single segment firms, (.104 in comparison to .185), the former have a higher average *Segment cash flow*. Conglomerate segments have significantly lower R&D expenditure but comparable levels of capital expenditure. Single segment firms are in industries with higher average Tobin's Q. We classify about 4% (3.9%) of conglomerate (single segment) segment-years as being in distress. We classify a slightly larger fraction of conglomerate segments as having high ability as compared to single segment firms.

In terms of firm level variables, as expected, conglomerates are significantly larger than single segment firms in terms of book value of total assets. Conglomerates also have lower Tobin's Q as compared to single segment firms but have higher average leverage ratios. The other important difference across the two panels is that single segment firms maintain significantly higher cash balances as a fraction of total assets as compared to conglomerates. We also find that a greater proportion of conglomerates than single segment firms have short-term credit rating from Standard and Poor. The average conglomerate discount in our sample is 21.9%, comparable to earlier studies. About 59% of the our sample conglomerate firms have high diversity. Before we describe the results of our empirical tests, we do some univariate analysis.

Table 2.3 compares the mean value of the key variables for conglomerate segments and single segment firms in both distressed and non-distressed industries. Prior research (see Chevalier (2004), Graham et al. (2002), and Campa and Kedia (2002)) highlights a number of important differences between conglomerate segments and single segment firms both in observable and unobservable characteristics and questions the validity of comparing the two. Taking this into account, to perform the univariate comparison, we first identify a set of single segment firms that are comparable to the conglomerate segments in terms of observable characteristics.[7] Specifically, we estimate the likelihood of any segment to belong to a conglomerate using a panel probit model similar to the one in Campa and Kedia (2002). The dependent variable in the model is *Conglomerate* and we include the following independent variables: *Segment investment*$_{t-1}$, *Segment profit*$_{t-1}$, *Industry Tobin's Q*$_{t-1}$, *Major exchange*, *GDP growth*, *GDP growth*$_{t-1}$, *Recession months*, *Recession months*$_{t-1}$, *Foreign*, *Number mergers*, *Value mergers*, *S&P index*, *Average cash flow*, *Average investment*, *Fraction conglomerate* and *Fraction conglomerate sales*. All the variables are described in Appendix A. Using the coefficient estimates, we predict the likelihood of any segment to belong to a conglomerate – the propensity score. For each conglomerate segment in our sample, we then randomly identify a matched single segment firm that has a propensity score within 1% of that of the conglomerate segment. We drop both the conglomerate segments for which we are not able to obtain a matched single segment firm as well as the unmatched single segment firms. We repeat this procedure for distress and non-distress periods as well as at the firm level. When estimating the probit model at the firm level, we replace the segment level variables with equivalent firm level variables.

Table 2.3 reports the mean values for the key variables for conglomerate segments and comparable single segment firms. *Pr(Conglomerate)* is the propensity score and we see that the sample of conglomerate segments and single segment firms are comparable in

[7] Since we lack an instrument for the population of conglomerate segments, we are unable to compare the two on unobservables as well.

terms of the average propensity score. Conglomerate segments are smaller than single segment firms. They have lower sales growth during non-distress years but have higher sales growth during distress years. This is consistent with single segment firms experiencing a greater decline in sales growth during industry distress as predicted by both the *Cross subsidization* and the *Financial constraints* hypotheses. Conglomerate segments have higher cash flows both during non-distress and distress years although the difference is greater during distress years. Conglomerate segments have lower research and development expenditure during both non-distress and distress years. Note that our conclusions from the multivariate analysis where we include segment and time fixed effects may be different. We also find that conglomerate segments have lower levels of investment only during non-distress years. We are more likely to classify a conglomerate segment as having high ability especially during non-distress years.

Comparing firm level variables, we again find that the sample of conglomerates and single segment firms are similar in terms of the average propensity score. Conglomerates are significantly larger than single segment firms but have lower Tobin's Q especially during non-distress years. Conglomerates have higher leverage ratios both during non-distress and distress years. Conglomerates have higher *Inventory/Assets* especially during distress years and lower *Receivables/Assets* especially during non distress years. Conglomerates have lower *Payables/Assets* during non distress years but higher levels during distress years. Conglomerates have significantly lower *Cash/Assets* both during non distress and distress years. A larger fraction of conglomerates have short-term credit rating. The mean value of *Q-Difference* is lower during distress years as compared to non-distress years.

2.3.4 Empirical results

With the data and empirical strategy in hand, we now proceed to test our empirical predictions.

Segment performance and industry distress

In the first set of tests, we compare *Segment sales growth*, *Segment cash flow*, and *Segment R&D* of single segment firms and segments of conglomerates during periods of industry distress. We do this by estimating the panel data regression (2.1) and report the results in Table 2.4. In the first two columns, our dependent variable is *Segment sales growth*. The negative coefficient on *Conglomerate* in Column (1) indicates that on average conglomerate segments have lower sales growth than single segment firms. The negative coefficient on *Distress* indicates that on average, firms experience a fall in sales growth during periods of industry distress. On the other hand, the positive coefficient on *Conglomerate* $\times$ *Distress* shows that segments of conglomerates in distressed industries have a higher sales growth as compared to single segment firms. We find that the sum of the coefficients on *Distress* and *Conglomerate* $\times$ *Distress* is -.075 and is statistically significant. This indicates that segments of conglomerates also experience a fall in sales growth during periods of industry distress. From the coefficients on the control variables we find that segments that generate higher cash flows in the past, that do more capital expenditure in the past and that are in industries with higher Tobin's Q experience a higher sales growth.

In Column (2) we differentiate segments based on ability. To better highlight the differential response of high- and low-ability conglomerate segments to industry distress, we include an interaction term *Low ability* × *Conglomerate* × *Distress* instead of *Conglomerate* × *Distress*, where *Low ability* = 1-*High ability*. The positive and significant coefficient on *High ability* × *Conglomerates* × *Distress* indicates that the higher *Segment sales growth* of conglomerate segments in comparison to single segment firms during industry distress is confined to the high-ability segments. In unreported tests we find that the coefficient on the two triple interaction terms are significantly different from each other.

In Columns (3) & (4), we compare *Segment cash flow* across conglomerate segments and single segment firms. The results in Column (3) show that while conglomerate segments have higher *Segment cash flow* on average (positive coefficient on *Conglomerate*), all segments experience a fall in cash flows during periods of industry distress (negative coefficient on *Distress*). The positive coefficient on *Conglomerate* × *Distress* indicates that segments of conglomerates in distressed industries have higher cash flows than single segment firms. We find that the sum of the coefficients on *Distress* and *Conglomerate* × *Distress* is -.026 and is statistically significant. In Column (4), we again differentiate between high- and low-ability segments and find that the higher *Segment cash flow* of distressed conglomerate segments as compared to single segment firms is confined to high ability segments. Here again we find that the coefficients on the two triple interaction terms are significantly different from each other.

In Columns (5) & (6) we compare the R&D expenditures of the segments of conglomerates and single segment firms. Our results in Column (5) indicate that while firms on average reduce R&D expenditure during periods of industry distress (negative coefficient on *Distress*), segments of conglomerates in distressed industries have a higher R&D expenditure than single segment firms (positive coefficient on *Conglomerate* $\times$ *Distress*). Overall, we find that the sum of the coefficient on *Distress* and *Conglomerate* $\times$ *Distress* is insignificant, indicating that conglomerate segments do not reduce R&D expenditure during periods of industry distress. From Column (6) we find that the higher R&D expenditure of conglomerate segments is present both for high- and low-ability segments.

Summarizing, our results so far indicate that conglomerate segments have higher sales growth, higher cash flows and higher R&D expenditure as compared to single segment firms during periods of industry distress. The higher sales growth and cash flows of conglomerate segments is confined to those with high ability while the higher R&D expenditure is present both for high- and low-ability segments. Our results are consistent with the *Cross subsidization* and the *Financial constraints* hypotheses, but are inconsistent with the *Flexibility* hypothesis.[8]

In Panel B, we differentiate between temporary and prolonged distress. To do this, we re-estimate (2.1) after replacing *Distress* with two dummy variables *Temporary distress* and *Prolonged distress*. We classify distress periods that last for one year as temporary and the rest as prolonged. Of the 2401 distressed segment-years in our sample, we classify 1571 as temporary distress periods and the rest as prolonged distress periods. The control variables in these regressions are similar to the ones in Panel A but we suppress

[8] In unreported tests, we use *Segment investment* as the dependent variable and find that while the coefficient on *Distress* is negative, the coefficient on *Conglomerate* $\times$ *Distress* is insignificant. Thus while all firms experience a fall in capital expenditure during periods of industry distress, segments of conglomerates do not show evidence of higher capital expenditure. Thus when it comes to investing during periods of industry distress, we find that conglomerate ICMs differentiate between short term capital expenditure and long term R&D.

their coefficients to conserve space. Our results in Column (1) indicate that conglomerate segments have higher sales growth only during periods of temporary distress. There is no significant difference in the sales growth of conglomerate segments and single segment firms during periods of prolonged distress. In Column (2) we differentiate between segments with high- and low-ability and find that the higher sales growth of high ability conglomerate segments as compared to single segment firms is present during both temporary and prolonged distress periods. From our results in Column (3) we find that segments of conglomerates have higher cash flows during both temporary and prolonged distress periods. But our results in Column (4) indicate that the higher cash flows of high ability conglomerate segments is present only during periods of temporary distress. Finally from Column (5) & (6) we find that conglomerate segments have higher R&D expenditure during both temporary and prolonged industry distress periods especially if they have high ability. Low ability conglomerate segments have higher R&D expenditure only during periods of prolonged distress.

Thus our results in Panel B provide some mixed evidence that the difference in performance of distressed conglomerate segments and single segment firms is greater during periods of temporary industry distress. This is consistent with conglomerate insiders being able to differentiate between periods of temporary and prolonged industry downturns and helping segments during temporary downturns.

Further tests within subsamples

In this section we specifically test the *Financial constraints* and *Cross subsidization* hypotheses by doing tests within subsamples. If the better performance of conglomerate segments during periods of industry distress is due to their ability to overcome financial constraints, then we expect the difference in performance to be greater among the subsample of firms that are ex ante likely to face greater financial constraints. We now test this prediction.

To identify firms that are likely to face financial constraints, we use the presence of credit ratings. Following existing literature, we classify firms with credit ratings as less constrained than firms without credit ratings. In Panel A of Table 2.5 we repeat our estimation in the subsample of rated and unrated firms. The dependent variable in Columns (1) & (2) is *Segment sales growth*. Our results indicate that consistent with the *Financial constraints* hypothesis the higher sales growth of conglomerate segments during periods of industry distress is confined to the sample of unrated firms.

In Columns (3) & (4) we repeat our tests with *Segment cash flow* as the dependent variable. Consistent with our evidence in Columns (1) & (2) the higher cash flows of conglomerate segments during periods of industry distress is confined to the subsample of unrated firms. In Columns (5) & (6) we repeat our tests with *Segment R&D* as the dependent variable and find that the higher R&D expenditure of conglomerate segments is present both among rated and unrated firms. Overall our evidence in this table provides significant support for the *Financial constraints* hypothesis.

In Panel B, we repeat our tests differentiating between high- and low-ability segments.

Our results in Columns (1) & (2) show that the higher sales growth of high ability conglomerate segments is confined to the subsample of unrated firms. In Columns (3) - (4) we repeat our tests with *Segment cash flow* as the dependent variable and again find that the higher cash flows of high ability conglomerate segments during periods of industry distress is confined to the subsample of unrated firms. Finally, the results in Columns (5) & (6) show that the higher R&D of conglomerate segments is present both among rated and unrated firms. Overall our results in this panel indicate that the higher sales growth and cash flow of conglomerate segments during periods of industry distress is confined to the subsample of unrated firms. This offers significant support for the *Financial constraints* hypothesis. Our evidence is complementary to and consistent with the evidence in Maksimovic and Phillips (2008) who show that conglomerates moderate the link between financial dependence and plant acquisitions in their more productive segments in growth industries.

Our evidence is also consistent with the findings in Dimitrov and Tice (2006) who show that during recessions, unrated conglomerates have a higher sales growth than focused firms. In unreported tests we repeat our estimates after including two terms *Recession* and *Recession* $\times$ *Conglomerate* to our specification, where *Recession* is a dummy variable that takes a value one for the years 1989, 1990-91, 2001, and 2007-08. We find that our results are robust to the inclusion of these controls. This ensures that our finding is not just driven by difference in performance of unrated conglomerate segments and single segment firms during recessions.

Apart from credit ratings, industry structure may also affect the extent of firm financial constraints. Firms in competitive industries are likely to have lower margins and hence lower cash flows. Such firms are more likely to depend on the external financial markets and face greater constraints during periods of industry distress. To see if industry distress disproportionately affects firms in competitive industries, in Panel C we use the industry Herfindahl index as a measure of competition and compare conglomerate segments and single segment firms in concentrated and competitive industries. Following Ali et al. (2009) we use the census data of manufacturing establishments to calculate the Herfindahl index. We calculate the Herfindahl index of each industry as the sum of the squares of the market shares of all firms in the industry. We obtain concentration measures for the years 1982, 1987, 1992, 1997, and 2002 from the census data and similar to Ali et al. (2009), use the most recent year's concentration measure for the missing years. Our sample in this table is confined to manufacturing firms. We divide our sample into firms in industries with below 20th percentile of Herfindahl (*Competitive* industries) and those in industries with above 20th percentile of Herfindahl (*Concentrated* industries) and repeat our estimation in the two subsamples.[9] Our results in Columns (1) & (2) show that while high ability conglomerate segments in both concentrated and competitive industries have a higher sales growth as compared to single segment firms during industry distress, the difference is almost twice as large in competitive industries as compared to concentrated ones. Similarly, only high ability conglomerate segments in competitive industries have a higher research and development expenditure as compared to single segment firms. On the otherhand, high ability conglomerate segments in both concentrated and competitive

[9]We use the 20th percentile to obtain comparable sizes for the concentrated and competitive industries subsamples.

industries have a higher cash flow as compared to single segment firms. Overall our results in this panel offer some evidence that the difference between conglomerate segments and single segment firms in distress is greater in competitive industries as compared to concentrated industries. This indicates the interesting manner in which industry structure interacts with firm organizational form to affect the firm's response to industry distress. Our evidence is also consistent with firms in competitive industries facing greater financial constraints.

In Table 2.6, we test the *Cross subsidization* hypothesis by estimating if the difference in performance between conglomerate segments and single segment firms during periods of industry distress is greater among the subsample of conglomerates that are more prone to cross-subsidize. Following Rajan et al. (2000) we use the asset size diversity among the segments of a conglomerate as a measure of the conglomerate's propensity to cross-subsidize. The idea is that a conglomerate with a greater degree of diversity among its segments is likely to have a greater incentive to cross-subsidize. We create a dummy variable *High diversity* (*Low diversity*) that takes a value one for conglomerates that have a value of diversity index above (below) the sample median. To test the *Cross subsidization* hypothesis, we re-estimate (2.1) after replacing *Conglomerate* × *Distress* with two interaction terms *High diversity* × *Distress* and *Low diversity* × *Distress* and present the results in Table 2.6. The positive coefficient on both *High diversity* × *Distress* and *Low diversity* × *Distress* in all three columns indicate that the better performance of conglomerate segments during periods of industry distress is present both in conglomerates with high- and low levels of diversity. Five of the six coefficients are statistically significant at conventional levels and the only one that is not significant is actually the one on *High diversity* $\times$ *Distress* in Column (2). Thus we do not find consistent evidence for the *Cross subsidization* hypothesis.

Other firm characteristics during industry distress

Our results that distressed segments of unrated conglomerates with high ability have a higher sales growth, cash flows, and R&D expenditure during periods of industry distress in comparison to similar single segment firms is consistent with the latter set of firms facing greater financial constraints. An interesting question that arises is why do financial constraints affect firm performance. One possible channel is by constraining a firm's ability to invest in non-cash working capital such as inventory and receivables. Constrained single segment firms may be forced to disproportionately cut down on their working capital investment which in turn may affect their performance. To test this, in Table 2.7 we compare the individual working capital items for conglomerates and single segment firms. For lack of segment-level data, we do this comparison at the firm level.[10]

In Column (1) of Table 2.7, we estimate (2.1) with *Receivable/Assets* as the dependent variable. The sample includes one observation per firm-year and we use *Firm distress* instead of *Distress*. As mentioned, *Firm distress* takes a value one for all single segment firms in distressed industries and also for all conglomerates that have at least one segment in distress. We include *EBITDA/Assets*, *Sales growth*, *Tobin's Q*, *Leverage* and *Rated* as

[10]Since conglomerates are diversified, even if the distressed segment of the conglomerate changes its working capital by the same extent as a single segment firm, our tests are likely to indicate a greater fall in working capital for single segment firms as compared to conglomerates. Our results have to be interpreted with this caveat in mind.

additional control variables. The significant negative coefficient on *Firm distress* indicates that all firms reduce their receivable levels during periods of industry distress. The positive coefficient on *Conglomerate* $\times$ *Firm distress* indicates that conglomerates have a higher level of receivables as a proportion of total assets during periods of industry distress. We find that the sum of the coefficients on *Firm distress* and *Conglomerate* $\times$ *Firm distress* is insignificant. In Column (2), we repeat our regression with *Inventory/Assets* as the dependent variable but do not find any significant change in inventory as a proportion of total assets during periods of distress. In Column (3) we repeat the estimation with *Payable/Assets* as the dependent variable and find that while single segment firms significantly reduce the level of payables, conglomerates actually increase the level of payables during periods of industry distress. This evidence is consistent with single segment firms not being able to access finance through trade-credit during periods of industry distress.

In a recent paper, Almeida et al. (2004) argue that firms facing financial constraints will increase the amount of cash they save so as to ensure that they have enough liquid assets to face any future adverse contingencies. If single segment firms face greater constraints in raising external finance during periods of industry distress, then according to Almeida et al. (2004) such firms should increase their cash balance in comparison to conglomerates. In Column (4) we test this prediction with *Cash/Assets* as the dependent variable. Consistent with the prediction, we do find that single segment firms significantly increase the amount of cash balance they retain during periods of industry distress. Conglomerates do not show a similar tendency to increase the level of cash balance. This result is consistent with single segment firms facing greater financial constraints during periods of industry distress.

Diversification discount in distressed industries

An important question that is yet to be answered is whether the better performance of conglomerate segments during periods of industry distress is value enhancing. To answer this question, we estimate how the diversification discount – a measure of conglomerate value in comparison to single segment firms – changes during periods of industry distress. If as predicted by the *Financial constraints* hypothesis, the better performance of conglomerate segments is efficient, we expect the discount to reduce during periods of distress.

To understand the effect of industry distress on the diversification discount, we plot its average value around the period of industry distress in Figure 1. Specifically, we plot the coefficient estimates from the following OLS model:

$$\begin{aligned} \text{Q-Difference}_{i,t} \quad = \quad & \beta_0 \text{Firm distress}_{i,t} + \sum_{s=1}^{3} \beta_s \text{Pre-distress(s)}_{i,t} + \beta_4 \text{Pre distress(4+)}_{i,t} \\ & + \sum_{s=1}^{3} \gamma_s \text{Post-distress(s)}_{i,t} + \gamma_4 \text{Post distress(4+)}_{i,t} + \epsilon_{i,t}, \qquad (2.2) \end{aligned}$$

where *Q-Difference* is the difference between the Tobin's Q of the conglomerate and the asset weighted Industry Tobin's Q of all the segments of the conglomerate. *Pre-distress(s)* (*Post-distress(s)*) is a dummy variable that takes a value one if it is s years before (after) industry distress. *Pre distress(4+)* (*Post distress(4+)*) is a dummy variable that takes a value one if it is four or more years years before (after) industry distress.

The sample includes all conglomerates with at least one division in distress during our sample period. In Figure 1 we plot the point estimates of $\{\beta_0,\ \beta_1,\ \beta_2,\ \beta_3,\ \gamma_1,\ \gamma_2\ \gamma_3\}$ and the 95% confidence interval. To ensure that the estimates are meaningful, we do not include a constant term, time or firm effects in the regression. From the first graph it is clear that the diversification discount significantly reduces during periods of industry distress. The average discount reduces from 20% in the year before industry distress to 6.9% in the year after industry distress. From the other two graphs we see that the fall in discount is present both for rated and un-rated conglomerates. We also see that the fall in discount persists for three years after the year of industry distress. This clearly indicates that the better performance of conglomerate segments during periods of industry distress is perceived to be value enhancing by the market. Note that the fall in discount for rated conglomerates is not inconsistent with the *Financial constraints* hypothesis because the hypothesis only predicts that unrated single-segment firms will face financial constraints in comparison to unrated conglomerates. It does not have anything to say about rated conglomerates.

In Table 2.8, we present the results of our formal regression analysis. The model is similar to (2.2) except that we now include all conglomerates and augment the model with time and firm fixed effects and a constant term. The results indicate that in the full sample, the diversification discount significantly goes down in the year following the year of industry distress. From Columns (2) & (3) we find that consistent with Figure 1, the discount goes down both in the year of and in the year following industry distress for both rated and unrated conglomerates, although the coefficients are not statistically significant at conventional levels. In Columns (4)-(6) we repeat our tests with with Δ *Q-Difference* as the dependent variable where Δ *Q-Difference* is the first difference of *Q-Difference* and obtain stronger results. Δ *Q-Difference* significantly goes down in the year of industry distress in the full sample. Furthermore when we split the sample into rated and unrated firms, we find that Δ *Q-Difference* is significantly lower only in the year of industry distress in the unrated subsample. Overall, our results indicate that conglomerates experience a significant reduction in the diversification discount when one of their segments is in distress. This is consistent with the *Financial constraints* hypothesis. We note that the average discount in our sample is 22%. Comparing this to the coefficients in Column (4), we find that the discount reduces by more than 40% in the year of distress.

Firm acquisition and industry distress

In this section we test if conglomerates and single segment firms differ in their acquisition activity during industry distress. We focus specifically on horizontal acquisitions to better understand the dynamics of industry consolidation during distress periods.[11] Before we conduct the multivariate analysis, in Figure 3 we examine the extent of horizontal acquisition activity by conglomerates and single segment firms around industry distress periods. To plot the graph, we obtain data on all completed mergers and acquisitions from SDC Platinum where the merged entity is an US firm or had an US parent. We

[11]In unreported tests we estimate the effect of industry distress on the likelihood of a firm doing any acquisition. We find that conglomerates are less likely to undertake acquisitions during periods of temporary distress and this is especially so if the distress affects a low ability segment.

then match the acquisition sample to our sample based on the CUSIP of the acquirer or its parent and identify all acquisitions in which the target and the acquirer (or one of its segments), are from the same three-digit SIC code industry. We then estimate a model similar to (2.2) with *Horizontal acquisition* as the dependent variable. *Horizontal acquisition* is a dummy variable that takes a value one in the year in which a firm undertakes at least one horizontal acquisition. In Figure 3, we plot the point estimates of the coefficients $\{\beta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2\ \gamma_3\}$ and the 95% confidence interval from (2.2). From the first graph we find some evidence for an increase in the likelihood of an horizontal acquisition in the year of industry distress. From the second graph we find some evidence for an increase in the acquisition likelihood for conglomerates. There is little evidence for an increase in the likelihood of a horizontal acquisition among single segment firms. One problem in interpreting these graphs is that in the case of conglomerates we do not know if the horizontal acquisition is in the distressed industry or not. To ensure that we analyze horizontal acquisitions within the distressed industry, we do multivariate analysis specifically focussing on such acquisitions.[12]

We create a dummy variable *Distress acquisition* that identifies firms that acquire distressed targets in their industry during the year. Since *Distress acquisition* only identifies acquisitions occurring in the distress year, it is likely to be positively correlated with *Firm distress* by construction. Since our interest is in identifying differences across conglomerates and single segment firms in their propensity to engage in such acquisitions, this is not

[12]In unreported tests we conduct multivariate analysis with *Horizontal acquisition* as the dependent variable and find that firms are more likely to undertake a horizontal acquisition during distress periods if they have high ability. We further find that conglomerates are less likely to undertake horizontal acquisitions if a low ability segment is in distress. These results are available upon request.

a problem.[13] We then estimate a model similar to (2.1) with *Distress acquisition* as the dependent variable and present the results in Table 2.9. The sample includes one observation per firm-year and we use *Firm distress* instead of *Distress*. Apart from time and firm fixed effects, we also include lagged values of *Industry Tobin's Q*, *Cash/Assets*, and *EBITDA/Assets* as control variables.[14] The results in Column (1) show that there is no difference between conglomerates and single segment firms in the likelihood of acquiring a distressed target. In Column (2) we differentiate between temporary and permanent distress and again find that there is no significant difference between conglomerates and single segment firms in their acquisition likelihood. In Column (3) we differentiate between distress in an industry in which the acquiring firm/segment has high versus low ability. We find that high-ability firms are more likely to acquire distressed targets. Finally in Columns (4) and (5) we differentiate between rated and unrated firms and find that while both rated and unrated firms with high ability are more likely to engage in acquisition of distressed targets, the probability is greater in the case of rated firms. Since we have a linear probability model, the coefficients represent marginal effects. Overall our results indicate that during industry distress, high ability firms that are not financially constrained are most likely to acquire distressed targets. The lack of evidence for less constrained conglomerates to engage in distressed acquisitions to a greater extent offers some partial evidence in support of the *Flexibility* hypothesis. Overall our results are

[13]In unreported tests we confine the sample to years of industry distress and repeat out estimation and obtain results similar to the ones reported.

[14]Although our dependent variable is a dummy variable we do not employ a non-linear probability model such as a probit model because including firm fixed effects in a non-linear model is subject to the incidental parameters problems (Wooldridge (2002)).

consistent with the neoclassical view of firm behavior in the market for corporate assets as proposed in Maksimovic and Phillips (2001).

Firm exit during industry distress

In this section we explore the likelihood of firms to exit an industry in response to industry distress. In our multivariate analysis we explore two alternative forms of exit. Before we conduct the multivariate analysis, in Figure 3 we plot the likelihood of firms to exit an industry through a merger around the time of industry distress. We do this by estimating a model similar to (2.2) with *Segment sold* as the dependent variable. *Segment sold* is a dummy variable that takes a value one in the year in which a single segment firm or a conglomerate segment is sold through a merger. We construct this variable by matching the SDC acquisition sample to our firm financial data using the CUSIP of the target or its ultimate parent, thereby identifying if any of the firms/segments in our sample are sold. In Figure 3, we plot the point estimates of the coefficients $\{\beta_0$, β_1, β_2, β_3, γ_1, γ_2 $\gamma_3\}$ and the 95% confidence interval from (2.2). From the first graph it is clear that firms are more likely to sell a segment during industry distress. The annual probability of a segment sale increases from 2% in the year before industry distress to 4% in the year of distress. From the other two graphs we see that the likelihood of a segment sale increases both for conglomerates and single segment firms. This highlights that periods of industry distresses are active periods of industry consolidation and is consistent with the literature that relates restructuring activity in an industry to its life-cycle (Gort and Klepper (1982), Jovanovic (1982), Klepper and Grady (1990), Klepper (1996)). One problem in interpreting these graphs is that in the case of conglomerates we do not know if the segment being sold is in distress or not. To ensure that, when we conduct our multivariate analysis we specifically focus on sale of distressed segments.[15]

In Table 2.10, we conduct multivariate analysis with the two alternative measures of firm exit. Our first measure identifies exit through mergers while our second measure is an all encompassing one that identifies exit due to bankruptcy, liquidation or a merger. To analyze if conglomerates (and single segments firms) engage in sale of distressed segments, in Columns (1)-(4) we model *Distress segment sold* a dummy variable that identifies single segment firms and conglomerate segments that are sold during industry distress. Note that *Distress segment sold* will take a value one only in the year of industry distress. Thus it will be positively correlated with *Firm distress* mechanically. This is not a problem because we are only interested in identifying differences between conglomerates and single segment firms in their propensity to sell distressed segments. We are able to identify 81 instances of sale of distressed firms and segments in our sample. Of these, 40 involve single segment firms and 41 involve segments of conglomerates.[16] Our sample in these regressions includes one observation per firm-year and apart from time and firm fixed effects, we also include lagged firm financials as control variables. Our choice of control variables is guided by the bankruptcy prediction literature (see Altman (1968) and Ohlson (1980)) and include *Current Assets/Current Liabilities*, *Total Liabilities/Assets*, *EBITDA/Assets*, *Retained*

[15]In unreported tests we do multivariate analysis by estimating (2.1) with *Segment sold* as the dependent variable and find that industry distress does not have a significant effect on the likelihood of a segment sale for conglomerates and single segment firms.

[16]In unreported tests, we study the likelihood of an asset sale in the year following industry distress and obtain results similar to the ones reported.

earnings/Assets, *Net Income/Assets*. We drop single segment firms from our sample the year after they are sold. Our results in Column (1) show that conglomerates are more likely to sell distressed segments during periods of industry distress. In Column (2) we differentiate between temporary and prolonged distress and find that conglomerates are more likely to sell segments during both temporary and prolonged distress periods. In Column (3) we differentiate between distress in high and low ability segments and find that while conglomerates are more likely to sell both high- and low-ability distressed segments, the probability is greater in the case of low ability segments. Finally in Column (4) we simultaneously differentiate between temporary and prolonged distress affecting high and low ability segments. Our results indicate that conglomerates are likely to sell low ability distressed segments during periods of temporary industry distress. The greater likelihood of conglomerates to engage in sale of segments during industry distress is consistent with prior evidence of conglomerates being more active participants in the market for mergers and acquisitions (Maksimovic and Phillips (2008)).

In Columns (5)-(8) we analyze a more comprehensive measure of firm exit. Our dependent variable in these columns is *Firm delisted*, a dummy variable that identifies firms that delist from the stock exchange during the year due to bankruptcy, liquidation, or a merger. We identify 1912 firms that delist during our sample period. Of these 1663 are single segment firms and 249 are conglomerates. In univariate tests (unreported) we find that firms are more likely to delist in the year of industry distress as compared to other years. Our sample and control variables in these regressions are similar to those in the earlier columns. The results in Column (5) show that after controlling for other observable characteristics, firms are not more likely to delist during industry distress. In Column (6) we differentiate between temporary and prolonged distress and find that compared to single segment firms, conglomerates are less likely to delist during periods of prolonged industry distress. In Column (7) we differentiate between distress that affects high ability segments from distress that affects low ability segments. Our results indicate that low ability single segment firms are more likely to delist during industry distress. Here again, conglomerates with low ability segments in distress are less likely to delist. In Column (8) we simultaneously differentiate between temporary and prolonged distress affecting high versus low ability segments. Our results indicate that low ability single segment firms are more likely to delist during periods of temporary industry distress. On the other hand, conglomerates are less likely to delist during prolonged distress affecting low ability segments.[17]

Overall our results indicate that both conglomerate segments and single segment firms that have low ability are more likely to exit industries during periods of distress. While low ability conglomerate segments exit through mergers, low ability single segment firms delist from the stock exchange. Our results complement the findings in Maksimovic and Phillips (2001) who show that firms sell their less productive plants following positive demand shocks.

[17] In unreported tests we estimate the likelihood of firms delisting in the year following industry distress and obtain results similar to the ones reported.

2.4 Additional Tests

We do a number of robustness tests of our results. First, we repeat our tests with alternative definitions of conglomerates. To recall, we define a firm as a conglomerate if it reports positive assets and sales in more than one three-digit SIC code industry. We repeat our tests by classifying firms as conglomerates if they report positive assets and sales in more than one four-digit SIC code industry and obtain results similar to the ones reported. We also define a firm as a conglomerate if it reports positive assets and sales in more than one Fama-French industry and get stronger results. Since the Financial Accounting Standards Board (FASB) changed the rule for reporting segment data in 1997, pooling data from before and after 1997 may be problematic. To overcome this, we repeat our regressions separately for the pre- and post-1997 samples. While our results are statistically less significant for some of the specifications, they are qualitatively similar in both the subsamples to the ones reported here.

Prior research has indicated that there is significant arbitrariness in the way Compustat and the firms identify individual segments. To control for any arbitrary changes in divisional identification, we repeat our tests after confining the sample to single segment firms and conglomerates that do not change the number of reported segments for one year before the industry distress and get results similar to the ones reported here.

2.5 Conclusion

The conglomerate as an organizational form has received tremendous attention from academics and investors. Research about conglomerates has thus far tried to answer the question of whether the ICMs in conglomerates are efficient. Stein (2003) suggests that instead of treating the bright-side and dark-side models of conglomerates as competing hypotheses, it might be more fruitful to ask,"When are internal capital markets most likely to add value?" Our paper is an attempt to answer this question. We compare the behavior of conglomerate segments to single segment firms during periods of industry distress to evaluate the applicability of the different theories.

We find that distressed conglomerate segments have a higher sales growth, higher cash flows and greater R&D expenditure than single segment firms. The differences in performance is greater in a subsample of unrated firms and in competitive industries. Single segment firms also reduce their receivables and significantly increase their cash holding during periods of industry distress. We find that the valuation discount for conglomerates in comparison to single segment firms reduces significantly when one of the conglomerates' segments is in distress. We find distress periods to be active periods of industry consolidation. While high ability firms, especially those with credit ratings acquire other distressed firms, both conglomerate segments and single segment firms with low ability exit the distressed industry at a greater frequency. Overall, our evidence is consistent with the role of conglomerates in enabling segments overcome financial constraints during periods of industry distress. We do not find any evidence for inefficient cross-subsidization by conglomerates during periods of industry distress.

Appendix A: Variable definitions

- *Average cash flow*: Is the average of *Segment cash flow* over the previous two years.
- *Average investment*: Is the average of *Segment investment* over the previous two years.
- *Cash/Assets*: The ratio of the book value of cash and marketable securities to lagged book value of total assets.
- *Conglomerate*: A dummy variable that identifies firms with more than one segment with positive sales in different three-digit SIC code industries.
- *Current Assets/Current Liabilities*: The ratio of current assets over current liabilities.
- *Distress*: A dummy variable that takes a value one for segments in distressed industries. We identify industries in distress using the methodology in Opler and Titman (1994).
- *Distress acquisition*: A dummy variable that identifies all firms that undertake a horizontal acquisition in a distressed industry.
- *Distress segment sold*: A dummy variable that identifies instances when a firm/segment is sold either in the year of industry distress.
- *EBITDA/Assets*: The ratio of earnings before interest depreciation and taxes over total assets.
- *Firm delisted*: A dummy variable that takes a value one in the year in which a firm delists from the stock exchange due to liquidation, bankruptcy or a merger.
- *Firm distress*: A dummy variable that takes a value one if the firm's or one of its segments' industry is in distress.
- *Foreign*: A dummy variable that identifies foreign firms.
- *Fraction conglomerate*: The proportion of conglomerates in an industry. We identify industry at the level of three-digit SIC code.

- *Fraction conglomerate sales*: The proportion of sales by multi-segment firms in an industry. We identify industry at the level of three-digit SIC code.

- *GDP growth*: The rate of growth of US GDP.

- *High ability*: A dummy variable that identifies segments that have high ability. We classify segments as having high ability during a year if the average abnormal cash flows over the previous two years is above sample median. We measure abnormal segment cash flows as the difference between segment cash flows and the median cash flows of all firms in the same three-digit SIC industry during the year.

- *High ability distress*: A dummy variable that identifies instances when the distress affects the industry in which the firm or one of its segments is classified as having high ability.

- *High diversity*: A dummy variable that identifies conglomerates that have a diversity index above the sample median. We measure the diversity index of a conglomerate following the procedure outlined in Rajan et al. (2000).

- *Horizontal acquisition*: A dummy variable that identifies years in which a firm undertakes at least one horizontal acquisition.

- *Industry Tobin's Q* is the median Tobin's Q of all firms in the same three-digit SIC code industry during the year.

- *Inventory/Assets*: The ratio of the book value of inventory at the end of the year to lagged book value of total assets.

- *Leverage*: The ratio of the book value of total debt to the book value of total assets.

- *Low ability*: A dummy variable that identifies segments that do not have high ability. It equals 1-*High ability.*

- *Low ability distress*: A dummy variable that identifies instances when the distress affects the industry in which the firm or one of its segments is classified as having low ability.

- *Major exchange*: A dummy variable that identifies firms that are listed in one of NYSE, Amex or Nasdaq.

- *Net Income/Assets*: The ratio of net income over total assets.
- *Number mergers*: The number of completed mergers announced during the year.
- *Payable/Assets*: The ratio of the book value of payables at the end of the year to lagged book value of total assets.
- *Pre-distress(s)*: A dummy variable that takes a value one if it is s years before industry distress in one of the segments of the conglomerate.
- *Pre-distress(4+)*: A dummy variable that takes a value one if it is four or more years before industry distress in one of the segments of the conglomerate.
- *Post-distress(s)*: A dummy variable that takes a value one if it is s years after industry distress in one of the segments of the conglomerate.
- *Post-distress(4+)*: A dummy variable that takes a value one if it is four or more years after industry distress in one of the segments of the conglomerate.
- *Prolonged distress*: A dummy variable that identifies distress periods that last for two or more successive years.
- *Q-Difference*: The difference between the conglomerate's Tobin's Q and an asset-weighted average industry-Q of all the segments of the conglomerate. We use the fraction of book value of assets of the conglomerate's segments as the weights for measuring average industry-Q. Δ *Q-Difference*: The first difference value of *Q-Difference*.
- *Rated*: A dummy variable that takes a value one if the firm has a short-term credit rating from S&P.
- *Receivable/Assets*: The ratio of the book value of receivables at the end of the year to lagged book value of total assets.
- *Recession months*: A variable that counts the number of months in a year the NBER classifies as recessionary.
- *Retained earnings/Assets*: The ratio of retained earnings over total assets.

- *S&P index*: A dummy variable that identifies firms that are constituents of one of the major S&P indices.
- *Segment acquired*: A dummy variable that takes a value one in the years in which a segment of a conglomerate or a single segment firm is acquired.
- *Segment assets*: The book-value of segment total assets in $ Million.
- *Segment cash flow*: The ratio of segment cash flows to lagged value of segment total assets. Segment cash flows as the sum of segment operating profit and segment depreciation.
- *Segment investment*: The ratio of segment capital expenditure to lagged value of segment total assets.
- *Segment profit*: The ratio of segment operating profit before depreciation to lagged value of segment total assets.
- *Segment R&D*: The ratio of segment research and development expenditure to lagged value of segment total assets.
- *Temporary distress*: A dummy variable that identifies distress periods that last for one year.
- *Tobin's Q*: The ratio of market value of total assets to the book value of total assets, where market value of total assets is the sum of book value of total assets and the market value of equity less the book value of equity.
- *Total Liabilities/Assets*: The ratio of total assets over total liabilities.
- *Value mergers*: The aggregate dollar value of completed mergers announced during the year.

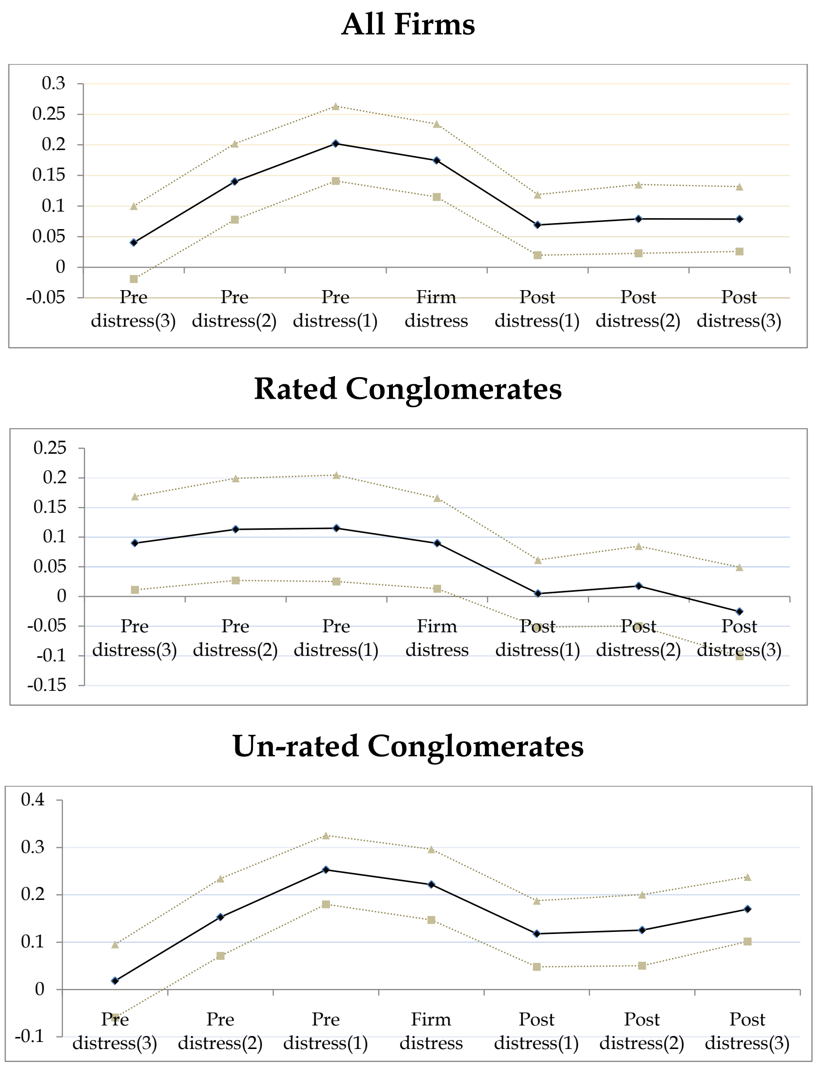
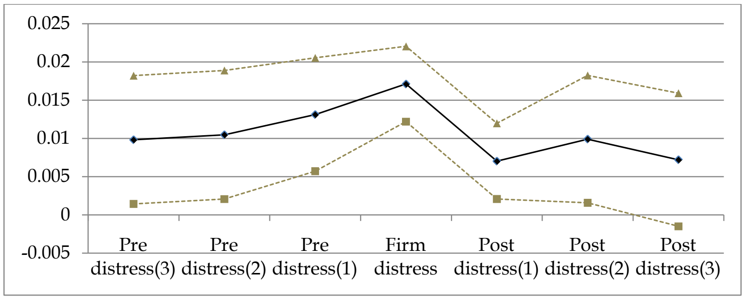


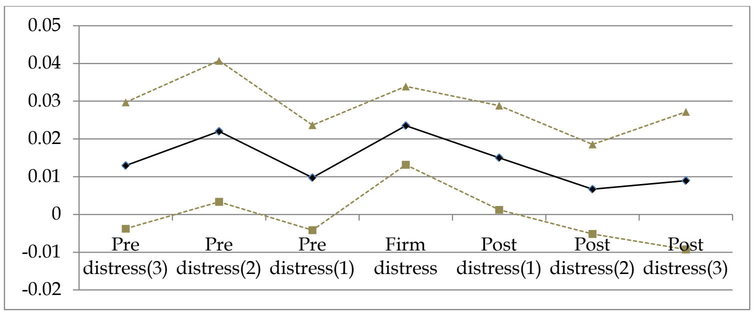
Figure 2.1: Q-Difference around industry distress

Each figure plots the point estimates from a separate OLS regression for each year relative to the year of industry distress. The sample includes all conglomerates with at least one segment in distress during our sample period. The dependent variable is *Q-Difference*, the difference between the Tobin's Q of the conglomerate and the asset weighted *Industry Tobin's Q* of all the segments. The model includes dummy variables for the seven years around the year of distress and two dummy variables for four or more years before and after the year of industry distress. We present the point estimates for the seven year period around the year of distress. The data covers the period 1986-2008. The stock price data is from CRSP; segment-level financial data is from the Compustat Business Segment Files; and firm-level data is from the Compustat Industrial Annual files. The standard errors are clustered at the industry level, and gray lines represent the 95 percentile confidence intervals.

All Firms



Conglomerates



Single segment firms

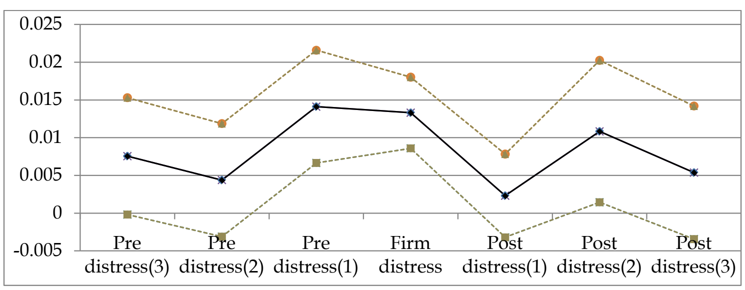


Figure 2.2: Horizontal acquisitions around industry distress

Each figure plots the point estimates from a separate OLS regression for each year relative to the year of industry distress. The sample includes all firms that are in distress for at least one year. The dependent variable is *Horizontal Acquisition*, a dummy variable that takes a value one in the year in which firms undertake a horizontal acquisition. The model includes dummy variables for the seven years around the year of distress and two dummy variables for four or more years before and after the year of industry distress. We present the point estimates for the seven year period around the year of distress. The data covers the period 1986-2008. The stock price data is from CRSP; segment-level financial data is from the Compustat Business Segment Files; and firm-level data is from the Compustat Industrial Annual files. The standard errors are clustered at the industry level, and gray lines represent the 95 percentile confidence intervals.

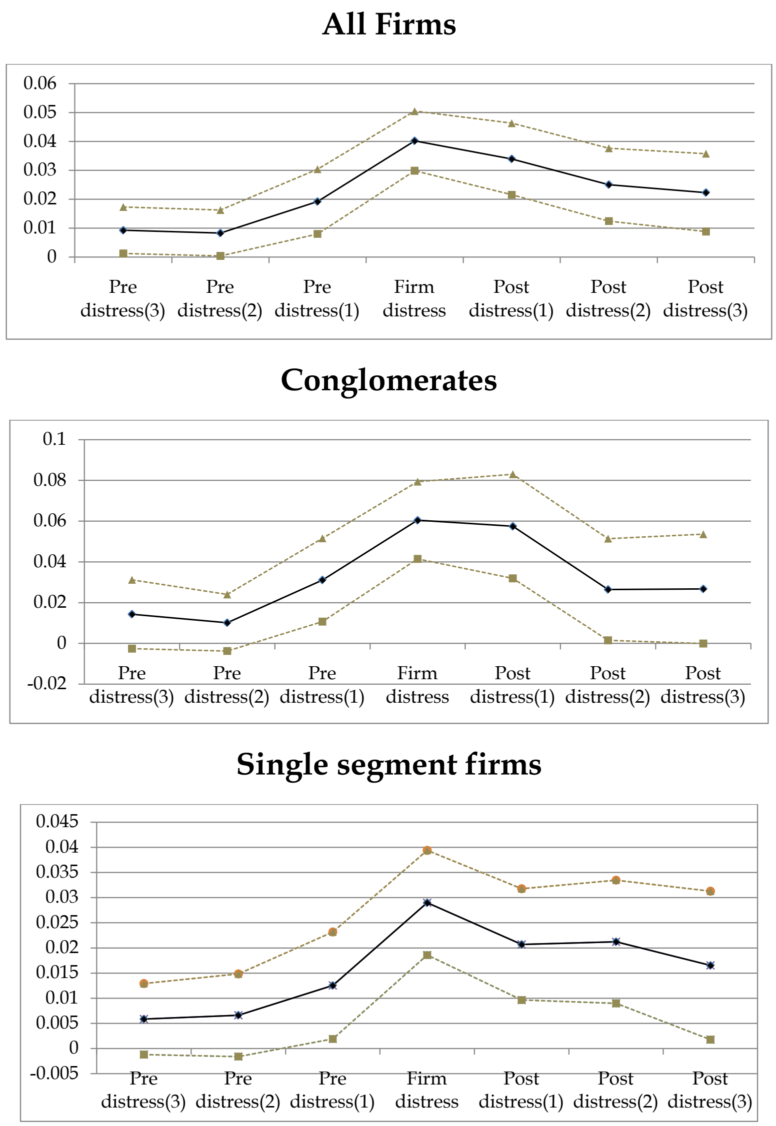


Figure 2.3: Firm exit around industry distress

Each figure plots the point estimates from a separate OLS regression for each year relative to the year of industry distress. The sample includes all firms that are in distress for at least one year. The dependent variable is *Segment sold*, a dummy variable that identifies the years in which a single segment firm or the segment of a conglomerate is sold. The model includes dummy variables for the seven years around the year of distress and two dummy variables for four or more years before and after the year of industry distress. We present the point estimates for the seven year period around the year of distress. The data covers the period 1986-2008. The stock price data is from CRSP; segment-level financial data is from the Compustat Business Segment Files; and firm-level data is from the Compustat Industrial Annual files. The standard errors are clustered at the industry level, and gray lines represent the 95 percentile confidence intervals.

Table 2.1: Year-wise distribution of distressed industries and segments

Year	Distressed industries	Non-distressed industries	Distressed segments	Non-distressed segments	Conglomerate segments	Single-segment firms
1986	6	183	175	2742	1291	1626
1987	4	189	36	2830	1226	1640
1988	5	192	58	2867	1174	1751
1989	15	185	129	2961	1181	1909
1990	22	184	197	2951	1245	1903
1991	13	190	129	3120	1294	1955
1992	8	194	58	3251	1315	1994
1993	3	200	12	3331	1247	2096
1994	1	202	4	3504	1231	2277
1995	3	200	8	3663	1205	2466
1996	2	200	9	3835	1195	2649
1997	8	205	50	3762	1092	2720
1998	15	193	143	3229	977	2395
1999	16	180	92	2841	857	2076
2000	22	177	241	2675	912	2004
2001	25	168	867	1948	877	1938
2002	2	185	11	2623	785	1849
2003	1	153	2	1471	339	1134
2004	0	143	0	1216	266	950
2005	2	142	3	1134	226	911
2006	5	149	7	1254	221	1040
2007	21	136	78	1156	204	1030
2008	15	48	92	184	26	250
Total	214	3998	2401	58548	20386	40563

This table reports the year-wise distribution of our sample. Column (1) reports the number of distressed industries and Column (2) the number of non-distressed industries. We identify industries at the level of three-digit SIC code. The number of segments in distressed and non-distressed industries is given in Columns (3) & (4) while the number of segments of conglomerates and single segment firms is given in Columns (5) & (6). We identify industries in distress following the procedure in Opler and Titman (1994). Specifically, we classify an industry identified by a three-digit SIC code as distressed if the median stock return for a two-year period is less than -30% and the median sales growth for the same two-year period is negative. We classify firms as conglomerates if they report positive sales and total assets in more than one three-digit SIC industry.

Table 2.2: Summary statistics

Panel A: Summary statistics for Conglomerates

Segment level variables

Variable	N	Mean	Median	Std. Dev.
Segment assets ($ Million)	20386	798.153	84.227	3853.079
Segment sales growth	20386	0.104	0.058	0.375
Segment cash flow	20386	0.166	0.162	0.208
Segment R&D	20386	0.005	0	0.032
Segment investment	20386	0.017	0	0.074
Industry Tobin's Q	20147	1.722	1.548	0.652
Distress	20386	0.04	0	0.197
High ability	15731	0.568	1	0.495

Firm level variables

	N	Mean	Median	Std. Dev.
Asset ($ Million)	10079	2238.681	241.594	9972.579
Tobin's Q	10079	1.57	1.278	1.016
Leverage	9681	0.46	0.455	0.201
Inventory/Assets	10018	0.188	0.159	0.155
Receivables/Assets	10012	0.215	0.188	0.142
Payables/Assets	10079	0.105	0.084	0.082
Cash/Assets	10079	0.105	0.052	0.136
Rated	10079	0.33	0	0.47
Q-Difference	10079	0.219	0.254	0.641
High diversity	10079	0.585	1	0.493

Panel B: Summary statistics for single segment firms

Segment level variables

Variable	N	Mean	Median	Std. Dev.
Segment assets ($ million)	40563	876.609	92.228	4632.142
Segment sales growth	40563	0.185	0.099	0.459
Segment cash flow	40563	0.088	0.118	0.222
Segment R&D	40563	0.059	0	0.098
Segment investment	40563	0.021	0.001	0.079
Industry Tobin's Q	40535	2.044	1.8	0.81
Distress	40563	0.039	0	0.193
High ability	32392	0.469	0	0.499

Firm level variables

	N	Mean	Median	Std. Dev.
Assets ($ million)	40563	876.609	92.228	4632.142
Tobin's Q	40563	2.016	1.464	1.555
Leverage	39821	0.42	0.399	0.231
Inventory/Assets	40164	0.164	0.115	0.175
Receivables/Assets	40263	0.205	0.175	0.163
Payables/Assets	40563	0.102	0.074	0.092
Cash/Assets	40562	0.186	0.098	0.212
Rated	40563	0.158	0	0.365

This table reports the summary statistics of the key variables used in our analysis. Panel A summarizes the data for segments of conglomerates while Panel B summarizes the data for single segment firms. All variables are defined in Appendix A. The data covers the period 1986-2008. The stock price data is from CRSP; segment-level financial data is from the Compustat Business Segment Files; and firm-level data is from the Compustat Industrial Annual files.

Table 2.3: Univariate tests

Segment Level Variables

Variable	Non distress years				Distress years			
	N	Conglomerate segments	Single segment firms	Difference	N	Conglomerate segments	Single segment firms	Difference
Pr(conglomerate)	14826	0.483	0.483	0	515	0.468	0.468	0
Segment assets	14826	819.736	1558.776	-739.04***	515	536.754	757.6	-220.846**
Segment sales growth	14826	0.096	0.14	-0.044***	515	0.038	-0.045	0.083***
Segment cash flow	14826	0.174	0.158	0.016***	515	0.127	0.081	0.046***
Segment R&D	14826	0.006	0.032	-0.026***	515	0.003	0.031	-0.028***
Segment investment	14826	0.016	0.019	-0.003***	515	0.013	0.01	0.003
Industry Tobin's Q	14826	1.737	1.752	-0.015**	515	1.445	1.495	-0.05
High ability	14826	0.567	0.534	0.033***	515	0.563	0.54	0.023

Firm level variables

Variable	Non distress years				Distress years			
	N	Conglomerates	Single segment firms	Difference	N	Conglomerates	Single segment firms	Difference
Pr(Conglomerate)	6650	0.32	0.32	0	594	0.502	0.502	0
Asset	6650	1883.422	1318.819	564.603***	594	1899.181	720.177	1179.004***
Tobin's Q	6650	1.592	1.844	-0.252***	594	1.441	1.541	-0.1
Leverage	6650	0.45	0.428	0.022***	594	0.473	0.444	0.029**
Inventory/Assets	6650	0.189	0.187	0.002	594	0.198	0.167	0.031***
Receivables/Assets	6650	0.215	0.221	-0.006***	594	0.202	0.194	0.008
Payables/Assets	6650	0.103	0.106	-0.003***	594	0.108	0.093	0.015***
Cash/Assets	6650	0.107	0.14	-0.033***	594	0.103	0.151	-0.048***
Rated	6650	0.306	0.254	0.052***	594	0.311	0.148	0.163***
Q-Difference	6650	0.236		0.236	594	0.168		0.168
High Diversity	6650	0.588		0.588	594	0.537		0.537

This table compares the mean values of the key variables for segments of conglomerates and single segment firms that are matched on the propensity score. We estimate the propensity of any segment belonging to a conglomerate using a model similar to the one in Campa and Kedia (2002). Specifically we estimate a panel probit model with the dummy variable *Conglomerate* as the dependent variable and the following independent variables: *Segment investment*$_{t-1}$, *Segment profit*$_{t-1}$, *Distress*, *Industry Tobin's* Q_{t-1}, *Major exchange*, *GDP growth*, *GDP growth*$_{t-1}$, *Recession*, *Recession*$_{t-1}$, *Foreign*, *Number mergers*, *Value mergers*, *S&P index*, *Average cash flow*, *Average investment*, *Fraction conglomerate* and *Fraction conglomerate sales*. All the variables are described in Appendix A. Based on the coefficient estimates, we predict the likelihood of any segment to belong to a conglomerate. For each conglomerate segment in our sample, we then randomly identify a matched single segment firm that has a propensity score within 1% point. We drop those conglomerate segments for which we are not able to obtain a matched single segment firm. We repeat this procedure for distress and non-distress periods separately. We also repeat this procedure at the firm level by suitably modifying the probit model by replacing segment-level variables with equivalent firm-level variables.

The table summarizes the key variables for the conglomerate segments and the matched single segment firms during distress and non-distress periods. All variables are defined in Appendix A. The data covers the period 1986-2008. The stock price data is from CRSP, segment-level financial data is from the Compustat Business Segment Files and firm-level data is from the Compustat Industrial Annual files.

Table 2.4: Performance of conglomerate segments and single segment firms in distressed industries

Panel A: Segment performance and industry distress

	Segment sales growth		Segment cash flow		Segment R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Conglomerate	-.088	-.097	.030	.021	-.024	-.025
	(.012)***	(.016)***	(.006)***	(.007)***	(.005)***	(.005)***
Distress	-.138	-.101	-.047	-.028	-.006	-.005
	(.021)***	(.021)***	(.008)***	(.008)***	(.002)***	(.002)***
Conglomerate × Distress	.063		.021		.007	
	(.018)***		(.008)***		(.002)***	
Conglomerate × High ability		-.006		.005		.003
		(.014)		(.005)		(.001)**
Distress × High ability		-.045		-.022		-.002
		(.021)**		(.007)***		(.003)
Conglomerate × Distress × High ability		.100		.022		.007
		(.020)***		(.009)**		(.002)***
Conglomerate × Distress × Low ability		.026		-.005		.005
		(.030)		(.015)		(.002)**
High ability		-.004		.047		-.001
		(.007)		(.005)***		(.0009)
Segment cash flow$_{t-1}$	-.306	-.273			-.014	-.012
	(.068)***	(.078)***			(.008)	(.008)
Segment investment$_{t-1}$	.503	.406	.020	-.022		
	(.071)***	(.066)***	(.018)	(.018)		
Segment sales growth$_{t-1}$			.020	.023	.002	.001
			(.004)***	(.004)***	(.0008)**	(.0007)*
Industry Tobin's Q$_{t-1}$	.034	.027	.014	.014	.0007	.0005
	(.008)***	(.008)***	(.005)***	(.004)***	(.001)	(.001)
Obs.	60949	48123	60949	48123	60949	48123
R^2	.358	.336	.707	.713	.844	.848

This table reports the results of a panel data regression of segment performance on segment and firm characteristics. Specifically, we estimate the following panel regression model:

$$y_{i,j,t} = \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Distress}_{j,t} + \beta_3 \text{Conglomerate}_{i,t} \times \text{Distress}_{j,t} + \gamma \text{Controls} + \text{Time FE} + \text{Segment FE},$$

where the dependent variable y is *Segment sales growth* in Columns (1) & (2), *Segment cash flow* in Columns (3) & (4) and *Segment R&D* in Columns (5) & (6). All variables are defined in Appendix A. In Columns (2), (4), and (6) we differentiate between high- and low ability segments. The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment files and firm-level data is from the Compustat Industrial Annual files.

Panel B: Differentiating between temporary and prolonged distress

	Segment sales growth		Segment cash flow		Segment R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Conglomerate	-.088 (.012)***	-.097 (.016)***	.029 (.006)***	.017 (.006)***	-.024 (.005)***	-.025 (.005)***
Temporary distress	-.126 (.014)***	-.104 (.020)***	-.042 (.006)***	-.014 (.014)	-.008 (.002)***	-.004 (.002)*
Prolonged distress	-.165 (.053)***	-.093 (.039)**	-.058 (.019)***	-.017 (.011)	-.003 (.002)*	-.007 (.003)**
Conglomerate × Temporary distress	.061 (.018)***		.017 (.010)*		.007 (.002)***	
Conglomerate × Prolonged distress	.070 (.042)		.032 (.015)**		.006 (.002)***	
Conglomerate × High ability		-.006 (.014)		-.0001 (.004)		.003 (.001)**
Temporary distress × High Ability		-.040 (.025)		-.035 (.013)***		-.003 (.003)
Prolonged distress × High Ability		-.061 (.027)**		-.040 (.013)***		.003 (.002)
Conglomerate × Temporary distress × High Ability		.096 (.025)***		.023 (.011)**		.006 (.003)**
Conglomerate × Temporary distress × Low Ability		.039 (.035)		-.014 (.016)		.004 (.003)
Conglomerate × Prolonged distress × High Ability		.107 (.034)***		.030 (.020)		.006 (.002)**
Conglomerate × Prolonged distress × Low Ability		-.010 (.044)		-.021 (.035)		.008 (.002)***
High ability		-.004 (.007)		.004 (.003)		-.001 (.0009)
Const.	.206 (.022)***	.129 (.034)***	.093 (.014)***	.051 (.011)***	.053 (.004)***	.032 (.003)***
Obs.	60949	48123	60949	48123	60949	48123
R^2	.358	.336	.707	.736	.844	.848

This panel reports the results of a OLS regression of segment performance on segment and firm characteristics. Specifically, we estimate the following panel regression model:

$$\begin{aligned} y_{i,j,t} &= \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Temporary distress}_{j,t} + \beta_3 \text{Prolonged distress}_{j,t} + \beta_4 \text{Conglomerate}_{i,t} \times \text{Temporary distress}_{j,t} \\ &+ \beta_5 \text{Conglomerate}_{i,t} \times \text{Prolonged distress}_{j,t} + \gamma \text{Controls} + \text{Time FE} + \text{Segment FE}, \end{aligned}$$

where the dependent variable y is *Segment sales growth* in Columns (1) & (2), *Segment cash flow* in Columns (3) & (4) and *Segment R&D* in Columns (5) & (6). *Temporary distress* is a dummy variable that identifies distress periods that last for one year while *Prolonged distress* is a dummy variable that identifies distress periods that last for two or more successive years. All other variables are defined in Appendix A. The control variables whose coefficients are suppressed include, lagged values of *Segment cash flow*, *Segment investment*, and *Industry Tobin's Q*, in Columns (1) & (2), *Segment sales growth*, *Segment investment*, and *Industry Tobin's Q*, in Columns (3) & (4), and *Segment cash flow*, *Segment sales growth*, *Segment investment*, and *Industry Tobin's Q*, in Columns (5) & (6). The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment files and firm-level data is from the Compustat Industrial Annual files.

Table 2.5: Further tests within subsamples

Panel A: Segment performance and industry distress: Rated vs Unrated firms

	Segment sales growth		Segment cash flow		Segment R&D	
	Rated	Unrated firms	Rated	Unrated firms	Rated	Unrated firms
	(1)	(2)	(3)	(4)	(5)	(6)
Conglomerate	-.118 (.016)***	-.084 (.016)***	.014 (.006)**	.036 (.007)***	-.012 (.003)***	-.029 (.006)***
Distress	-.143 (.034)***	-.137 (.022)***	-.017 (.011)	-.050 (.008)***	-.008 (.003)**	-.005 (.001)***
Conglomerate × Distress (β_3)	.036 (.034)	.075 (.022)***	.003 (.012)	.020 (.011)*	.008 (.003)**	.006 (.002)**
Segment cash flow$_{t-1}$	-.081 (.057)	-.350 (.073)***			.003 (.003)	-.016 (.009)*
Segment investment$_{t-1}$	.383 (.100)***	.497 (.083)***	-.076 (.024)***	.031 (.021)		
Segment sales growth$_{t-1}$			.005 (.005)	.021 (.004)***	-.0006 (.0009)	.001 (.0009)
Industry Tobin's Q$_{t-1}$	.045 (.012)***	.028 (.008)***	.023 (.005)***	.011 (.005)**	.0007 (.001)	.0007 (.001)
Obs.	13821	47128	13821	47128	13821	47128
R^2	.449	.361	.68	.714	.829	.845

This panel reports the results of a regression of segment performance on segment and firm characteristics. Specifically we estimate the panel regression

$$y_{i,j,t} = \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Distress}_{j,t} + \beta_3 \text{Conglomerate}_{i,t} \times \text{Distress}_{j,t} + \gamma \text{Controls} + \text{Time FE} + \text{Segment FE},$$

where the dependent variable y is *Segment sales growth* in Columns (1) & (2), *Segment cash flow* in Columns (3) & (4) and *Segment R&D* in Columns (5) & (6). All variables are defined in Appendix A. The sample in Columns (1), (3), and (5) is confined to rated firms while the sample in Columns (2), (4), and (6) is confined to unrated firms. The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment Files and firm level data is from the Compustat Industrial Annual files.

Panel B: Differentiating between high- and low-ability segments: Rated vs Unrated firms

	Segment sales growth		Segment cash flow		Segment R&D	
	Rated firms	Unrated firms	Rated firms	Unrated firms	Rated firms	Unrated firms
	(1)	(2)	(3)	(4)	(5)	(6)
Conglomerate	-.137	-.086	-.004	.027	-.010	-.030
	(.025)***	(.020)***	(.007)	(.008)***	(.003)***	(.006)***
Distress	-.087	-.105	-.003	-.030	-.004	-.004
	(.051)*	(.022)***	(.014)	(.008)***	(.003)	(.002)**
Conglomerate × High ability	.009	-.017	.017	.008	-.003	.004
	(.018)	(.018)	(.006)***	(.007)	(.002)*	(.002)**
Distress × High ability	-.065	-.038	-.020	-.024	-.007	.0004
	(.074)	(.021)*	(.019)	(.008)***	(.005)	(.003)
Conglomerate × Distress × High ability (β_5)	.058	.118	.002	.026	.011	.004
	(.052)	(.024)***	(.017)	(.011)**	(.005)**	(.002)*
Conglomerate × Distress × Low ability	.008	.031	-.013	-.007	.003	.006
	(.059)	(.038)	(.020)	(.021)	(.003)	(.003)**
High ability	-.017	-.001	.017	.050	.002	-.001
	(.017)	(.008)	(.005)***	(.005)***	(.001)*	(.001)
Segment cash flow$_{t-1}$	-.070	-.318			.005	-.014
	(.052)	(.085)***			(.004)	(.009)
Segment investment$_{t-1}$	.384	.384	-.088	-.013		
	(.103)***	(.071)***	(.023)***	(.022)		
Segment sales growth$_{t-1}$			.006	.025	-.001	.001
			(.005)	(.004)***	(.001)	(.0008)
Industry Tobin's Q$_{t-1}$	.037	.023	.020	.012	.0007	.0005
	(.014)***	(.009)**	(.005)***	(.005)**	(.001)	(.001)
Obs.	11203	36920	11203	36920	11203	36920
R^2	.444	.335	.685	.719	.83	.849

This panel reports the results of a regression similar to the one in Panel A. In this panel we differentiate between high- and low ability segments. The sample in Columns (1), (3), and (5) is confined to rated firms while the sample in Columns (2), (4), and (6) is confined to unrated firms. The data and the control variables are similar to the ones in Panel A.

Panel C: Segment performance and industry distress: Concentrated vs Competitive manufacturing industries

	Segment sales growth		Segment cash flow		Segment R&D	
	Concentrated	Competitive	Concentrated	Competitive	Concentrated	Competitive
	(1)	(2)	(3)	(4)	(5)	(6)
Conglomerate	-.090 (.025)***	-.142 (.044)***	.018 (.012)	.029 (.009)***	-.041 (.008)***	-.042 (.010)***
Distress	-.145 (.033)***	-.037 (.062)	-.032 (.012)***	-.007 (.015)	-.003 (.003)	-.003 (.002)
Conglomerate × High ability	.020 (.022)	.021 (.029)	-.010 (.010)	-.010 (.011)	.004 (.004)	.007 (.003)**
Distress × High ability	-.020 (.041)	-.134 (.064)**	-.048 (.011)***	-.053 (.013)***	.0007 (.007)	-.005 (.005)
Conglomerate × Distress × High ability (β_5)	.099 (.035)***	.184 (.056)***	.039 (.022)*	.032 (.019)*	.009 (.007)	.011 (.003)***
Conglomerate × Distress × Low ability	.066 (.067)	-.007 (.066)	-.017 (.035)	-.012 (.021)	.006 (.003)*	.005 (.003)
High ability	.002 (.010)	-.026 (.021)	.051 (.008)***	.050 (.011)***	.001 (.002)	-.004 (.003)
Segment cash flow$_{t-1}$	-.445 (.165)***	-.349 (.108)***			-.012 (.021)	-.016 (.009)*
Segment investment$_{t-1}$	.206 (.108)*	.135 (.102)	-.071 (.052)	-.044 (.035)		
Segment sales growth$_{t-1}$			.023 (.006)***	.018 (.004)***	-.0008 (.002)	-.0002 (.001)
Industry Tobin's Q$_{t-1}$	.047 (.013)***	.041 (.013)***	.013 (.008)	.022 (.005)***	-.001 (.002)	-.003 (.0009)***
Obs.	11310	10810	11310	10810	11310	10810
R^2	.351	.343	.763	.75	.86	.842

This panel reports the results of a regression similar to the one in Panel A. The sample in Columns (1), (3), and (5) is confined to segments in concentrated manufacturing industries while the sample in Columns (2), (4), and (6) is confined to segments in competitive manufacturing industries. We identify an industry as competitive (concentrated) if it has an herfindahl index value above sample median. Following Ali et al. (2009), we use data from the US Census of all manufacturing establishments to measure industry concentration. We obtain concentration values for the years 1982, 1987, 1992, 1997, and 2002. We use the most recent year's concentration measure for the missing years. The data and the control variables are similar to the ones in Panel A.

Table 2.6: Further tests within subsamples - Conglomerate diversity and industry distress

	Segment sales growth	Segment cash flow	Segment R&D
	(1)	(2)	(3)
Conglomerate	-.083	.031	-.023
	(.013)***	(.006)***	(.005)***
Distress	-.138	-.047	-.006
	(.021)***	(.008)***	(.002)***
High diversity × Distress	.052	.005	.005
	(.020)***	(.009)	(.002)***
Low diversity × Distress	.076	.042	.009
	(.022)***	(.009)***	(.003)***
High diversity	-.008	-.002	-.001
	(.009)	(.003)	(.001)
Segment cashflow	-.306		-.014
	(.068)***		(.008)*
Segment investment	.504	.020	-.0009
	(.071)***	(.018)	(.003)
Segment sales growth		.020	.002
		(.004)***	(.0008)**
Industry Tobin's Q	.034	.014	.0007
	(.008)***	(.004)***	(.001)
Const.	.204	.092	.053
	(.023)***	(.014)***	(.004)***
Obs.	60949	60949	60949
R^2	.358	.707	.844

This table reports the results of a panel data regression of segment performance on segment and firm characteristics. Specifically we estimate the panel regression

$$\begin{aligned} y_{i,j,t} &= \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Distress}_{j,t} + \beta_3 \text{High diversity}_{i,t} \times \text{Distress}_{j,t} + \beta_4 \text{Low diversity}_{i,t} \times \text{Distress}_{j,t} \\ &\quad + \beta_5 \text{High diversity}_{i,t} + \gamma \text{Controls} + \text{Time FE} + \text{Segment FE}, \end{aligned}$$

where the dependent variable y is *Segment sales growth* in Column (1), *Segment cash flow* in Column (2) and *Segment R&D* in Column (3). *High diversity* is a dummy variable that identifies conglomerates that have a diversity index above the sample median. We measure the diversity index of a conglomerate following the procedure outlined in Rajan et al. (2000). All other variables are defined in Appendix A. The control variables whose coefficients are suppressed include, lagged values of The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment Files and firm level data is from the Compustat Industrial Annual files.

Table 2.7: Other firm characteristics and industry distress

	Receivable/Assets	Inventory/Assets	Payable/Assets	Cash/Assets
	(1)	(2)	(3)	(4)
Conglomerate	.014	.004	.003	-.017
	(.003)***	(.004)	(.002)*	(.004)***
Firm distress	-.009	-.004	-.007	.009
	(.003)***	(.004)	(.002)***	(.003)***
Conglomerate × Firm distress	.010	.005	.009	-.006
	(.004)***	(.005)	(.003)***	(.004)*
EBITDA/Assets	.194	.087	.039	-.018
	(.013)***	(.012)***	(.004)***	(.007)**
Sales growth	.061	.038	.034	-.011
	(.012)***	(.009)***	(.006)***	(.004)***
Tobin's Q	.009	.001	.005	.012
	(.0006)***	(.001)	(.0009)***	(.001)***
Leverage	.077	.052	.102	-.241
	(.005)***	(.006)***	(.006)***	(.013)***
Rated	-.018	-.009	-.018	.011
	(.003)***	(.003)***	(.002)***	(.003)***
Obs.	49265	49175	49501	49500
R^2	.797	.861	.76	.81

This table reports the results of a panel data regression of firm investment in working capital on firm and industry characteristics. Specifically, we estimate the panel regression

$$y_{i,t} = \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Firm distress}_{j,t} + \beta_3 \text{Conglomerate}_{i,t} \times \text{Firm distress}_{j,t} + \gamma \text{Controls} + \text{Time FE} + \text{Firm FE},$$

where the dependent variable y is *Receivables/Assets* in Column (1), *Inventory/Assets* in Column (2), *Payable/Assets* in Column (3) and *Cash/Assetss* in Column (4). All variables are described in Appendix A. The data covers the period 1986-2008. The stock price data is from CRSP; segment-level financial data is from the Compustat Business Segment Files; and firm-level data is from the Compustat Industrial Annual files.

Table 2.8: Q-Difference and industry distress

	Q-Difference			Δ Q-Difference		
	Full sample	Sub-samples on rating		Full sample	Sub-samples on rating	
		Rated	Non-Rated		Rated	Non-Rated
	(1)	(2)	(3)	(4)	(5)	(6)
Pre distress (4+)	.012	.028	.004	.00003	.016	.008
	(.028)	(.034)	(.039)	(.025)	(.027)	(.041)
Pre distress (3)	-.004	.033	-.037	-.081	-.053	-.097
	(.026)	(.028)	(.035)	(.022)***	(.030)*	(.031)***
Pre distress (2)	.055	.040	.067	.049	.0005	.089
	(.024)**	(.031)	(.032)**	(.029)*	(.042)	(.043)**
Pre distress (1)	.062	.038	.079	-.007	-.007	-.008
	(.025)**	(.031)	(.034)**	(.029)	(.032)	(.040)
Firm distress	-.035	-.035	-.019	-.089	-.060	-.099
	(.032)	(.045)	(.041)	(.035)**	(.042)	(.051)*
Post distress (1)	-.046	-.048	-.037	-.012	-.002	-.008
	(.026)*	(.037)	(.033)	(.030)	(.034)	(.042)
Post distress (2)	-.014	-.031	.015	.044	.027	.060
	(.028)	(.036)	(.037)	(.024)*	(.032)	(.032)*
Post distress (3)	.016	-.047	.084	.028	-.014	.061
	(.024)	(.031)	(.035)**	(.026)	(.028)	(.044)
Post distress (4+)	-.056	-.060	-.006	-.019	-.004	-.025
	(.033)*	(.044)	(.040)	(.024)	(.034)	(.035)
Obs.	10079	3323	6756	7590	2621	4969
R^2	.662	.677	.675	.208	.241	.216

This table reports the results of a panel regression that investigates the effect of industry distress on *Q-Difference*. Specifically we estimate the panel regression

$$\begin{aligned} \mathrm{y}_{i,t} &= \alpha + \beta_0 \text{Firm distress}_{i,t} + \sum_{s=1}^{3} \beta_s \text{Pre-distress(s)}_{i,t} + \beta_4 \text{Pre distress(4+)}_{i,t} + \sum_{s=1}^{3} \gamma_s \text{Post-distress(s)}_{i,t} \\ &\quad + \gamma_4 \text{Post distress(4+)}_{i,t} + \text{Time FE} + \text{Firm FE}, \end{aligned}$$

where y is *Q-Difference* in Columns (1)-(3) and Δ *Q-Difference* Columns (4)-(6). All variables are described in Appendix A. In Columns (1) & (4) we estimate the regression on all conglomerates, while the sample in Columns (2) & (5) (Columns (3) & (6)) is confined to conglomerates with (without) a credit rating. The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment Files and firm level data is from the Compustat Industrial Annual files. The standard errors are robust to heteroskedasticity and clustered at the three-digit SIC code industry level.

Table 2.9: Acquisition activity and industry distress

	Pr(Distress acquisition)				
	All Firms			Rated Firms	Unrated Firms
	(1)	(2)	(3)	(4)	(5)
Conglomerate	-.001 (.0006)**	-.001 (.0006)**	-.0008 (.0006)	-.003 (.002)*	-1.00e-05 (.0005)
Firm distress	.014 (.003)***				
Conglomerate × Firm distress	.005 (.005)				
Temporary firm distress		.015 (.003)***			
Prolonged firm distress		.012 (.007)*			
Conglomerate × Prolonged firm distress		.013 (.010)			
Conglomerate × Temporary firm distress		.001 (.006)			
High ability distress			.023 (.005)***	.038 (.019)*	.020 (.005)***
Low ability distress			.006 (.004)	.011 (.007)	.005 (.003)
Conglomerate × High ability distress			.013 (.011)	.006 (.026)	.011 (.011)
Conglomerate × Low ability distress			.001 (.005)	.001 (.005)	-.00009 (.007)
Obs.	50640	50640	50640	9724	40916
R^2	.181	.181	.186	.272	.183

This table reports the results of a panel regression that investigates the effect of industry distress on the likelihood of firm acquiring a distressed target. Specifically we estimate the panel regression

$$\begin{aligned}\text{Distress acquisition}_{i,t} \quad &= \quad \alpha + \beta_1 \text{Conglomerate}_{i,t} + \beta_2 \text{Firm distress}_{j,t} + \beta_3 \text{Conglomerate}_{i,t} \times \text{Firm distress}_{j,t} \\ &\quad + \gamma \text{Controls} + \text{Time FE} + \text{Firm FE},\end{aligned}$$

Distress acquisition is a dummy variable that identifies firms that acquire distressed targets in their industry during the year. All other variables are described in Appendix A. The control variables whose coefficients are suppressed include, lagged values of *Industry Tobin's Q*, *EBITDA/Assets*, and *Cash/Assets.* The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment Files, firm level data is from the Compustat Industrial Annual files and data on mergers and acquisitions is from SDC Platinum. The standard errors are robust to heteroskedasticity and clustered at the three-digit SIC code industry level.

Table 2.10: Firm exit and industry distress

	Distress segment sold				Firm delisted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conglomerate	-.003 (.001)**	-.003 (.001)**	-.0009 (.001)	-.0009 (.001)	-.006 (.005)	-.006 (.005)	-.005 (.005)	-.005 (.005)
Firm distress	.020 (.004)***				.009 (.007)			
Conglomerate × Firm distress	.032 (.009)***				-.008 (.009)			
Temporary firm distress		.019 (.005)***				.009 (.009)		
Prolonged firm distress		.025 (.008)***				.007 (.010)		
Conglomerate × Temporary firm distress		.026 (.009)***				9.86e-06 (.012)		
Conglomerate × Prolonged firm distress		.041 (.018)**				-.024 (.011)**		
High ability distress			.029 (.007)***				.006 (.009)	
Low ability distress			.015 (.005)***				.045 (.014)***	
Conglomerate × High ability distress			.029 (.016)*				-.017 (.011)	
Conglomerate × Low ability distress			.045 (.018)**				-.036 (.017)**	
High ability temporary distress				.027 (.009)***				.009 (.011)
High ability prolonged distress				.033 (.009)***				-.003 (.012)
Low ability temporary distress				.011 (.005)**				.056 (.020)***
Low ability prolonged distress				.023 (.010)**				.021 (.019)
Conglomerate × High ability temporary distress				.025 (.021)				-.017 (.015)
Conglomerate × High ability prolonged distress				.029 (.023)				-.011 (.013)
Conglomerate × Low ability temporary distress				.049 (.025)**				-.027 (.027)
Conglomerate × Low ability prolonged distress				.035 (.025)				-.040 (.018)**
Obs.	42384	42384	42384	42384	42384	42384	42384	42384
R^2	.355	.356	.354	.354	.431	.431	.431	.431

This table reports the results of a panel regression that investigates the effect of industry distress on the likelihood of firm exiting the industry. Specifically we estimate the panel regression

$$\begin{aligned} \mathrm{y}_{i,t} &= \alpha + \beta_1 \mathrm{Conglomerate}_{i,t} + \beta_2 \mathrm{Firm\ distress}_{j,t} + \beta_3 \mathrm{Conglomerate}_{i,t} \times \mathrm{Firm\ distress}_{j,t} \\ &\quad + \gamma \mathrm{Controls} + \mathrm{Time\ FE} + \mathrm{Firm\ FE}, \end{aligned}$$

where $y_{i,t}$ is *Distress segment sold* in Columns (1)-(3) and *Firm delisted* in Columns (4)-(6). All variables are described in Appendix A. The control variables whose coefficients are suppressed include, lagged values of *Current Assets/Current Liabilities*, *Total Liabilities/Assets*, *EBITDA/Assets*, *Retained earnings/TA*, *Net Income/Assets*. The data covers the period 1986-2008. The stock price data is from CRSP, segment level financial data is from the Compustat Business Segment Files, firm level data is from the Compustat Industrial Annual files and data on mergers and acquisitions is from SDC Platinum. The standard errors are robust to heteroskedasticity and clustered at the three-digit SIC code industry level.

Chapter 3

But What Will It Do For My EPS? An Unflattering But Powerful Motive for Mergers

*

3.1 Introduction

It has recently been argued that acquisitions are driven by mis-valuation rather than the synergies or managerial objectives stressed in the earlier literature (Shleifer and Vishny (2003); Jensen (2005); Rhodes-Kropf and Viswanathan (2004)). This view is buttressed by evidence that bidders are more highly valued than their targets (Dong et al. (2006)), and that both parties tend to be in temporarily high-valued industries (Rhodes-Kropf et al. (2005)). The economic importance of the valuation motive remains unclear. In particular, how likely are two firms with different valuations to consummate a merger, and how important is the effect relative to other well-known drivers? We find that valuation differences are twice as important as recent industry activity (stressed by Mitchell and

* This chapter is a joint work with Gerald Garvey and Todd Milbourn.

Mulherin (1996) and Harford (2005)), and dwarf the effect of size, leverage, profitability, or any stand-alone valuation ratio.

Our evidence also suggests that the driving force is more a desire to increase earnings or book value per share (the "bootstrap game" in the classic text of Brealey et al. (2007)) than to exploit market mispricing. We find that a firm is more likely to be a target when other firms in the industry could acquire them in a stock-swap merger that is accretive to the buyer even after paying the target a substantial premium. The resulting measure is similar to the dispersion of valuation multiples within an industry (as used in Harford, 2005), but is grounded in a specific model of managerial behavior and empirically is much stronger than dispersion. The effects are somewhat weaker when we use more sophisticated valuation models, and we do not find that earnings accretion becomes important relative to book in industries where earnings are more persistent. One finding is consistent with models of market mis-valuation, however, as suggested by Rhodes-Kropf and Vishwanathan (2004) and Rhodes-Kropf et al (2005). Our effects are stronger when average industry multiples are temporarily elevated.

Our basic approach is to deem two firms as a viable candidate to merge if they are in the same 2-sigit SIC industry, and if by using stock as the method of payment can increase the per-share earnings or book of the buyer (literally, the party with the higher multiple) in the hypothetical deal. Controlling for both year and industry fixed effects, as well as a continuous measure of recent merger activity by industry, we find strong evidence that a firm is more likely to be sold (and at a higher premium) if it has more viable buyers.

Our results are robust to the assumed premium the buyer must pay. We find strong results if we require the deal to be accretive on a book or earnings basis, but less so when we combine book and earnings into a more defensible (residual income-based) valuation framework. This last result needs to be interpreted with some caution as we follow Dong et al (2006) and require analyst forecast information for our residual income formulation. A less data-intensive way to ask if acquirers care more about economic value than accounting data is to see if earnings weighs more heavily than book in industries where earnings are more persistent (and hence would loom larger relative to book in fundamental valuation for the firm). We do not find this effect in the data, suggesting either that managers are seeking aspects of synergies that we cannot observe, or as suggested by survey evidence in Graham and Harvey (2001), that they care more about accounting ratios than about value as defined in finance theory.

There is a rich literature on both the theoretical and empirical sides with respect to whether misvaluation drives merger activity. First, we discuss the main theories. Shleifer and Vishny (2003) develop a model in which the CEOs of acquirers take advantage of market misvaluation by using overvalued stock as currency to buy relatively less overvalued targets. Valuation is a multiple of the capital of the firm. There is short-term misvaluation on the capital of both firms, although in the long run the valuation of the capital of both firms will be the same. The acquirer has a higher multiple and hence is more overvalued. The market will assign a multiple to evaluate the capital of combined firm. The multiple will fall between the multiple for the capital of the acquirer and the multiple for the capital of the target. So, the target benefits in the short term by getting a premium in the deal, although they actually get less share of the combined firm in terms of their long-run value. The acquirer actually benefits in the long term by getting a larger share of the combined firm than they can get if both firms are evaluated in the long run value. Thus, the acquirer turns the overvalued equity into hard assets. Our screens capture a simple version of their model where the managers believe the market will apply the acquirer's multiple to the combined entity ($s = 1$ in their terminology) and where relative bargaining power (q in their model) is such that the buyer must pay a 20 percent premium for the target. Our results are robust to reasonable alterations in these parameters.

Fuller and Jensen (2002) maintain that some CEOs engage in an earnings game by catering to analysts with high guidance on earnings. Jensen (2005) further predicts that overvalued equity may lead to bad acquisitions, which reduces the core value of the firms and results in poor long-term operating performance. This approach is also consistent with our approach; in terms of the Shleifer and Vishny (2003) (hereafter SV) model it would be that managers mistakenly or carelessly believe that the market will use the acquirer's multiple for the combined entity.

Rhodes-Kropf and Viswanathan (2004) (hereafter RKV) offer a model also based on market misvaluation, but target CEOs are not myopoc nor self-interested as in Shleifer and Vishny (2003). Instead, the stock values of both targets and acquirers can deviate from their long-run fundamental values. RKV separates misvaluation into a market-wide (or sector) component and a firm component. The target CEOs cannot tell how much of this misvaluation is due to firm specific reasons or market/sector misvaluation. The market-wide component in misevaluations is common to both firms. The target CEOs correctly adjust downward the stock offer by the acquirer, but they still accept the offer because they overestimate the synergies owing to the common misvaluation of market (or sector).

Dong, Hirshleifer, Richardson and Teoh (2006) test both misvaluation and Q theories of mergers. They use price-to-book to proxy for a firm's growth opportunities in Q theory and also as a proxy for misvaluation. They also use price-to-value as an additional proxy for misvaluation. They adopt a similar approach as Lee et al. (1999) to calculate the residual income value of a firm. They test the two theories by linking these two proxies to the characteristics of merger deals. They find evidence for both hypotheses, and further find that the evidence for Q hypothesis is stronger in the pre-1990s period than in the 1990-2000 period, while the evidence for misvaluation is stronger in the 1990-2000 period. One key difference from our paper is that their tests focus only on deals that actually take place. Our sample will include nearly all firms for which there is publicly-available data.

Rhodes-Kropf et al. (2005) test the RKV and SV models using a valuation model that includes book values, net income and leverage to decompose the market value mispricing into three components: a firm specific error, a sector mispricing error and a long-run mispricing error. They find that both targets and acquirers have higher market-to-book (M/B) relative to non-merger firms, and high M/B targets are bought by even higher M/B acquirers. The firm-specific error is higher for acquirers than targets in the overall merger sample and for the stock-financed sample. However, they also find that low long-run value-to-book firms acquire high long-run value-to-book targets. This is puzzling given existing theory, especially Q theory which says that firms with high growth opportunities buy firms with low growth opportunities. They argue that the contradicting results of high M/B buying low M/B and long-run value-to-book buying high long-run value-to-book call for some form of market inefficiency and informational asymmetry. However, one can argue that the puzzle may be also attributed to their empirical model of valuation since it most likely omits some other risk factors and also relies on peek-ahead to identify misvaluation. Specifically, they say that a sector is over-priced when its regression-based valuation multiple is above the full-sample average. The latter information would only be available to actual participants at the end of the sample.

There are some other papers focusing on testing whether the acquisitions benefit or hurt the shareholders of the acquiring firms. Ang and Cheng (2006) use the similar P/B and P/V approach and have similar findings as in Dong et al (2006). Further, they show that the shareholders of acquirers in stock mergers are as well off as, if not better off than, the shareholders of similarly overvalued non-acquiring firms. Moeller et al. (2005) find that negative bidder returns from 1998 to 2001 are driven by a few deals in which the bidders of extremely high valuation suffer huge losses after merger. They find that such firms have high q's and high market-to-book ratios. Thus, this provides support for Fuller and Jensen (2002) that managers of high valuation firms make poor acquisitions. However, the negative returns can also be due to the market's adjustment of the true stand-alone value of such firms. Song (2007) uses the trading of insiders as an indication of the overvaluation of their firms. She finds a strong relation between the insider selling prior to the merger announcement and long-run post-acquisition performance in the "hot market" period of 1997-2000.

Bouwman et al. (2009) find that acquisitions in high valuation period generate a significantly lower long-term abnormal return for the buyers and suffer a significantly lower long-run operating performance. However, they show that market timing is not likely an explanation for the underperformance of acquirers in high valuation market. Fu et al. (2009) investigate whether acquirer shareholders benefit from acquisitions driven by equity overvaluation. They sort acquisitions by relative overvaluation before announcement. Their findings support Jensen's (2005) hypothesis that equity overvaluation generates substantial agency costs for shareholders. Bi and Gregory (2009) use UK data and find more support for the market misvaluation hypothesis than the Q theory, however they cannot comprehensively reject Q theory explanation.

In contrast to much of the aforementioned literature, our setup is appealing because it does not require specifying an asset pricing model. Just as importantly, we need not condition on a deal or even a bid taking place. Future research can overlay proxies for market misvaluation and/or managerial incentive alignment to tease out who, if anyone, is at fault in what we uncover. What we can say, however, is that valuation differences are economically important to the market for corporate control.

The remainder of the paper is organized as follows. Section 2 develops a simple model of mergers based on the framework of Shleifer and Vishny (2003) and describes our viable buyer and target approach and the corresponding predictions. Section 3 describes the sample and methodology, and Section 4 presents the empirical results, including the results obtained when the acquisition premium is varied. Section 5 concludes. Appendix

A contains details related to the SDC dataset, and Appendix B is a summary of our empirical variables definitions.

3.2 A Simple Model of Mergers and Hypothesis

We develop a simple model of mergers following Shleifer and Vishny (2003) and then derive two new, empirically-testable predictions. As in SV, consider a representative merger pair, denoted firm 0 and firm 1. Firm 0 (firm 1) has K_0 (K_1) units of capital and the stock price is a multiple Q_0 (Q_1) of capital. Assume without loss of generality that $Q_1 > Q_0$, so firm 1 is the prospective acquirer and firm 0 the prospective target. The key parameter in SV is s, the synergy that the market attaches to the combined entity. Specifically, the market value of the combined entity is $(K_1 + K_0) * (sQ1 + (1 - s)Q_0)$. SV refer to this as the short-term market value, so that s can contain pricing errors. In the baseline case where there are no synergies and the market is efficient, $s = K_1/(K_1 + K_0)$. The target firm shareholders and management are assumed able to cash out immediately after the deal closes so they are not concerned with longer-term value. Hence what really matters for the viability of the combination is the bidding firm's view of s.

The second component of SV's model is the longer-term return to the two entities. The key component of this analysis for our purposes (predicting the incidence of mergers) is the fact that the bidder must pay a non-zero premium given by a percent of target value. Finally, assume without loss of generality that both firms have a single share outstanding and that the acquirer issues an additional m shares to the target. We now have two conditions for a merger pair to be viable. First, the bidder must provide enough shares m to cover the required premium of Π:

$$(m/(1+m))(sQ1 + (1-s)Q_0)(K_1 + K_0) = Q_0 K_0 (1+\Pi). \tag{A1}$$

Second, the bidder must not expect to lose market value from the bid:

$$(1/(1+m))(sQ_1 + (1-s)Q_0)(K_1 + K_0) \geq Q_1 K_1. \tag{A2}$$

The problem with taking this to the data is that we cannot observe s. Two extreme cases are instructive. In an efficient market with no synergies (i.e., the case where $s = K_1/(K_1 + K_0)$), then the two conditions above can never be satisfied for any $\Pi > 0$. This simply says that the bidder cannot offer a premium if there is no gain to the merger, efficiency-based or otherwise. At the other extreme, if $s = 1$ the bidder at least believes the market will apply her higher multiple to the target's assets, then conditions (1) and (2) are satisfied so long as:

$$Q_1/Q_0 \geq 1 + \Pi. \tag{A3}$$

This is a straightforward, if extreme, bootstrapping result. The bidder expects the market to apply her multiple to all the target's assets, so as long as her multiple exceeds that of the target by more than the premium, the deal is viable. The starkness of the result makes it useful for expositional purposes, but taking it to the real-world data requires us to consider (at least) three issues.

First, for most reasonable premia, the dispersion of multiples by industry means that many firms have multiple viable buyers; this implies an unconditional likelihood of takeover at least an order of magnitude greater than what we observe in the data. A simple way to accommodate this fact is to posit that most potential bidders, say a fraction X of the population, do not believe in the bootstrap game. Since only one viable bidder is required for the firm to be taken over, if we denote the number of firms that satisfy conditions (1) and (2) by n, a potential target is taken over with probability $1 - X^n$. While we do not actually know X, this observation suggests we should apply a concave transformation to the number of viable bidders when we come to our empirical tests.[2]

Secondly, relative size does not matter, because when $s = 1$ even a small bidder can apply her multiple to a big target. This may seem counterintuitive, but Harford (1999) surprisingly finds that targets are not on average small firms and we confirm this basic result in our data. To further investigate the idea, in the robustness section we experiment with adding the requirement that the bidder's assets be greater than those of the target ($K_1 > K_0$).

And finally, we have thus far adopted the Shleifer-Vishny model assumption that differences in multiples are primarily due to mispricing rather than appropriate valuation of different risk or expected cash-flows (at least, we have done so in the $s = 1$ case). Much of the subsequent empirical literature (Dong et al 2004, Rhodes-Kropf et al 2005) attempt to specify valuation models in order to isolate mispricing. Our approach does not hinge on the correctness of pricing model, so far as the errors in the pricing model are

[2]This is particularly the case if we were to endogenize the required premium; it is likely to increase in the number of viable bidders and accentuate the diminishing-returns effect.

uniform among merger firms and non-merger firms, our relative measure of viable buyers or targets are able to filter out the errors and hence do a better test.

Our approach hinges on a critical intuition, that is, in order for the misvaluation theories to work, it is not enough for a stock to be overpriced relative to its own intrinsic valuation. *It must be that the stock is overvalued relative to other stocks in the economy such that using stock as currency in the acquisition becomes attractive to the acquirer.* One way to measure whether it is an attractive deal to the acquirer is whether the deal can increase the book value per share. In fact, the theories either implicitly or explicitly argue that the CEOs of the acquirers care whether a deal is accretive on a book value (or earnings) per share basis or not. We do not argue whether issuing stock to increase book value (or earnings) per share is efficient or not as the theories have opposing predictions. But no matter whether it is efficient or not, for a deal to happen, the acquirer must gain something, which in our context is the acquisition of the target's assets on the cheap.

Mis-valuation happens when a firm's stock is either undervalued or overvalued. However, for misvaluation to drive stock-based mergers, it also requires that one firm's stock price relative to another firm becomes so mispriced such that a deal with a decent premium is attractive to both firms. For the target, so far as the premium exceeds its undervaluation, the deal is acceptable. For the buyer, so far as the deal can increase its book value per share after issuing shares to pay the target, the deal is viable. We then argue that the merger likelihood is related to the number of viable buyers or targets. For a firm to sell itself, the possibility for it to find a buyer which is able to pay it a desired premium increases with the number of viable buyers. The more viable buyers, the larger the chance that some of the viable buyers are able to pay target's desired premium. This is more likely to happen when the stock price is undervalued relative to other firms or there are more overvalued stocks. Similarly, the possibility for a firm to make a stock-based acquisition increases with the number of viable targets. The more viable targets, the higher the chance that some of the viable targets are able to increase the book value per share of the buyer to its desired level. This is also more likely to happen when the stock price is overvalued relative to other firms or there are more undervalued stocks.

Hence, we obtain the following two predictions based on misvaluation-driven-merger theories and our approach of viable buyers and targets.

H1: The likelihood of a firm being a target is positively related to the number of viable buyers.

Furthermore, since we argue that merger activities are driven by relative misvaluation which is captured by our viable buyers and targets based on stock financed deals, we have the following additional prediction.

H2: The likelihood of the use of stock as method of payment is positively related to the number of viable buyers and viable targets.

In the next section, we will take these predictions to the data.

3.3 Sample and Empirical Methodology

We begin by detailing our data collection process, then lay out a roadmap for our empirical specification, our variables of interest, and our controls. We close this section by revealing our summary statistics.

3.3.1 Data

The merger data are from SDC Platinum dataset. We download deals with domestic targets from the SDC database from year 1979 to year 2008. The search criteria include the following: 1. The form of the transaction must be either "M", "AM", "A" or "AA". 2. Deal type is either 1, 2, 3 or 4. (See the Appendix for the definitions from SDC.) We do not include other types of deals because we are only interested in deals where the buyers have a controlling interest after the deals, and hence can integrate (or consolidate) the targets' assets into their balance sheet to reflect the change of book value per share.

We then drop the duplicate records when all of target's cusip, acquirer's cusip, date announced, and status are the same. All together we have 173,719 records of announcements. We further drop the record if the same target and acquirer pair was recorded more than once in the same year (drops 385 records) or was recorded in the prior year (drops 328 records). Then, we further drop the record if the same target was reported more than once in the same year (drops 3,594 records) and was reported the prior year (drops 2,632 records). After applying these filters, each target has only one record for each calendar year.[3]

We next merge the SDC data with a file called 'stocknames' from WRDS in order to attach eight digit cusip to the targets. Then, we calculate target excess return using the market model, obtaining 11,276 records target firms' excess returns. To merge with

[3]We relegate investigation of the situations where targets receive bids from multiple bidders to future work.

CRSP_Compustat, we first obtain the calendar year from data date of CRSP_Compustat (the date is the day on the end of the fiscal year up to which the company reports it annual statement). Then, we merge SDC with CRSP_Compustat by matching cusip and calendar year. This step matches 2,721 target firms into CRSP_Compustat and we create a dummy variable takeover which equals to 1 for the target in the calendar year. However, some target firms didn't provide annual reports in the year when they were acquired.

The above combination process misses many target firms. To overcome this problem, we artificially delay the calendar year of announcement by one year and then merge it with CRSP_Compustat again. This actually merges the target information to the CRSP_Compustat dataset one year before the merge announcement when the targets have information there. However, for those targets who do have annual reports on CRSP_Compustat on the year of merger, this process creates duplicate records. So, if in the combined dataset, a firm has a takeover information next year, we replace the takeover dummy to 0 and set the current year's merge information to missing. This step corrects 2,695 duplicate merge records. The second step adds 2,567 takeover records into the CRSP_Compustat dataset and now the CRSP_Compustat has total of 5,288 takeover target firm-year records. In the final analysis, we restrict the sample to 1981 to 2007, resulting in 4,978 targets. For the acquirer sample, it is relatively easy because usually the acquirers's financial data are available in the merger year. We also restrict this sample to 1981 to 2007, resulting in 4,867 acquirer firm-years. The number is actually smaller than that of targets alone because we only allow a firm to be an acquirer once a year.

To calculate EPS-based and intrinsic value-based numbers of viable buyers and targets, we also use I/B/E/S earnings annual forecast data. We use the fiscal year one's average EPS forecast in I/B/E/S as the expected EPS for the firms in the year. In order to use the residual income model to calculate a firm's intrinsic value, we also use I/B/E/S year two and year three (when available) EPS forecasts, along with the long-term growth rate forecast. We will discuss it in detail next.

3.3.2 Empirical Specification and Key variable

In our empirical tests, we are interested in finding out whether our measure of the number of viable buyers or targets are related to the likelihood of a firm being a target. We test it by estimating the following Probit regression model for merger likelihood:

$$y_{i,t} = f(\alpha + \beta_1 V_{i,t-1} + \beta_2 X_{i,t-1} + \beta_3 Z_t + \beta_4 W_{t-1} + \mu_t + v_j). \tag{A4}$$

The subscript i refers to firm i, the subscript t refers to time in years, the subscript j refers to industry, μ_t refers to time fixed effects and v_j refers to industry fixed effects. The dependent variable y is a dummy variable for merger. In the regression of target likelihood, y will be equal to 1 if firm i is a target at year t and 0 otherwise. The corresponding V is the number of viable buyers for firm i at year $t-1$. X's are the control variables including firm i's size, market to book ratio, return on assets, leverage, price to earning ratio and liquidity. Z is the level and standard deviation of the related key variable within the industry at year t. W is the number of takeover happened in firm i's industry j. In the regression of the likelihood of using stock as the method of payment, y is the dummy variable which equals to 1 if the deal uses only stock as the method of payment and 0 otherwise.

3.3.3 Test Variables

To compute the number of viable buyers for each firm, we assume that any potential buyer will pay for the target with its own equity. For a given firm each year, we compute the number of firms that are able to make an equity-financed deal that is earnings per share accretive and pays a 20% acquisition premium to the target. For example, we identify firm B as a viable buyer for firm A if firm B uses its stock to pay a 20% premium for firm A's equity (in market value terms) and the resulting earnings per share of firm B after absorbing firm A increases. We denote the number of viable buyers based on EPS as Accretive Bidders. Simultaneously, we identify firm A as a viable target for firm B when firm B is a viable buyer of firm A. The number of such firms for which the buyer is potentially viable are referred to as Accretive Targets. We run an analogous exercise using book values, and denote a deal as book value accretive if firm B's book value per share increases after acquiring firm A via an equity-financed deal paying a 20% premium. We denote the number of such viable buyers for each potential target firm as Book Bidders, and the number of viable targets for each potential buyer as Book Targets.[4]

We search for viable buyer-target matches at the two-digit SIC industry level. We apply only one filter to make our search more realistic, that is, a firm can only buy another

[4] We exclude firms with negative book values of equity since it's difficult to interpret their economic meaning. We'll apply the same condition below when using the screen that identifies only deals that increase intrinsic value.

firm which is less than four times its own asset size. Such a restriction is reasonable because such mega deals are both rare and pose potentially greater integration difficulties for the buyers. In the actual merger deals, less than 2% of acquirers bought firms that are four times as big as its own asset size. Without such a restriction, an overvalued small firm may issue a ridiculous multiple of its existing shares to buy a relatively undervalued big firm.

For the hypothesized deals that are either earnings accretive or increase intrinsic value, we turn to the I/B/E/S data set for earnings forecasts. We use the forecasted earnings from I/B/E/S and the mean of analysts' EPS forecast to proxy for the expected earnings in each firm. I/B/E/S typically provides annual earning forecasts out two years into the future. For the EPS-based viability measure, we only use the next year's forecast. But for the intrinsic value-based viability measure, we rely on the first two years' forecast and the estimated rate of long-term growth. I/B/E/S updates analysts' forecasts every month. Since we are doing the estimation on a yearly basis, we use only one month's forecast. We choose the month when the forecasted date becomes the one year forecast for the first time. This usually happens when a firm announces its annual report and the analysts start to shift their forecast to the following year. Thus, it should capture the new information available in the beginning of this fiscal year.

We follow mostly the method described in Dong et al (2006) to estimate a firm's intrinsic value from the residual income model (RIM). We exclude 23,173 firm years with negative book values per share, and an addition 5,854 firm years when the dividend payout ratio is greater than 1. Since our sample includes all non-merger firms and is much bigger than Dong et al (2006)'s paper, we adopt the additional criteria of Frankel and Lee (1998), who examine the predictive power of the residual income model for stock returns in a large sample. They argue that some firms have extremely high ROEs due to low book equity value, and that firms with low stock prices have unstable B/P ratios and poor market liquidity. Following their criteria, we further exclude 15,466 firm years with stock prices less than $1 per share in the year and further exclude 30,455 firms year if any of current ROE or future ROEs of one year, two year and third year are greater than 1. Still, we have 20,071 firm years with negative intrinsic values. We exclude them by setting those values to missing. This leaves us with a sizeable sample of 104,369 firm years to compute the number of viable buyers (targets) based on intrinsic value. However, we are using a smaller sample in computing viable intrinsic value buyers and targets than we did in identifying the analogous measures using EPS and book values. Ultimately, we denote the number of viable buyers for each firm as RIM Bidders, and the number of viable targets for each firm as RIM Targets.

3.3.4 Control variable

Since we are first trying to predict the likelihood of a firm becoming a target, we rely on the relevant control variables based on the merger prediction literature. We use size (log of assets) to proxy for the transaction cost of integration and the barrier to takeover. Past studies (Hasbrouck (1985); Palepu (1986); Mikkelson and Partch (1989)) show that the likelihood of being a target is negatively related to the size of the firm. We also control for each firm's equity's market-to-book ratio. Hasbrouck (1985) argues that it can be a proxy for management incompetence and low cost resources for acquirers. In the declining industry, takeover is more likely in industries with the ratio less than 1. He finds negative and significant effect of market to book ratio on likelihood of being a takeover target. We also control for a firm's Tobin's q, which is the market-to-book value of a firm's assets, where the market value of assets is defined as total assets plus market value of common stock minus book common equity and differed taxes. Cremers et al. (2009) finds that a firm's q is negatively related to the probability of being a target.[5]

We control for return on assets (ROA) which is the ratio of net income before extraordinary items and discontinued operations to the total assets. Low ROA implies inefficient and hence the firm is more likely to be target. Cremers et al.(2008) find that ROA is negatively related to the likelihood of being a target. Since Cremers et al. (2008) also find that leverage has a positive and significant effect on being a takeover target, we also include leverage measured as book value of debt divided by total assets as a control. Harford (1999) shows that the stock price to earning ratio is positively related to the likelihood of being a target, so we also control for it. We include liquidity as a control variable as in Hasbrouck (1985) because it is easier for a bidder to secure a toehold in a more liquid target. Lastly, we use the same set of firm's financial variables in the regression of likelihood of being an acquirer as we expect such variables should have opposite effects. For the ratio variables, we winsorize them at the 1% level to trim extreme outliers.

Next, we sort the data by two-digit SIC (Standard Industrial Classification code) and

[5]We use a firm's q in the regressions. However, since q and M/B ratio is highly correlated with a correlation coefficient of 0.8, the sign of M/B sometimes becomes odd. Hence we do not report the results of regressions with q variable. Importantly, the inclusion of q variable doesn't change any of the our major results.

calendar year. We then compute the number of takeover variable ("Num_Takeover") which measures the total number of takeovers in the industry in the year. We expect the takeover activities in the industry will cause other firms to take similar action due to the change of competitive cost advantage.

We also include year and industry fixed effects and cluster the standard errors at the industry level. It is generally agreed that mergers happen more frequently in booming markets (see Figure 1 which highlights the positive correlation between the number of acquisitions and the level of the S&P 500 Index) and cluster in some industries. We want to be sure that our results are not caused simply by shocks to the entire economy or just in some industries, and also that we are not picking up any other year effect. An economic shock will cause overall stock price movement in the entire economy or the industry, but we are more interested in how the relative misvaluation differences caused by the shock relates to observed merger activities. To make sure our results are not driven by any industry change, we also include industry level (mean) and standard deviation of the following variables: price-to-earning ratio, market-to-book ratio and the price-to-intrinsic-value ratio. These are all relevant to our computation of the viable buyers and targets. Buttressing this claim, Figure 2 illustrates the positive relation between the number of deals and the market-to-book dispersion each year).

3.3.5 Summary Statistics

We first present the summary statistics of our key variables in the Panel A of Table 3.1, focussing on lagged values of each. Target Sample includes all firms that were a target in a particular year, and Non-Target Sample includes the complement set of firms. The Acquirer and Non-Acquirer Samples were similarly constructed. From Panel A, we can see that the average number of viable buyers in the target sample is significantly larger than that in the non-target sample across all measures of viability. Similarly, we find that the number of viable targets in the acquirer sample is significantly larger than that in the non-acquirer sample. Hence, our viable buyers and viable targets have the potential to explain the likelihood of being a target or an acquirer. The mean differences are all significant at 1% level. Due to the increased restrictions in sample selection, the number of observations in the target sample using the intrinsic value based measure (RIM Bidders and RIM Targets) are approximately one fourth lower than those in either the EPS or Book based measures. Observe that the means and medians of viable buyers (and viable targets) are quite different. Figure 3 highlights that the distribution is seriously right-skewed. Hence, following Aggarwal and Samwick (1999) and Milbourn (2003), we use the empirical cumulative density function (CDF) to normalize the independent variables and run regression with these transformed variables.[6]

In Panel B of Table 3.1, we also report the lagged means and medians of our control variables. The mean differences between the target sample and non-target sample (and between the acquirer sample and non-acquirer sample) are all significant, and almost always at the 1% level. Some of the differences are in accordance to the literature. For example, the market to book ratio for the target sample is lower than that of the non-

[6]We also use the natural log value of the number of viable buyers and viable targets and obtain similar regression results as with our CDF transformed variables. We do not report the results of such regressions in the paper, but these are available upon request.

target sample. Also, the price to earning ratio in the acquirer sample is much larger than that in the non-acquirer sample. Hence, these variables are arguably relevant controls for our tests.

We also calculate the correlation between our test variables, and these are in contained in Panel C. The viable buyers variables are positively correlated among themselves, but not perfectly so, suggesting that our measures of viability are picking up different facets of managerial behavior. The viable target variables are similarly correlated. The correlations between viable buyers and targets are very low, and even negative for RIM based variables. Otherwise, there are few surprises revealed here.

3.4 Main Empirical Results

We present our results in the following order. We first investigate the likelihood of being a target and then the likelihood of use of stock as the method of payment. In testing both of these hypotheses, we begin by using our EPS-based test variable to capture the number of viable buyers, identified by Accretive Bidders. We then turn to our alternative definitions of "viable", including the book-based measure (Book Bidders) and our residual-income-based measure (RIM Bidders). In all cases, we report the marginal effects of the probit regressions.

3.4.1 Predicting Takeover Targets Based on the Number of Viable Buyers

We first use our proxy for the number of viable buyers and targets based on whether a deal is EPS accretive to the buyer. These results are in Table 3.2. We estimate a probit model to test whether the likelihood of being a takeover target is related to the number of viable buyers. The dependent variable is a dummy variable which equals 1 if the firm is a takeover target and 0 otherwise. We use the CDF transformation of independent variables in the regressions. We run a baseline regression in column 1, add the target's Industry P/E level in the second column, and lastly add the target's Industry P/E Standard Deviation in the third column. The coefficients for viable buyer measure (Accretive Bidders) in the three regressions are all positive and significant at the 1% level. Observe that the coefficients for Industry P/E Level and Standard Deviation are small and not significant.

We can calculate the marginal effects of the probit regressions in order to interpret the economic significance. The predicted probability of being a target in the third regression (column 3) is 2.5% at the mean of regression variables. So, for a firm with average attributes across the board, including the number of viable buyers, the (unconditional) probability of being a target is 2.5%. The coefficient for the variable Accretive Bidders in this marginal regression is 0.034. Hence, if the number of viable buyers goes up from the median (i.e. the mean of the CDF transformed variable) level to the maximum, the probability of being a target increases to 4.2%. Hence, our result is economically significant. Also, the magnitude of the coefficient on the variable Accretive Bidders is bigger than those of the control variables, which indicates the viable buyer variable has a dominant effect on a firm to be a takeover target. Some of the control variables have signs in accordance with the literature, while some have opposite signs. The number of takeovers in a firm's industry in the previous year increases the firm's likelihood of being a target. A firm's return on assets is negatively related to the target likelihood. The firm's level of liquidity also increases the probability of being target.

Most striking is our result related to the effect of firm size on the likelihood of being a takeover target, which is quite different from the prior literature. When we allow for only a linear relationship with respect to firm size, we find that a firm's size is *positively* related to the likelihood of being a target. Harford (1999) also uses the log value of target asset as proxy for size and finds that the coefficient is not significant in the prediction of merger targets. To further investigate the issue of size, we also split the sample according to the firm size. In unreported results, we find that the coefficient for size is negative in the sub-sample of firms above the median size and positive in the sub-sample of firms below the median size, with both significant at the 1% level. Hence the finding on the size effect from prior literature is more likely from the relatively large firms, which is reasonable because large firms create a greater barrier to being acquired. Thus, our finding points a nonlinear relationship between size and the likelihood of being a target. Since the effect of size on merger activity is not the primary issue in our paper, we simply add the square of the size in the regression to control for this nonlinear relationship. Then, the sign of size becomes negative and not significant, as shown in Table 3.2.

Next, we present our tests related to whether the likelihood of being a target is related to the number of viable buyers based on book value and report the results in Table 3.3. From the first three columns, we find that the variable Book Bidders is positively associated with the probability of being a takeover target and is significant at the 1% level. The magnitude of the coefficient is almost the same (0.034) as that of Accretive Bidders, while the Industry M/B Level and Standard Deviation again have no effect on likelihood of being a target. In columns 4 through 6, we add Accretive Bidders to the regression specification. The size of the coefficient of Book Bidders drops to 0.021, while the coefficient of Accretive Bidders is similar as before at 0.032. Importantly, both are significant at the 1% level, suggesting that we are picking up two independent and real effects related to the motives for undergoing an acquisition.

In columns 5 and 6 of Table 3.3, we separate the sample into two sub samples according to the earning persistence of each firm's industry. Based on the accounting literature, we argue that earning persistence of a firm is related to the industry in which it operates. Industries for which earnings are more persistent may induce managers to seek out more earnings accretive acquisition deals. Hence, we roughly classify a firm's earning persistence according to its one digit SIC code. For firms with SIC code 2, 5, 7, 8 and 9 (which are mostly the Food, Services and Administration industries), we assume that their earnings tend to be relatively persistent. For firms with SIC codes of 0, 1, 3, 4 and 6 (which are commodity firms, heavy machinery and manufacturing, transportation and financial firms), we assume that their earnings tend to be only weakly persistent. These latter industries are more cyclical, and as per Dechow et al. (1999), Richardson et al. (2005), and Richardson (2006). Column 5 contains the firms in industries denoted as strongly persistent, whereas column 6 contains those firms in industries with less persistent earnings. We find that the effect of our viable buyer variables are much stronger in the sub-sample of firms with stronger earning persistence. This indicates that acquisitive firms in the earning-persistent industries may be more likely to seek out accretive deals as the primary motivation for undergoing a deal.

In Table 3.4, we then test whether our measure of viable buyers based on intrinsic value (RIM Bidders) is related to the likelihood of being a target. Due to the increased restrictions on the sample selection owing to data availability, the number of observations in the analysis based on the intrinsic value-based variable (RIM Bidders and RIM Targets) is lower than the EPS and Book based variables, so some caution is warranted in contrasting these with the earlier results contained in Tables 3.2 and 3.3. That said, while some observations are lost, we believe that by using a valuation model, we are better able to distinguish between the market-driven story (where rational managers take advantage of irrational market) and the agency story (where the managers make mistakes or are doing empire building and destroying shareholders' value). A valuation model helps us reduce errors in pricing the targets by combining both book value and earnings into a single metric in a theoretically coherently way. If the rational managers-irrational markets story is true, then after removing errors in our measure of viable buyers (and targets), we should observe an increase in our estimated coefficients. If we see the opposite, then it's most likely driven by managerial errors (or agency problem) and not market mis-valuation.

We find that our viable buyer variable, RIM Bidders, is positively related to the likelihood of being a target with a coefficient of 0.041 and is significant at the 1% level.

Hence, if the number of RIM Bidders goes up from the median level to the maximum, the probability of being a target increases by 2% in absolute terms, which is a fairly significant increase of 74% from the predicted probability of 2.7% at the mean. Hence, the coefficients have significant economic meanings. In column 4, we add the Accretive Bidders and Book Bidders. The Accretive Bidders variable has a similar effect as in Tables 2 and 3, with a coefficient of 0.041 while Book Bidders is slightly negative and insignificant. The coefficient of RIM Bidders drops to 0.022 while still significant at 1%. Hence, the number of EPS based viable buyers has the most important effect on the likelihood of being a target.

Overall, the evidence presented in Tables 3.2 through 3.4 provides strong support for Hypothesis 1, suggesting that when a firm has more viable buyers, it is more likely to be acquired. Extending this result to those firms that make acquisitions, Brealey et al.'s (2007) "bootstrap" game is arguably still played these days.

3.4.2 Predicting the Likelihood of Stock-Financed Deals Based on the Number of Viable Buyers

Given that we find the positive association between merger activities and the number of viable buyers, we now investigate whether our measures of viable buyers or targets are related to the use of stock as the medium of exchange in the acquisition. We run probit regressions with time and industry fixed effects and cluster the standard errors at industry level. In addition to the control variables of targets' financial information in merger likelihood, we also use the deal characteristics (i.e., whether the deal is tender offer or not) as control variables in the regressions as the literature generally finds it relevant. The dependent variables is a dummy variable Stock_Only takes the value of 1 if the deal only uses stock as method of payment and 0 otherwise. We pair the target's number of viable buyers and the acquirer's number of viable targets in each regression. Again, we use the CDF transformation of the independent variables in the regressions.

We first estimate probit regressions with the number of viable buyers and targets based on whether the deal is earnings accretive and report the results of the marginal effects in Table 3.5. We find that the use of stock is positively related to the variables Accretive Bidders and Accretive Targets, although the coefficients are not significant. The signs of the control variables mostly agree with the literature. Tender offer and leverage both predict a less likelihood of using stock in payment while market to book ratio predicts a higher chance of using stock in payment. Also, we find that when the targets have more liquidity, the deals are more likely to be paid in stock.

In Table 3.6, we investigate the use of stock and book based viable buyers and targets. Columns 1 to 3 consider only those viable bidders/targest based on book value. The use of stock is negatively related to Book Bidders, however the coefficients are not significant. More importantly, we find that the use of stock is positively related to the number of viable targets (Book Targets) and the coefficients are significant at 5% level. In column 4, we add the EPS-based variables (Accretive Bidders and Accretive Targets) and the estimated coefficient for Book Targets increases. We also test the effect of book buyers and targets in the sub samples of firms with strong earning persistence (column 5) and firms with weak earning persistence (column 6). We find that the effect of number of book targets on the use of stock is stronger (with a coefficient of 0.183) in the group of firms with weak earning persistence. The coefficient for Book Targets is still positive but not significant in the group of firms with strong earning persistence (see column 5).

To highlight the economic significance of our findings, we use the result from the third regression as shown in column 3. The predicted probability of using stock as the only method of payment in the third regression is 23.2% at the mean of regression variables. So, for a firm with average attributes across the board, including the number of viable buyers and targets, the (unconditional) probability of using stock as the only method of payment is 23.2%. Observe that the coefficient for the Book Targets in this marginal regression is 0.11. Hence, if the number of viable targets for an acquirer goes up from the median level to the maximum, the probability of Stock_Only deals increases by 5.5%, which is a fairly significant increase of 23.7% from the predicted probability of 23.2% at the mean. Here again, it appears that our results are economically meaningful.

In Table 3.7, we also investigate whether our measures of viable buyers and targets based on intrinsic value (RIM Bidders and RIM Targets) are related to the use of stock in the acquisition. We find that the use of stock is positively related to the viable buyers. The coefficient for RIM Bidders is 0.12 at 5% significant level after adding Industry P/V Level and Standard Deviation in column 3. However, it's no longer significant after adding EPS and Book based viable buyers and targets variables (as see in column 4). Book Targets has a coefficient of 0.207 and is significant at 1% level.

Overall, the results provide some evidence supporting our second hypothesis, in particular, for the number of viable targets based on book values. This suggests that when a firm's stock price is high relative to other firms in the same industry, the firm tends to use stock as method of payment to swap it for hard assets.

3.4.3 Robustness of Results to the Acquisition Premium

One may argue that our specification of 20% premium is arbitrary, hence we run a sensitivity analysis with different specifications of the premium. We use premia of 30% and 40% in our hypothesized deals. We then calculate the corresponding viable buyers and targets and repeat the regressions. What we find is that while the size of the coefficients drops slightly as compared with the results reported earlier, the significance levels are almost the same. Hence, our results are not likely to be caused by our specification of 20% premium. The drop of magnitude can be due to the lower economic value gleaned with the higher required premium in the hypothesized deals while the average premium in actual deals is only 25%.

3.5 Conclusion

In this paper, we take a novel approach to testing theories relating acquisitions to market misvaluation. We argue that prior empirical tests of this relationship suffer from two problems. First, they either focus on the ex post sample of merger firms or second, they rely on some valuation model which may be of little interest to the actual merger decision-makers. We take the core of the theories that the acquirers want to swap their stocks for cheap assets. An economic shock can cause an uneven adjustment of stock prices among firms in the economy, creating opportunities for such stock-based mergers. We compute three measures of the number of viable buyers for a target firm based on whether the deal is accretive to the acquirers based on earnings, book values, or intrinsic value. We find that the likelihood of being a target is positively related to the number of viable buyers for the firm, and that the likelihood of observing stock as a method of payment is positively related the number of viable buyers for each target and the number of stock targets for each acquirer. Overall, our findings provide a direct link between the likelihood of a merger and market mispricing. Our results indicate that even though managers appear to be trying to increase their earnings or book value, they may be trying to increase their firms' intrinsic values as well.

Appendix A: SDC Data Details

Form of the Transaction: 10 codes describing the specific form of the transaction:

M (MERGER): A combination of business takes place or 100% of the stock of a public or private company is acquired.

A (ACQUISITION): deal in which 100% of a company is spun off or split off is classified as an acquisition by shareholders.

AM (ACQ OF MAJORITY INTEREST): the acquiror must have held less than 50% and be seeking to acquire 50% or more, but less than 100% of the target company's stock.

AP (ACQ OF PARTIAL INTEREST): deals in which the acquiror holds less than 50% and is seeking to acquire less than 50%, or the acquiror holds over 50% and is seeking less than 100% of the target company's stock.

AR (ACQ OF REMAINING INTEREST): deals in which the acquiror holds over 50% and is seeking to acquire 100% of the target company's stock.

AA (ACQ OF ASSETS): deals in which the assets of a company, subsidiary, division, or branch are acquired. This code is used in all transactions when a company is being acquired and the consideration sought is not given.

AC: (ACQ OF CERTAIN ASSETS): deals in which sources state that "certain assets" of a company, subsidiary, or division are acquired.

R (RECAPITALIZATION): deals in which a company undergoes a shareholders' Leveraged recapitalization in which the company issues a special one-time dividend (in the form of cash, debt securities, preferred stock, or assets) allowing shareholders to retain an equity interest in the company.

B (BUYBACK): deals in which the company buys back its equity securities or securities convertible into equity, either on the open market, through privately negotiated transactions, or through a tender offer. Board authorized repurchases are included.

EO (EXCHANGE OFFER): deals in which a company offers to exchange new securities for its equity securities outstanding or its securities convertible into equity.

Transaction Type Code: Code number for the type of transaction (e.g. 1=DI):

1 = Disclosed Value: indicates all deals that have a disclosed dollar value and the acquiror is acquiring an interest of 50% or over in a target, raising its interest from below 50% to above 50%, or acquiring the remaining interest it does not already own.

2 = Undisclosed Value: indicates all deals that do not have a disclosed dollar value and the acquiror is acquiring an interest of 50% or over in a target, raising its interest from below 50% to above 50%, or acquiring the remaining interest it does not already own.

3 = Leveraged Buyouts: indicates that the transaction is a leveraged buyout. An "LBO" occurs when an investor group, investor, or firm offers to acquire a company, taking on an extraordinary amount of debt, with plans to repay it with funds generated from the company or with revenue earned by selling off the newly acquired company's assets. TF considers a deal an LBO if the investor group includes management or the transaction is identified as such in the financial press and 100% of the company is acquired.

4 = Tender Offers: indicates a tender offer is launched for the target. A tender offer is a

formal offer of determined duration to acquire a public company's shares made to equity holders. The offer is often conditioned upon certain requirements such as a minimum number of shares being tendered.

5 = Spinoffs: indicates a "spinoff," which is the tax free distribution of shares by a company of a unit, subsidiary, division, or another company's stock, or any portion thereof, to its shareholders. TF tracks spinoffs of any percentage.

6 = Recapitalizations: indicates a deal is a recapitalization, or deal is part of a recapitalization plan, in which the company issues a special one-time dividend in the form of cash, debt securities, preferred stock, or assets, while allowing shareholders to retain an equity interest in the company. 7 = Self-Tenders: indicates all deals in which a company announces a self-tender offer, recapitalization, or exchange offer. In a self-tender offer a company offers to buy back its equity securities or securities convertible into equity through a tender offer. A company essentially launches a tender offer on itself to buy back shares.

8 = Exchange Offers: indicates a deal where a public company offers to exchange new securities for its outstanding securities. Only those offers seeking to exchange consideration for equity, or securities convertible into equity, are covered in the M&A database. See EXCHANGE OFFER DATABASE for transactions involving debt. 9 = Repurchases: indicates all deals in which a company buys back its shares in the open market or in privately negotiated transactions or a company's board authorizes the repurchase of a portion of its shares.

10 = SP: indicates all deals in which a company is acquiring a minority stake (i.e. up to 49.99% or from 50.1% to 99.9%) in the target company. 11 = Acquisitions of Remaining Interest: indicates all deals in which a company is acquiring the remaining minority stake (i.e. from at least 50.1% ownership to 100% ownership), which it did not already own, in a target company. The acquiring company must have already owned at least 50.1% of the target company and would own 100% of the target company at completion.

12 = Privatizations: indicates a government or government controlled entity sells shares or assets to a non-government entity. Privatizations include both direct and indirect sales of up to a 100% stake to an identifiable buyer and floatations of stock on a stock exchange. The former is considered an M&A transaction and will be included in the quarterly rankings; the latter will not.

Appendix B: Empirical Variable Definitions

The variables used in the empirical analysis are defined as follows:

- *Size* is the natural logarithm of the book value of total assets.
- *M/B* is the ratio of market value of common equity to book value of common equity.
- *ROA* is the ratio of net income to total assets.
- *Leverage* is the ratio of sum of long term and short term debt (Compustat items: dltt and dlc) to total assets.
- *P/E* is the ratio of stock price to the earning per share.
- *Liquidity* is the ratio of net current asset (i.e. current asset minus current liabilities) to total assets
- *Num_Takeover* is the number of takeovers in the target's SIC two digit industry.
- *Tender Offer* is a dummy variable equal to 1 if the deal form is tender offer and 0 otherwise.
- *Accretive Bidders* is the number of EPS based viable buyers for a firm (see section 3.4 for more detailed explanation).
- *Accretive Targets* is the number of EPS based viable targets for a firm (see section 3.4 for more detailed explanation).
- *Book Bidders* is the number of book value based viable buyers for a firm (see section 3.4 for more detailed explanation).
- *Book Targets* is the number of book value based viable targets for a firm (see section 3.4 for more detailed explanation).
- *RIM Bidders* is the number of intrinsic value (calculated by residual income model) based viable buyers for a firm (see section 3.4 for more detailed explanation).
- *RIM Targets* is the number of intrinsic value (calculated by residual income model) based viable targets for a firm (see section 3.4 for more detailed explanation).

Table 3.1: Summary Statistics and Correlation

Panel A: Summary Statistics for Key Variabless

	Non Target Sample			Target Sample				
	N	mean	Median	N	mean	Median	Mean Difference	p value
Lag Accretive Bidders	142442	81.4	38	4709	118.7	65	-37.3	0.00
Lag Book Bidder	138665	78.1	32	4605	107.4	47	-29.3	0.00
Lag RIM Bidders	90185	53.8	23	3303	86.6	44	-32.8	0.00

	Non Acquirer Sample			Acquirer Sample				
	N	mean	Median	N	mean	Median	Mean Difference	p value
Lag Accretive Targets	142506	88.8	44	4636	135.5	79	-46.8	0.00
Lag Book Targets	138674	84.1	39	4590	162.0	87	-77.9	0.00
Lag RIM Targets	89926	53.4	24	3559	97.3	57	-43.9	0.00

Panel B: Summary Statistics Control Variables

	Non Target Sample			Target Sample				
	N	mean	Median	N	mean	Median	Mean Difference	p value
Lag Size (log asset)	147053	5.07	4.93	4789	5.37	5.26	-0.30	0.00
Lag M/B	145344	2.81	1.71	4779	2.66	1.73	0.15	0.01
Lag ROA	146747	-0.03	0.03	4784	-0.02	0.02	-0.01	0.00
Lag Leverage	145963	0.23	0.19	4746	0.22	0.17	0.02	0.00
Lag P/E	143754	12.68	11.29	4746	13.65	12.15	-0.98	0.06
Lag Liquidity	121257	0.27	0.25	3562	0.29	0.27	-0.02	0.00
Lag Num_Takeover	160444	10.90	5.00	4932	18.42	10.00	-7.52	0.00

	Non Acquirer Sample			Acquirer Sample				
	N	mean	Median	N	mean	Median	Mean Difference	p value
Lag Size (log asset)	147134	5.01	4.88	4707	7.13	7.25	-2.12	0.00
Lag M/B	145432	2.79	1.70	4689	3.19	2.07	-0.39	0.01
Lag ROA	146826	-0.03	0.03	4698	0.02	0.03	-0.05	0.00
Lag Leverage	146054	0.23	0.19	4654	0.22	0.19	0.01	0.00
Lag P/E	143836	12.53	11.21	4659	18.06	14.55	-5.53	0.06
Lag Liquidity	121493	0.27	0.26	3321	0.24	0.20	0.03	0.00
Lag Num_Takeover	160582	10.01	5.00	4787	16.84	10.00	-6.83	0.00

Panel C : Correlations Among Key Variables and Controls

	Accretive Bidders	Accretive Targets	Book Bidders	Book Targets	RIM Bidders	RIM Targets	M/B Level	P/E Level	P/V Level	M/B SD	P/E SD	P/V SD	Size	M/B	ROA	Leverage	P/E	Liquidity	Num_Takeover
Accretive Bidders	1.00																		
Accretive Targets	0.02	1.00																	
Book Bidder	0.79	0.28	1.00																
Book Targets	0.23	0.75	0.17	1.00															
RIM Bidders	0.66	0.21	0.81	0.14	1.00														
RIM Targets	0.16	0.69	0.12	0.87	-0.04	1.00													
M/B Level	0.34	0.38	0.37	0.37	0.28	0.30	1.00												
P/E Level	-0.12	-0.15	-0.14	-0.11	-0.05	-0.05	-0.15	1.00											
P/V Level	0.06	0.07	0.08	0.07	0.05	0.05	0.20	-0.05	1.00										
M/B SD	0.29	0.34	0.32	0.32	0.24	0.26	0.86	-0.23	0.20	1.00									
P/E SD	0.25	0.29	0.28	0.29	0.23	0.25	0.54	0.19	0.21	0.46	1.00								
P/V SD	0.15	0.17	0.18	0.18	0.14	0.15	0.27	-0.06	0.92	0.28	0.28	1.00							
Size	-0.32	0.12	-0.39	0.11	-0.32	0.15	-0.03	-0.03	-0.18	-0.04	-0.08	-0.18	1.00						
M/B	-0.20	0.50	0.03	0.28	-0.04	0.24	0.26	-0.03	0.05	0.20	0.15	0.07	-0.04	1.00					
ROA	-0.17	0.04	-0.11	-0.08	-0.12	0.03	-0.07	0.06	-0.02	-0.07	-0.06	-0.03	0.11	0.00	1.00				
Leverage	-0.19	-0.19	-0.23	-0.19	-0.18	-0.16	-0.21	0.01	-0.04	-0.17	-0.15	-0.08	0.23	-0.10	-0.12	1.00			
P/E	-0.04	0.13	-0.01	0.10	-0.04	0.11	0.08	0.02	0.02	0.06	0.06	0.03	-0.02	0.17	0.15	-0.06	1.00		
Liquidity	0.24	0.15	0.27	0.17	0.23	0.14	0.15	0.00	0.08	0.14	0.13	0.13	-0.43	0.06	0.06	-0.50	0.06	1.00	
Num_takeover	0.56	0.66	0.65	0.65	0.50	0.55	0.50	-0.19	0.09	0.41	0.37	0.19	-0.06	0.22	-0.10	-0.21	0.06	0.16	1.00

Table 3.2: Likelihood of Being a Target and the Number of Accretive Bidders

The dependent variable is takeover dummy variable equal to 1 if a firm is a takeover target and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). We run probit regressions and report the marginal effects in the table. We control the year fixed effect and industry fixed effect in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***,** and * represents 1%, 5% and 10% significant level.

	(1)	(2)	(3)
Accretive Bidders	0.034	0.034	0.034
	(0.005)***	(0.005)***	(0.005)***
Ind P/E Level		0.004	0.004
		(0.003)	(0.003)
Ind P/E SD			-0.001
			(0.003)
Ind Num Takeover	0.017	0.017	0.017
	(0.006)**	(0.006)**	(0.006)**
Size	-0.036	-0.035	-0.035
	(0.053)	(0.053)	(0.053)
Size^2	0.065	0.065	0.065
	(0.053)	(0.053)	(0.053)
M/B	0.004	0.004	0.004
	(0.002)**	(0.002)**	(0.002)**
ROA	-0.014	-0.014	-0.014
	(0.003)***	(0.003)***	(0.003)***
Leverage	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)
P/E	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)
Liquidity	0.011	0.011	0.011
	(0.002)***	(0.002)***	(0.002)***
Observations	119443	119443	119428
Pseudo R^2	0.035	0.035	0.035

Table 3.3: Likelihood of Being a Target and the Number of Book Bidders

The dependent variable is takeover dummy variable equal to 1 if a firm is a takeover target and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). Column 5 includes only firms in industries with strong earning persistence and column 6 includes only firms in industries with weak earning persistence. We run probit regressions and report the marginal effects in the table. We control the year fixed effect and industry fixed effect in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***,** and * represents 1%, 5% and 10% significant level.

	(1)	(2)	(3)	(4)	(5)	(6)
Book Bidders	0.034	0.035	0.034	0.021	0.029	0.014
	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.004)***	(0.007)*
Ind M/B Level		-0.002	0.001	0.007	-0.004	0.018
		(0.005)	(0.007)	(0.007)	(0.012)	(0.009)*
Ind M/B SD			-0.003	-0.006	0.004	-0.016
			(0.005)	(0.004)	(0.007)	(0.007)*
Ind num takeover	0.018	0.018	0.018	0.014	0.015	0.010
	(0.006)**	(0.006)**	(0.006)**	(0.006)*	(0.010)	(0.006)
Size	-0.029	-0.029	-0.029	-0.032	-0.018	-0.043
	(0.052)	(0.052)	(0.052)	(0.048)	(0.053)	(0.080)
$Size^2$	0.056	0.056	0.056	0.068	0.064	0.071
	(0.051)	(0.051)	(0.051)	(0.048)	(0.054)	(0.080)
M/B	0.023	0.023	0.023	0.018	0.023	0.013
	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.004)***	(0.004)**
ROA	-0.008	-0.008	-0.008	-0.014	-0.016	-0.012
	(0.002)**	(0.002)**	(0.002)**	(0.003)***	(0.004)***	(0.003)***
Leverage	-0.000	-0.000	-0.000	-0.002	-0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
P/E	0.002	0.002	0.002	0.002	-0.000	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Liquidity	0.010	0.010	0.010	0.009	0.009	0.008
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.003)*
Accretive Bidders				0.032	0.038	0.028
				(0.004)***	(0.006)***	(0.006)***
Observations	115603	115603	115580	115580	54134	61446
Pseudo R^2	0.032	0.032	0.031	0.036	0.044	0.033

Table 3.4: Likelihood of Being a Target and the Number of RIM Bidders

The dependent variable is takeover dummy variable equal to 1 if a firm is a takeover target and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). We run probit regressions and report the marginal effects in the table. We control the year fixed effect and industry fixed effect in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***,** and * represents 1%, 5% and 10% significant level.

	(1)	(2)	(3)	(4)
RIM Bidders	0.041	0.041	0.041	0.022
	(0.004)***	(0.004)***	(0.004)***	(0.003)***
Ind P/V Level		0.001	0.032	0.029
		(0.003)	(0.014)*	(0.014)*
Ind P/V SD			-0.029	-0.027
			(0.013)*	(0.013)*
Ind Num Takeover	0.021	0.022	0.022	0.017
	(0.007)**	(0.007)**	(0.007)**	(0.007)*
Size	-4.439	-4.455	-4.408	-4.003
	(1.881)*	(1.885)*	(1.890)*	(1.763)*
Size^2	4.455	4.470	4.424	4.033
	(1.879)*	(1.883)*	(1.888)*	(1.761)*
M/B	0.011	0.011	0.011	0.013
	(0.002)***	(0.002)***	(0.002)***	(0.004)**
ROA	-0.020	-0.020	-0.020	-0.022
	(0.003)***	(0.004)***	(0.004)***	(0.003)***
Leverage	0.000	0.000	0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
P/E	0.003	0.003	0.003	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
Liquidity	0.011	0.011	0.011	0.010
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Accretive Bidders				0.041
				(0.007)***
Book Bidders				-0.003
				(0.006)
Observations	74526	74364	74044	74044
Pseudo R^2	0.043	0.042	0.042	0.045

Table 3.5: Likelihood of Stock-Financed Deals and the Number of Accretive Bidders

The dependent variable is stock_only dummy variable equal to 1 if the deal only uses stock as method of payment and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). We run probit regressions and report the marginal effects in the table. We control the year fixed effect and industry fixed effect in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***,** and * represents 1%, 5% and 10% significant level.

	(1)	(2)	(3)
Accretive bidders	0.054	0.057	0.055
	(0.040)	(0.040)	(0.039)
Accretive Targets	0.028	0.030	0.026
	(0.032)	(0.032)	(0.032)
Ind P/E Level		0.048	0.012
		(0.036)	(0.039)
Ind P/E SD			0.107
			(0.061)
Ind Num Takeover	-0.200	-0.191	-0.207
	(0.122)	(0.124)	(0.130)
Size	4.100	4.243	4.282
	(2.350)	(2.342)	(2.328)
Size^2	-4.191	-4.334	-4.373
	(2.360)	(2.351)	(2.337)
M/B	0.139	0.138	0.136
	(0.035)***	(0.035)***	(0.034)***
ROA	0.009	0.008	0.011
	(0.037)	(0.037)	(0.037)
Leverage	-0.158	-0.160	-0.158
	(0.051)**	(0.051)**	(0.051)**
P/E	-0.003	-0.005	-0.007
	(0.040)	(0.040)	(0.040)
Liquidity	0.123	0.122	0.121
	(0.035)***	(0.035)***	(0.034)***
Tender Offer	-0.343	-0.343	-0.342
	(0.008)***	(0.008)***	(0.008)***
Observations	3452	3452	3452
Pseudo R^2	0.234	0.234	0.235

Table 3.6: Likelihood of Stock-Financed Deals and the Number of Book Bidders

The dependent variable is stock_only dummy variable equal to 1 if the deal only uses stock as method of payment and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). Column 5 includes only firms in industries with strong earning persistence and column 6 includes only firms in industries with weak earning persistence. We run probit regressions and report the marginal effects in the table. We control the year fixed effect and industry fixed effect in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***,** and * represents 1%, 5% and 10% significant level.

	(1)	(2)	(3)	(4)	(5)	(6)
Book Bidders	-0.032	-0.038	-0.036	-0.058	-0.105	-0.064
	(0.080)	(0.077)	(0.076)	(0.082)	(0.125)	(0.105)
Book Targets	0.109	0.110	0.110	0.135	0.089	0.183
	(0.038)**	(0.038)**	(0.038)**	(0.042)**	(0.055)	(0.062)**
Ind M/B Level		0.061	0.027	0.036	0.115	0.005
		(0.098)	(0.142)	(0.140)	(0.157)	(0.210)
Ind M/B SD			0.033	0.028	-0.210	0.170
			(0.118)	(0.117)	(0.134)	(0.180)
Ind Num Takeover	-0.202	-0.200	-0.200	-0.213	-0.150	-0.166
	(0.120)	(0.120)	(0.120)	(0.122)	(0.134)	(0.143)
Size	-268.554	-266.385	-266.679	-257.293	-267.982	-326.458
	(137.706)	(137.307)	(137.021)	(135.778)	(254.136)	(162.925)*
Size^2	268.396	266.227	266.521	257.154	267.741	326.353
	(137.703)	(137.304)	(137.018)	(135.773)	(254.116)	(162.930)*
M/B	0.121	0.115	0.116	0.110	0.199	0.023
	(0.066)	(0.063)	(0.062)	(0.062)	(0.081)*	(0.081)
ROA	0.012	0.012	0.012	-0.004	-0.014	0.002
	(0.041)	(0.041)	(0.041)	(0.039)	(0.043)	(0.058)
Leverage	-0.175	-0.176	-0.175	-0.177	-0.157	-0.185
	(0.048)***	(0.048)***	(0.048)***	(0.047)***	(0.059)**	(0.078)*
P/E	-0.005	-0.006	-0.006	-0.005	0.039	-0.035
	(0.042)	(0.042)	(0.042)	(0.042)	(0.037)	(0.061)
Liquidity	0.115	0.115	0.115	0.117	0.145	0.083
	(0.036)**	(0.036)**	(0.036)**	(0.036)**	(0.040)***	(0.064)
Tender Offer	-0.351	-0.351	-0.351	-0.352	-0.368	-0.352
	(0.008)***	(0.007)***	(0.007)***	(0.008)***	(0.011)***	(0.011)***
Accretive Bidders				0.068	0.114	0.039
				(0.046)	(0.052)*	(0.054)
Accretive Targets				-0.044	-0.013	-0.067
				(0.033)	(0.035)	(0.049)
Observations	3350	3350	3350	3350	1531	1751
Pseudo R^2	0.240	0.240	0.240	0.241	0.280	0.216

Table 3.7: Likelihood of Stock-Financed Deals and the Number of RIM Bidders

The dependent variable is stock_only dummy variable equal to 1 if the deal only uses stock as method of payment and 0 otherwise. The independent variables (except dummy variables) in the regressions are transformed by empirical cumulative distribution function (CDF). We run probit regressions and report the marginal effects in the table. We control the year fixed effect and industry fixed effect in all regressions and cluster the standard errors at the industry level. We report standard errors in parentheses. ***,** and * represents 1%, 5% and 10% significant level.

	(1)	(2)	(3)	(4)
RIM Bidders	0.115	0.115	0.120	0.108
	(0.046)*	(0.046)*	(0.044)**	(0.069)
RIM Targets	0.033	0.033	0.028	-0.040
	(0.045)	(0.046)	(0.046)	(0.056)
Ind P/V Level		0.004	0.186	0.182
		(0.060)	(0.217)	(0.214)
Ind P/V SD			-0.159	-0.154
			(0.186)	(0.184)
Ind Num Takeover	-0.229	-0.230	-0.223	-0.237
	(0.104)*	(0.105)*	(0.109)*	(0.116)*
Size	-75.064	-75.033	-66.346	-74.679
	(207.045)	(207.144)	(207.048)	(201.697)
Size^2	74.975	74.944	66.261	74.568
	(207.045)	(207.144)	(207.047)	(201.685)
M/B	0.259	0.259	0.260	0.202
	(0.054)***	(0.054)***	(0.054)***	(0.083)*
ROA	-0.033	-0.033	-0.031	-0.034
	(0.042)	(0.042)	(0.041)	(0.040)
Leverage	-0.146	-0.146	-0.150	-0.141
	(0.053)**	(0.053)**	(0.055)**	(0.056)*
P/E	-0.001	-0.001	-0.002	-0.005
	(0.047)	(0.046)	(0.046)	(0.045)
Liquidity	0.098	0.098	0.097	0.093
	(0.061)	(0.061)	(0.060)	(0.059)
Tender Offer	-0.355	-0.355	-0.355	-0.354
	(0.010)***	(0.011)***	(0.011)***	(0.010)***
Accretive Bidders				0.029
				(0.119)
Accretive Targets				-0.046
				(0.059)
Book Bidders				-0.060
				(0.113)
Book Targets				0.207
				(0.062)***
Observations	2323	2322	2320	2320
Pseudo R^2	0.271	0.271	0.273	0.277

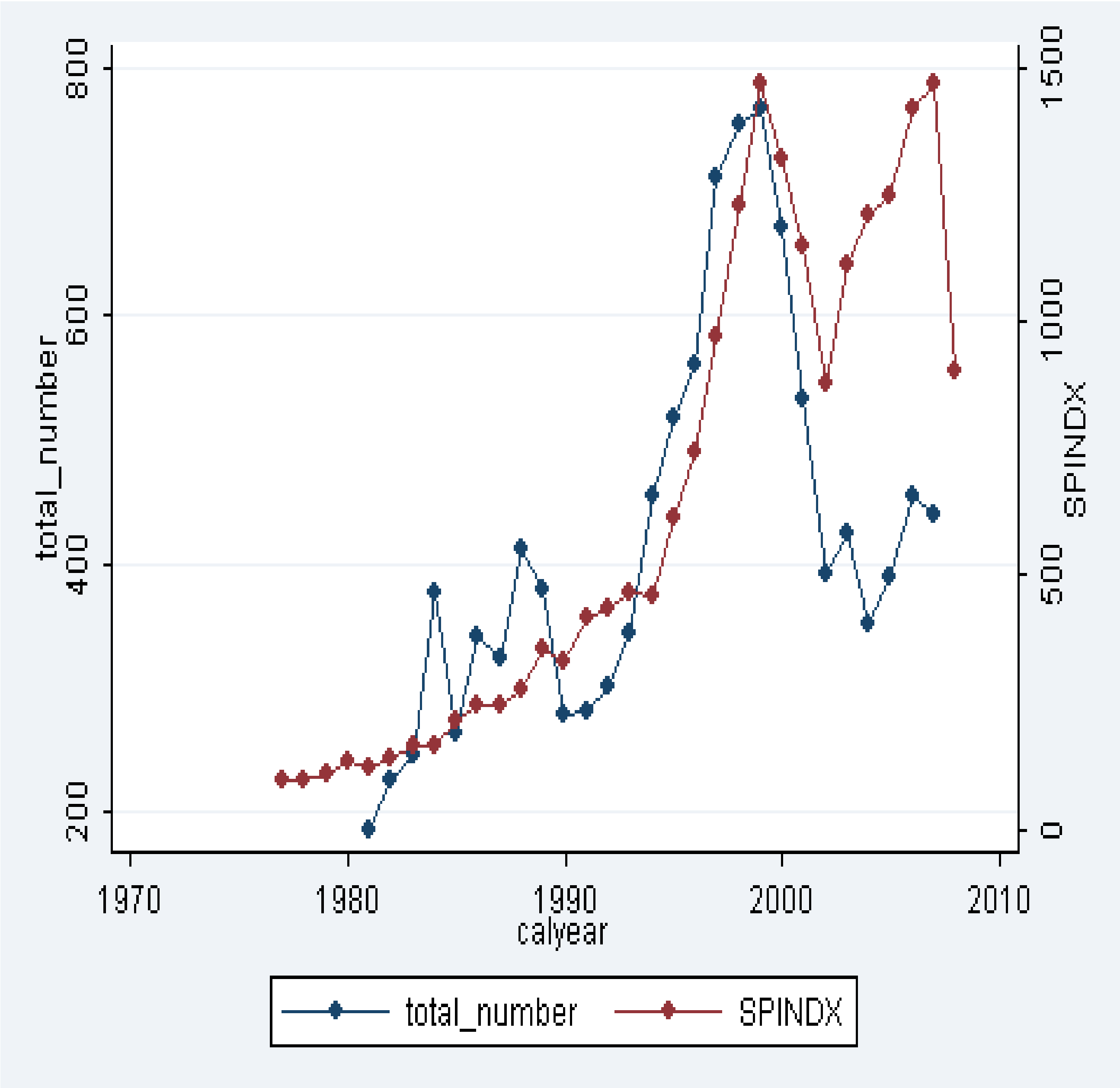


Figure 3.1: Number of deals of public firms vs level of S&P 500

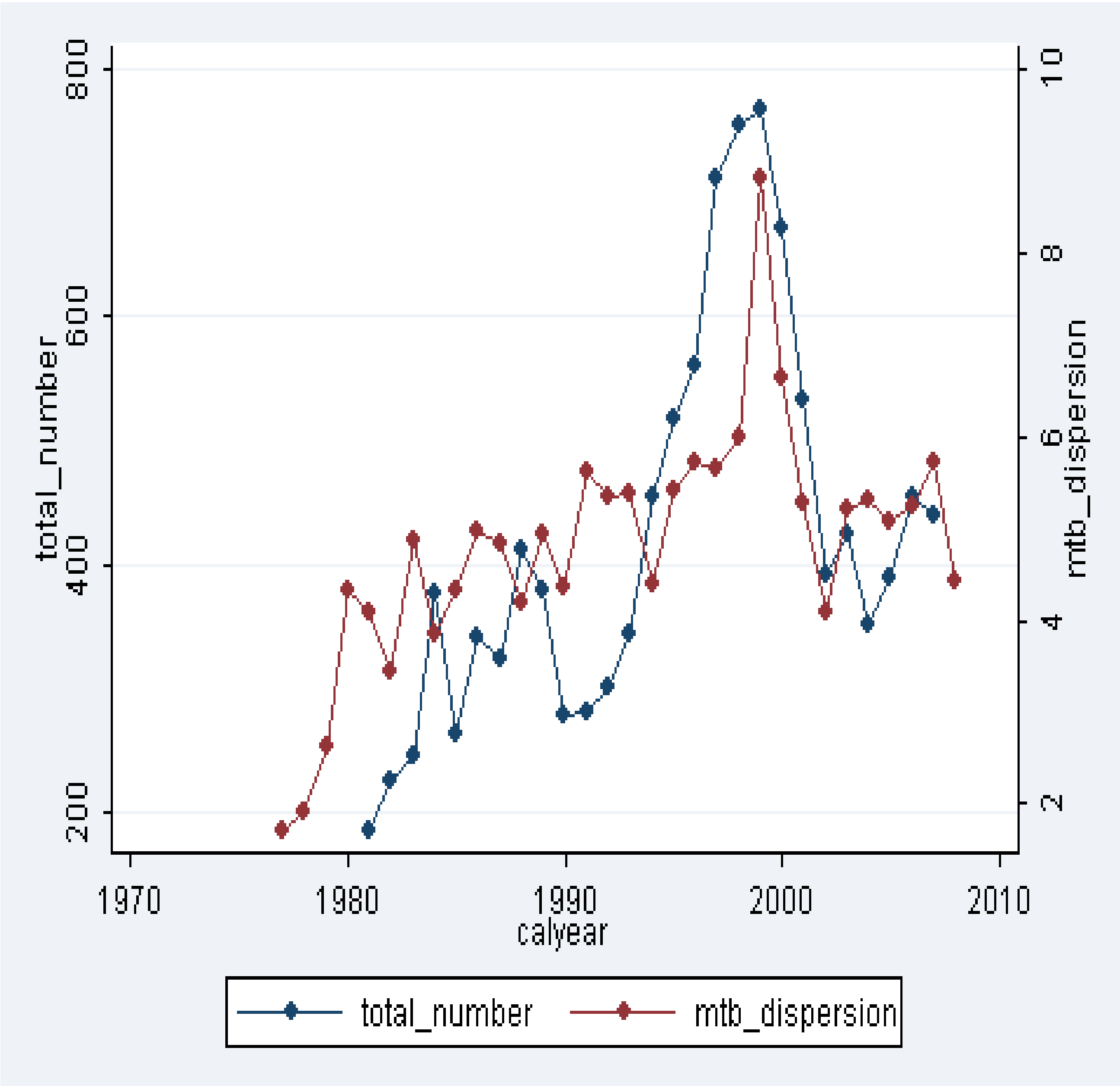


Figure 3.2: Number of deals of public firms vs Standard Deviation of Market to Book Ratio

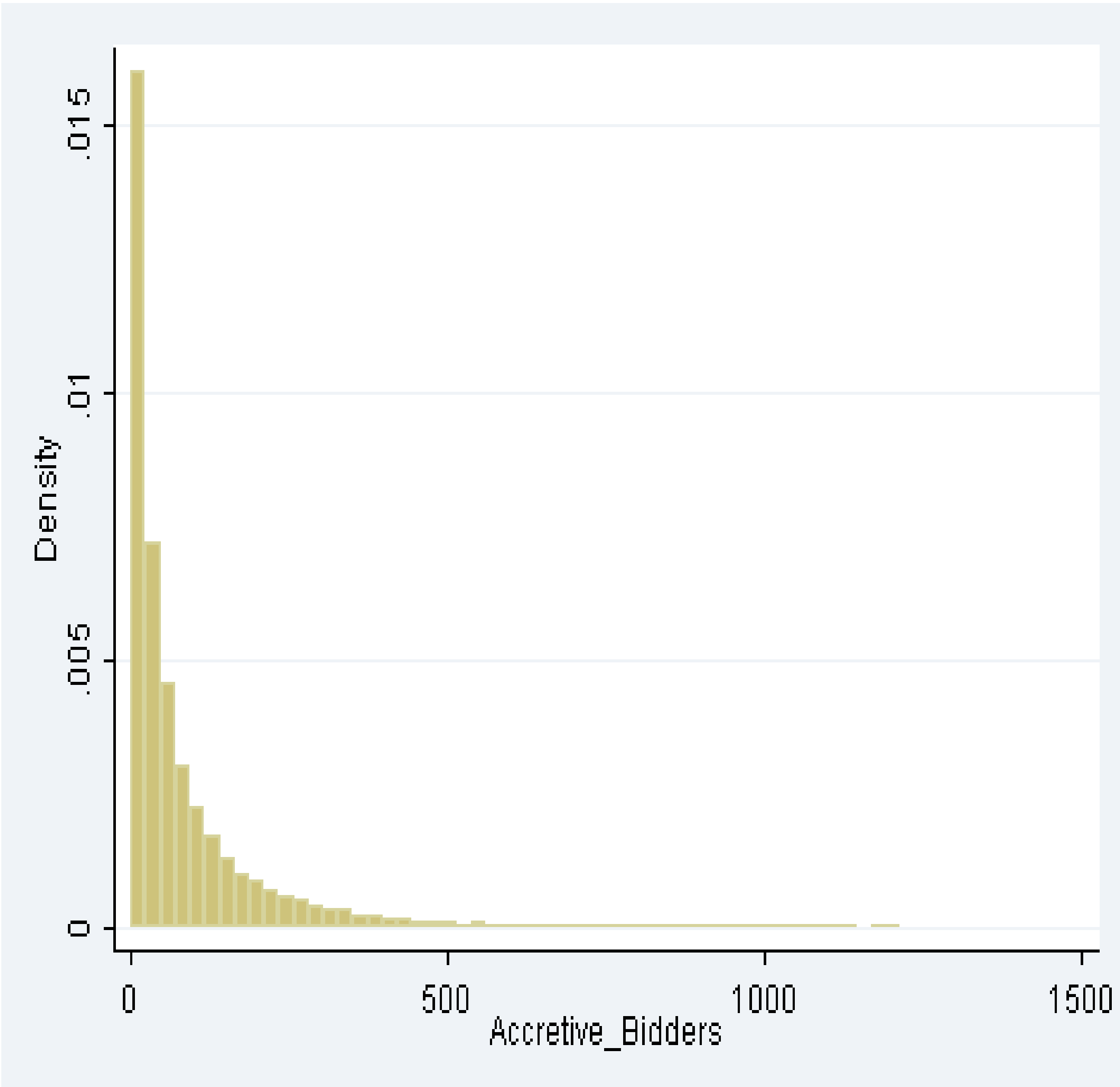


Figure 3.3: Histogram of the Number of Accretive Bidders

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