EFFICIENCY IN CORPORATE TAKEOVERS

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To Te and Wenxin,

my precious

Preface

As a milestone in my academic life, this dissertation concludes my three-year hard work, as well as provides a precious opportunity for me to thank all of those who companied, encouraged, and helped me through all the process.

My first gratitude goes to my excellent supervisors – Han Smit and Sebastian Gryglewicz. I still remember the first time that I met Han. At the first sight, I was so impressed by his warm smile that I felt I was already one member of his research team. His pleasant personality soon becomes an indispensable part of our research project. His passion for research cheers every meeting with excitement. His supportive attitude strengthens my determination to overcome difficulties. His deep knowledge of practical finance turns complicated mathematics into vivid reflection of finance activity. By Han's introduction, I got to know Sebastian, another intelligent scholar. Sebastian owns every merit of a great supervisor. He is insightful, good at finding the key questions. He is smart, with excellent skill in modeling. He is diligent, with high attention to details. He is also easy-going, caring and supportive, willing to share his experience and give advice whenever I need. Han's contagious enthusiasm and Sebastian's patient guidance as well as their outstanding research skills constitute perfect mentorship, which makes my PhD life not only joyful but also fruitful. I am glad to publish our first joint paper before my graduation, and my research ability has developed and grown during this process, which will surely become a valuable asset of my life.

Someone once told me that, doing a PhD was similar to running a start-up. It begins with finding a promising project, and requires investment of numerous time and effort. If the R&D turns successful (i.e. a paper is written), you need to learn how to present your

product (by conference presentation) and sell it to the market (by publication of the paper). Sometimes, this course can be tedious and lonely because you need to do it all by yourself. Fortunately, my PhD journey is never boring thanks to the company of my fellow researchers. I am grateful to Agbeko, Christel, Gosia, Jiangyu, Liting, Natalya, Noemie, Olivier, Philipe, Xinying, and Yang for the delightful discussions and cooperation in the study groups for TI courses. To Kyle, Marc, Patrick, Remco, Sander, Xiaoming, and Xiaoyu for their inspiring comments on my research. To Joris, Guangyao, Tiantian, and Zhenxing for their help on my students' thesis defenses. To Pinar and Ona for their nice presence as good officemates. To Lerby for the incentive he offered to my swimming learning. To Leontine for her help on my Dutch. To Chen, Dan, Guangyuan, Hong, Jiansong, Jindi, Lin, Mike, Qibai, Ran, Siyu, Wei, Xiye, Xiaolong, Xin, Xuedong, Yijing, Yu, Yue, Yueshen, Zhenzhen, Zhengyuan, and Zhiling, for the wonderful time that we spent together.

Finally, I would like to thank my family for their endless love and unconditional support. I am greatly indebted to my parents for their understanding when I decided to study in the Netherlands, to my sister for her devotion to family, and to my parents-in-law for their generous help. My deepest gratitude goes to my husband, Te: meeting him is the most beautiful thing that ever happened to me. Without Te's support, I would have not come so far. This dissertation is dedicated to Te and Wenxin (our daughter), who brighten my life, fuel my energy and encourage me to discover the best out of life.

Contents

Chapter 1

Introduction

1.1. Research Questions

Corporate takeover is a very important economic activity that generates profound consequences on many classes of market participants. The great financing needs and transaction costs directly change the wealth of both shareholders and creditors. The corporate restructuring induced by the takeover results in a significant impact on the welfare of management, employees, and customers. The reshaped industrial map due to the takeover further influences the competition strategies of other firms. Moreover, the changes in the taxable revenues when the takeover happens across the industry can also affect the tax income to the government. The paramount impact on corporations and the economy highlights the importance of studying the efficiency in corporate takeovers. This dissertation contributes to the discussion on takeover efficiency by exploring three key questions.

The first question is about the optimal bidding strategy in takeover contests. Since corporate takeover is a costly process, it is critical to make the right decisions on (1) Whether to enter a takeover contest or (2) How to select an optimal bid. Following

Fishman (1988), we model the takeover contests as auctions with sequential entry, and find that the optimal entry and bidding strategies depend heavily on the similarity level of acquirers' valuations of the target. When acquirers' valuations are dissimilar, the first bid of the first bidder is mainly about their own value. The following bidder is easily deterred by a high first bid, because it signals the high value of the first bidder. However, when the similarity level increases, the first bid is embedded with higher information externality. A high first bid not only signals the high value of the first bidder, but also implies the high value of the following bidder. It becomes harder to deter the competition, and the first bidder needs to offer a higher first bid to pre-empt others. However, when the similarity level exceeds a certain threshold, the competition between very similar acquirers becomes so severe that pre-emption becomes easier and the first bidder can use a lower first bid to deter the following bidders. These non-monotonic effects of similarity on acquirers' entry and bidding decisions are further confirmed in controlled laboratory experiments.

The second question is about the efficiency evaluation of takeover strategies. Different from the static viewpoint in most studies, we introduce a dynamic framework in answering this question. By studying how the efficiency of takeovers with toeholds[1] changes over time, we propose that an evolutionary perspective is important in evaluating the performance of a takeover strategy. Although the toehold bidding is accompanied with worse performance than the non-toehold bidding in the early 1990s, its efficiency is improving over time. From 1990 to 2006, takeovers with toeholds experience significant increases in terms of returns to bidders and synergy value created through transactions. The discovery of a significant time pattern in the toehold bidding shows that the dynamic

[1] *Toeholds* refer to the minority ownership of the target's shares owned by the acquirer before a takeover is initiated.

perspective is very important in evaluating the efficiency of takeover strategies. Overlooking it may lead to biased or inaccurate conclusions.

The third question is how to improve firms' performance in corporate takeovers. This question can be divided into two sub-questions: (1) How to improve acquirers' efficiency in carrying out corporate takeovers; and (2) How to improve targets' response to takeover threats. Related literatures suggest that corporate governance can be a promising candidate (Shleifer, and Vishny, 1986; Schranz 1993; Nickell et al, 1997; Allen *et al.*, 2000; Gillan and Stark, 2000; Hartzell and Stark, 2003; Gaspar *et al.*, 2005; Chen *et al.*, 2007). We therefore, examine the interaction between the firms' performance and their corporate governance qualities. In the study on the efficiency of toehold bidding, we introduce institutional ownership as a measure of monitoring strength, and investigate its impact on the toehold performance. We find that the magnitude of the institutional investment well explains the efficiency evolution in toehold performance, which suggests that the monitoring from institutional investors can enhance acquirers' ability to benefit from the toehold bidding. We further examine the relationship between the target firms' response to takeover threats and two different governance mechanisms—monitoring from institutional investors and product market competition. We find little impact of corporate governance on the target firms' post-takeover restructuring. The influence of both the internal monitoring (the institutional ownership) and the external discipline (the product market competition) is very limited. Neither of them can result in a systematic improvement in firms' performance after takeovers. The difference in the impacts of corporate governance on the performance of acquirers and targets is illuminating. It suggests that the effectiveness of corporate governance depends on whether the firms have the initiative. When a firm is actively participating in the corporate takeover, that is, as an acquirer, its corporate governance can help in making wise decisions. On the contrary, when a firm is passively involved in a takeover, that is, as a target, the takeover threat is so strong that it is forced to make changes regardless of its corporate governance quality.

In addition to exploring the efficiency in corporate takeovers, this dissertation tries to provide innovative thinking on several interesting puzzles or issues in takeover literature.

The first puzzle is the insignificant relationship between the number of bidders and takeover returns. Although the number of the bidders is usually regarded as an intuitive measure of competition intensity, previous studies (Kale et al., 2003; Betton et al., 2008; Boone and Mulherin, 2008) show that it cannot explain the variation in prices and returns in corporate takeovers. Our study points out a new measure of the competition level in takeovers; that is, the similarity in bidders' valuations, which is a key consideration in bidders' entry decisions and bidding strategies. The single-bidder contests are more likely to occur when the similarity level is either low or high, compared with the case of the intermediate similarity level. The acquisition prices are higher at the intermediate similarity level than at the low or high similarity level. Hence, multiple-bidder contests are most likely at the intermediate level of similarity at which expected prices in multiple-bidder contests are the highest, whereas single-bidder acquisitions are most likely at very low and very high levels of similarity when expected prices in single-bidder contests are lower. Furthermore, given the level of similarity, targets' returns can be higher in single-bidder acquisitions than in multiple-bidder contests, because a premium is offered to deter competition. This non-monotonic impact of the similarity level explains the unclear relationship between the number of bidders and the prices and returns in takeovers. Without controlling for the level of similarity, the relationship between the number of bidders and target returns can show either signs in a cross-section study of acquisitions.

The second puzzle is the well-known toehold puzzle in takeover literature. *Toehold* refers to the acquirer's ownership of the target's share before a takeover is initiated. Theoretically, toeholds can grant the owner a favorable position. They strengthen the toehold owner's competitiveness by mitigating the free-rider problem, increasing the winning probability and accumulating insider information (Shleifer and Vishny, 1986; Burkart 1995; Singh 1998; Bulow et al., 1999). However, in the past decades, less than 10% of acquisitions were acquired with toeholds. The sharp contradiction between the attractive merits of the toehold acquisition strategy and its scare adoption constitutes a "toehold puzzle." We propose that the "learning effect" in takeovers with toeholds can be a possible explanation, where qualified acquirers learn to use the strategy effectively, whereas unqualified acquirers have learned to walk away. As discussed earlier, we find a significant efficiency improvement in the toehold performance from 1990 to 2006. However, the decline in the popularity of the toehold strategy indicates that this improvement is not unconditional. As suggested by the adverse impact of toeholds in the early period, the toehold bidding does not guarantee beneficial outcomes, and to properly use toeholds to generate higher returns requires some qualifications. Bidders gradually learn their qualifications while using the toehold strategy, and they self-select to stay or give up this strategy increases. With the passing of time, the proportion of qualified acquirers using the toehold strategy, which results in a co-existence of a decrease in the frequency of toehold acquisitions and an improvement in the toehold performance. Using self-selection models, we identify and confirm this learning effect in takeovers with toeholds, which for explains the toehold puzzle from a new evolutionary perspective.

The third controversial topic is the interplay among different mechanisms of corporate governance: whether they are complements or substitutes? There is no conclusive answer. Some research supports the complements view (Denis and Serrano, 1996; Hadlock and Lumer, 1997; Mikkelson and Parch, 1997); some speak for the substitutes view (Giroud and Mueller, 2010; Atanassov 2013); and other studies demonstrate no interaction between the internal and external governance mechanism (Huson, Parrino, and Starks, 2001; Denis and Kruse 2000). To contribute to this discussion, I select a special group of firms—targets in failed takeovers and their industry peers—to examine the impact of different governance mechanisms on firms' responses to takeover threats. The special feature of this sample is that it differentiates between two cases with different strengths of takeover threats: target firms facing direct and strong threats and peer firms facing indirect and weak threats. This enables me to investigate the complements argument in a comprehensive manner. Are governance mechanisms complementary to the takeover threat in their disciplinary power? If so, do their roles differ in the presence of strong or weak takeover threats? The results show that corporate governance is a weak complement to takeover threats. First, its impact is limited to a few post-takeover policy changes. There is no general or comprehensive enhancement on restructuring outcomes. Second, the market perception reflected by stock performance does not differ in the governance quality. Furthermore, the limited impact of corporate governance mainly occurs with regard to target firms' performance, that is, when the takeover threat is strong. Corporate governance cannot increase peer firms' sensitivity to takeover threats or make a difference in firms' post-takeover restructuring.

Lastly, the contribution of the thesis is also methodological. It combines theory, experimental and empirical studies while addressing different questions. There has been a large experimental literature on asset pricing pioneered by Smith et al. (1988), whereas little experimental work was done on topics related to corporate finance. By introducing experimental methods to the study on corporate takeovers, the dissertation adds more evidence to experimental corporate finance. Besides the experimental method, the perspective from learning and evolutionary selection in studying toehold puzzles is also innovative.

1.2. Outline

This dissertation studies three interesting questions in takeover contests related to efficiency in corporate takeovers. The results are reported in three chapters. Each chapter is self-contained, with its own introductions, conclusions, and appendix.

Chapter 2 is developed from the paper "Similar Bidders in Takeover Contests" (Dai, Gryglewicz, Smit, and De Maeseneire, 2013, *Games and Economic Behavior*). It studies the optimal bidding strategies in corporate takeovers when an acquirer is facing a similar/dissimilar competing acquirer. With a theoretical model, we show that the similarity level in acquirers' valuations about the target has two implications. On the one hand, it affects the information content of bids. On the other hand, it determines the competition intensity between acquirers. As a result, the acquisition prices and the probability of multiple-bidder contests are predicted to be the highest for intermediately similar acquirers. The non-monotonic effects of similarity with regard to prices and the frequency of multiple-bidder contests are further confirmed by a laboratory experiment in which we control the similarity between bidders and ask subjects to choose their bidding and entry decisions.

Chapter 3 is based on a working paper "The Learning Effect in Takeovers with Toeholds" (Dai, Gryglewicz and Smit, 2013). It investigates the evolution in the toehold performance and proposes a new explanation to the toehold puzzle. With four efficiency measures, we show that the performance of the toehold strategy is improving over time, though the frequency of toehold acquisitions is decreasing. The discrepancy between the toeholds efficiency and its popularity can be attributed to an improvement in the self-selection procedure, where qualified acquirers learn to use this strategy whereas unqualified acquirers learn to walk away. With self-selection models, we provide strong and significant support to the improved efficiency of self-selection in toehold acquisition. Furthermore, corporate governance, such as institutional holdings, improves outcomes in a toehold acquisition strategy, and indicates that firms with better monitoring quality can become more qualified toehold acquirers.

Chapter 4, "Are corporate governance mechanisms complements? Evidence from Failed Takeovers" (Dai, 2013), studies the impact of corporate governance on firms' responses to control threats. By restricting the sample to failed takeovers, I identify firms who received concrete control threats but without a change in corporate control, and investigate whether their operational change will be affected by the quality of their corporate governance. Furthermore, I use the stock performance and analysts' forecast to check whether the investors expect different responses from firms with good/bad corporate governance. The result shows that, in the presence of strong control threats, corporate governance has little influence on firms' restructuring, and investors do not differentiate between firms with different corporate governance while trading on stocks facing takeover threat.

Chapter 2

Similar Bidders in Takeover Contests[2]

2.1. Introduction

Returns in mergers and acquisitions for acquirer and target not only depend on the value that is created, but also on acquisition premium that is paid. Empirical research indicates that, overall, acquisitions do create value (Andrade, Mitchell and Stafford, 2001; Bargeron, Schlingemann, Stulz, and Zutter, 2008; Betton, Eckbo, and Thorburn, 2008) but gains accrue mostly to targets. Acquiring firms' returns are, on average, close to zero and exhibit large variation (Stulz, Walkling, and Song, 1990; Leeth, and Borg, 2000; Fuller, Netter, and Stegemoller, 2002; Moeller, Schlingemann, and Stulz, 2005). Taken together, the evidence suggests that acquisition prices are determinative for the division of takeover surplus.

[2] This chapter is based on Dai, Grylewicz, Smit and De Maeseneire (2013).

The underlying causes of this variation in prices and returns have been subject to continuous scrutiny in the empirical literature. Surprisingly, the level of competition as measured by the number of bidders does not seem to explain this variation (Boone and Mulherin, 2008).[3] However, characteristics of buyers do appear to be successful in explaining returns.[4]

Guided by this evidence, we develop a model of takeover contests in which the characteristics of potential acquirers matter and affect the intensity of competition. We want to take into account that potential acquirers can be similar or dissimilar because they may have very similar or very unique resources, capabilities, and post-acquisition strategies. More specifically, we analyze a model of two potential bidders that may sequentially enter a takeover contest. If the bidders are similar, their private values of a target are correlated. After observing the initial bid, the second bidder may decide to pay an entry cost to learn its valuation and to participate in the contest. Entering takeover contests is costly since information on target value requires due diligence costs such as fees for consultants, lawyers and investment bankers. The first bidder may offer a high (preemptive) bid in an attempt to deter the competing firm from entering. Alternatively, a low (accommodating) offer by the first bidder may induce entry by the second bidder and

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[3] Boone and Mulherin (2008) use an extensive data set on potential bidders and control for the endogeneity between returns and the level of competition. Some earlier studies using less detailed data sets show either no significant relation (Kale, Kini, and Ryan, 2003; Betton, Eckbo, and Thorburn, 2008) or mixed results (Schwert, 2000).

[4] Bidder size is responsible for a large portion of variation in returns (Moeller, Schlingemann, and Stulz, 2004, 2005). Acquirers with more uncertain growth prospects gain less in acquisitions (Moeller, Schlingemann, and Stulz, 2007). Furthermore, the premiums paid to targets depend significantly on the public status of acquirers and whether acquirers are operating firms or private equity funds (Bargeron, Schlingemann, Stulz, and Zutter, 2008). Among operating firms, acquirer returns depend on the strategic objectives of acquiring firms (such as vertical integration, horizontal integration, or diversification) (Walker, 2000).

start a competitive auction. The signaling effect of an opening offer depends critically on the similarity between bidders.

The interdependence of bidders' valuations has two opposing effects on contest participation. On the one hand, a bid from a bidder that is similar creates a greater informational externality and thereby encourages entry by a rival. On the other hand, if bidders are more closely related, the bidding contest is expected to be more competitive. The resulting high prices reduce expected payoffs from participation and thus discourage entry. We show that neither of the effects is dominant but their relative strengths depend on the level of similarity and radically affect bidding strategies, price, and bidders' participation. Our analysis provides several important new insights and implications.

First, conditional on observing a takeover, the probability of single-bidder acquisitions and multiple-bidder contests varies in similarity between potential bidders. Multiple-bidder contests are most likely between intermediately similar competitors, due to the strength of informational externalities of initial bids that attracts followers. Initial bids from very similar bidders promise an even higher expected target value, but also indicate a fierce bidding competition. As a result, single-bidder contests are expected mostly between dissimilar (when informational externalities are low) and very similar competitors (when potential competition is high).

Second, expected prices for targets demonstrate an inverted U-shape in the level of bidder similarity. This pattern applies for prices in both single-bidder acquisitions and in multiple-bidder contests. The initial bid embeds informational externalities that signal value, making it attractive for competitors to enter. In single-bidder acquisitions, this means that high preemptive bids are required to deter a competitor that shares some of the sources of value. However, if bidders become very similar, the competition effect on prices starts to dominate informational externalities, and deterrence is possible with a relatively low preemptive bid. When multiple-bidder contests occur, competitive bidding yields higher prices when rivals are more similar. However, when rivals are almost identical, the initial bidder will accommodate only if its valuation is low, but this means that the expected price in the contest will be low as well.

Third, our analysis indicates that in an environment with interdependent values, the similarity of potential bidders is an important measure of competition intensity. Targets' returns are higher in single-bidder acquisitions than in multiple-bidder contests for any given level of similarity because a premium is required to preempt a rival. However, this does not necessarily imply that empirical data should demonstrate higher target returns in single-bidder acquisitions. As discussed above, multiple-bidder contests are most likely at intermediate levels of similarity at which expected prices are the highest. Conversely, single-bidder acquisitions are most likely at very low and very high levels of similarity when expected prices are lower. This implies that, in a cross-section of acquisitions, the relation between the number of bidders and target returns may show either signs if the level of similarity is not controlled for.

The theoretical predictions of the model are difficult to test empirically using historical acquisition data because information about the identity of preempted bidders, and so their similarity with acquirers, is not readily observable by researchers. To overcome this difficulty, we employ a laboratory experiment with financially well-trained subjects. Relative to tests using field data where many relevant factors change simultaneously, controlled environments of laboratory experiments allow for clear comparative static tests. At the same time, laboratory experiments raise questions about external validity—is the behavior of students-subjects informative about investment strategies of firms? We believe that the experiment can inform us about the validity of our theory. First, the academic literature on takeovers shows that *individuals* play an important role in investment and acquisition decisions. CEOs, like all other people, have behavioral biases and these biases not only drive takeovers (Roll, 1986; Berkovitch and Narayanan, 1993), but also affect premiums paid in acquisition (Hayward and Hambrick, 1997; Malmendier and Tate, 2008; Levi, Li and Zhang, 2010). Second, human behavior often deviates from theoretical predictions even in simple auctions [see Kagel (1995) for a survey]. People in general demonstrate systematic biases that may intensify some predicted forces and weaken others. The aim of our experiment is to verify if people respond to the tradeoffs in our model. As such, a laboratory test is a first and important step to validate the relevance of our theoretical predictions to corporate environments.[5]

The experimental design replicates the model specification. Two groups of subjects play the roles of first or second bidder in an auction for a target. Their valuations are correlated with a correlation coefficient called "similarity level". The first bidder chooses his first bid and the second bidder can decide to enter or not depending on the first bid and the similarity level. In this way, we collect data about preemptive bidding behavior and conditional entry decisions.

The experimental results support the main insights of the model. Our first observation is that high first bids deter second bidders from entering in line with the preemption arguments. We then find that the frequency of multiple-bidder contests demonstrates a non-monotonic pattern in similarity levels. Furthermore, prices in both single- and

[5] Several other papers also use experiments to test corporate takeovers theories, e.g., Kale and Noe (1997), Weber and Camerer (2003), Croson, Gomes, McGinn and Nöth (2004), Gillette and Noe (2006), and Kogan and Morgan (2010).

multiple-bidder contents first increase in similarity and then decrease, as predicted by the theory.

This paper is related to the literature on sequential bidding in takeover contests initiated by Fishman (1988). With sequential entry, there is information externality from initial bids. Hence, a high first bid, which signals a high value of initial bidders for the target, can deter competition. Others have extended this model in various directions. Fishman (1989) shows that the medium of exchange can be a supplementary tool for preemption in addition to a high bid. Chowdhry and Nanda (1993) claim that issuing debt commits the bidder to overbidding, which can be preemptive. Burkart (1995), Singh (1998), Bulow, Huang and Klemperer (1999), and Ravid and Spiegel (1999) study overbidding induced by toeholds. Hirshleifer and Png (1989), Daniel and Hirshleifer (1998) explore takeovers from the perspective of efficiency, and find that, although preemption reduces competition, it may raise expected social welfare if bidding is costly. Che and Lewis (2007) apply the preemption model to a policy analysis of lockups, and discuss how lockups affect competition levels and allocation efficiency. Bulow and Klemperer (2009) compare simultaneous auctions and sequential-entry takeover contests and rationalize the target’s preference for auctions rather than for sequential bidding by showing how preemptive bids transfer surplus from sellers to buyers. The model presented here differs from all these papers in that it investigates the impact of similarity between bidders on equilibrium bids, participation, and returns by assuming private correlated values. Our experiment is the first direct test in a controlled environment of the underling model of sequential-entry takeover contrasts.

2.2. A model of takeover contests

2.2.1. Bidders and target values

Two potential bidders, firms A and B, compete to acquire a target.[6] The private values of the target for the two bidders are allowed to be interdependent. The valuation of firm *i* is denoted by v_i, $i = A, B$. Both valuations are drawn from normal distributions with equal means, v_0, standard deviations, σ, and are correlated with coefficient $\rho \geq 0$. f_i and F_i denote probability density and cumulative distribution functions of $\tilde{v}_i$. Below we use the notation $\tilde{v}_A$ and $\tilde{v}_B$ for the random values and v_A and v_B for their realizations to clarify the distinction. The bidders know the distributions of both values, but can observe the realizations of their own values only after conducting costly valuation and cannot directly observe the value realizations of the opponent. Target value without a takeover is equal to v_0. This means that uninformed bidders expect neither to create nor to destroy value in the takeover. The target accepts any offer at or above v_0.

We model the interdependence of values using non-negative correlation instead of the commonly-used affiliation, mostly because correlation is easier to understand for the subjects in our experiment.[7] It is important to understand how to interpret different levels

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[6] Our focus on the single-bidder and two-bidder contests should be not seen as very limiting as few contests have more than two bidders. Bradley, Desai, and Han (1988) report only eight instances of more than two public bidders in their sample of 286 contests. The number of *potential* bidders may be higher, but Boone and Mulherin (2008), who also identify potential bidders that did not publicly place a bid, provide evidence that our assumption is close to reality in most situations. They show that the average number of potential buyers (those signing confidentiality agreements to access non-public information about the target) is 3.14 (median 1), of private-bid bidders is 1.24 (median 1) and of public-bid bidders is 1.12 (median 1). The low numbers also indicate that it should be relatively easy for firms to identify other potential buyers.

[7] Note that affiliation is a subset of positive correlation.

of the correlation coefficient. The correlation between bidders' valuations reflects the degree of similarity of the rival bidders' resources, capabilities, and post-acquisition strategies. More specifically, we have the following examples in mind. Private equity funds often have very similar post-acquisition strategies and are therefore likely to face high correlation between valuations. For example, in leveraged buyouts, the added value is mainly generated by tax shields, high managerial participation, improved monitoring stemming from concentrated ownership and the disciplining effect of leverage. These value drivers are relatively homogenous and can be obtained by a number of capable investors. Strategic buyers are more heterogeneous as they may have built up unique assets and are likely to create unique synergies that depend on the bidders' assets and resources and their match with the target. Clearly, in some such cases the correlation may be positive and high (e.g., two industry competitors competing for a horizontal merger with a third firm), but in other situations it can be much lower (e.g., an industry leader aiming at horizontal integration and industry consolidation competing against an industry supplier aiming at limiting bargaining power). Zero correlation can be expected if two bidders derive values from a completely different match of resources or industry forces, for example, a hostile bidder with an asset-stripping strategy and a strategic bidder valuing the target as a going concern.

2.2.2. Bidding and payoffs

We consider the following bidding contest. First, bidder A finds a potential target that is suitable for acquisition. Following Fishman (1989), we assume that there are few potential targets so that it is not profitable for acquirers to perform costly due diligence on random firms. Bidder A pays entry cost c_A to get informed about its private valuation v_A of the target. Next, if v_A exceeds the seller's reservation price, v_0, then bidder A places an initial offer *b*. If bidder A does not place a bid, the contest is over, as bidder B does not know the potential target. After observing *b*, bidder B decides whether to enter the contest and to learn its valuation v_B of the target. We denote bidder B's decision by $e_B \in \{0,1\}$, where $e_B = 0$ indicates that bidder B does not enter the contest and $e_B = 1$ indicates that bidder B pays entry cost c_B and learns v_B. Finally, if bidder B enters, the price is determined by an English auction. This means that the bidder with the highest valuation wins the auction and pays the value of the losing bidder.[8,9]

Entry is assumed to be costly. The entry costs of both bidders include due diligence costs required to learn the value of the target in acquisition. This includes fees to consultants and investment bankers but also other costs such as disclosure costs, financing fees, or opportunity cost of management time. In effect, we assume that a bidder can participate in the takeover contest only if it pays the entry cost. We simplify the analysis and assume that the entry cost of bidder A, c_A, is sufficiently low so that bidder A always performs due diligence if it identifies a potential target. Because the game is trivial if bidder A does not place a bid, this is with little loss of generality.

In the game after bidder A's entry, we derive equilibrium decisions of bidder A to place the initial bid and of bidder B to enter the takeover contest. This signaling game can

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[8] English auction is also assumed to represent a sequential bidding contest in takeovers in other related studies (Fishman, 1988; Chowdhry and Jegadeesh, 1994; Burkart, 1995; Bulow, Huang, and Klemperer, 1999; and Ravid and Spiegel, 1999; Che and Lewis, 2007). English auction in our model also ensures that the target is sold to the bidder with highest valuation. This is consistent with legal requirements on target management to solicit the highest tender price (see Che and Lewis, 2007).

[9] We note that in our setup a clock auction and an action allowing for jump bidding are equivalent; it is always a dominant strategy to bid up to one's value.

have multiple equilibria. We focus on the perfect Bayesian equilibrium that is most profitable for bidder A. This is equivalent to selecting the perfect sequential equilibrium or the one satisfying the credibility refinement.[10]

With this game specification, we can determine the bidders' payoffs contingent on their valuations and actions. Denote by $\pi_i(v_A, v_B, b, e_B)$ the payoff of bidder i as a function of $v_A, v_B, b,$ and e_B. The payoff function of bidder A, if it places a bid, can be written as

$$\begin{aligned} &\pi_A(v_A, v_B, b, 0) = v_A - b - c_A; \\ &\pi_A(v_A, v_B, b, 1) = \begin{cases} v_A - b - c_A & \text{if} \quad v_B \leq b \\ v_A - v_B - c_A & \text{if} \quad b < v_B \leq v_A \\ -c_A & \text{if} \quad v_B > v_A. \end{cases} \end{aligned} \tag{1}$$

Upon winning the contest, bidder A receives the payoff equal to its valuation of the target v_A minus the price paid and minus the entry cost. The winning bidder pays the value of the losing bidder, so the price paid by winning bidder A if $b < v_B \leq v_A$ is v_B. Bidder A loses the contest if $v_B > v_A$ and its payoff is then just $-c_A$. Similarly, bidder B's payoffs are the following:

$$\begin{aligned} &\pi_B(v_A, v_B, b, 0) = 0; \\ &\pi_B(v_A, v_B, b, 1) = \begin{cases} -c_B & \text{if} \quad v_B \leq v_A \\ v_B - v_A - c_B & \text{if} \quad v_B > v_A. \end{cases} \end{aligned} \tag{2}$$

[10] The equilibrium selection follows Fishman (1988). See also Che and Lewis (2007) and Bulow and Klemperer (2009, footnotes 11 and 21) for more detailed discussions.

2.2.3. Informational externalities and competition

We take a first look at the influence of bidder A's offer on bidder B's beliefs and payoff. An important observation is that the expected payoff may either increase or decrease in the level of similarity between the valuations. Intuition suggests that there are two effects due to correlated valuations. First, if valuations are dependent, then the second bidder can infer some information about its own value of the target from the first offer. Second, if both bidders enter the contest, the level of similarity will affect the competitiveness of the contest and the price paid by the winning bidder. We refer to the former effect as the informational externality effect and to the latter as the competition effect.

Suppose now that bidder A's strategy is fully revealing. From observing a bid b, bidder B can exactly infer the realization of bidder A's value v_A. In other words, we assume here that bidder A's strategy is separating and each valuation realization stipulates a different bid. Because v_A and v_B are correlated, information about the realization of v_A affects the posterior distribution of v_B. Given bidder A's value v_A, the posterior distribution of the value of bidder B is again normal with probability density function denoted by $f_{B|A}$. The expected value is updated to

$$\mu_{B|A} = E\left[v_B \mid v_A\right] = \rho v_A + (1-\rho)v_0. \tag{3}$$

It follows from (3) that the informational externality effect of increasing ρ on bidder B's expected value is positive for all ρ as long as $v_A > v_0$. Because bidder A places a bid only if v_A exceeds v_0, the informational externality effect encourages bidder B to participate and bidder B is better off with a correlation with bidder A that is as high as possible.

The posterior standard deviation of v_B is updated to $\sigma_{B|A} = \sigma\sqrt{1-\rho^2}$. It is the largest at $\rho = 0$ and decreases as the value of ρ increases. The posterior standard deviation is related to the competition effect and it works through the expected payoff that bidder B obtains from entering the contest. If bidder B knows the realization of v_A, this payoff is given by

$$\begin{aligned} E\left[\pi_B(v_A, \tilde{v}_B, b, 1)\right] &= -\int_{-\infty}^{v_A} c_B f_{B|A}(v)dv + \int_{v_A}^{\infty} \left(v - v_A - c_B\right) f_{B|A}(v)dv \\ &= \sigma\sqrt{1-\rho^2}\left[\phi(z_A) - z_A(1-\Phi(z_A))\right] - c_B, \end{aligned} \tag{4}$$

where $z_A = (v_A - \mu_{B|A}) / \sigma_{B|A}$, and ϕ and Φ denote probability density and cumulative distribution functions of the standard normal distribution.

To isolate the competition effect, we set $v_A = v_0$, at which the informational externality effect is absent. Taking the derivative of (4) with respect to ρ, we obtain

$$\frac{-\rho}{\sqrt{1-\rho^2}} \frac{\sigma}{\sqrt{2\pi}}. \tag{5}$$

The sign of this expression—reflecting the competition effect of similarity—is negative if $\rho > 0$. When taking into account only the competition effect, bidder B prefers the correlation to be equal to zero. Intuitively, if both bidders enter the contest and their valuations are not dispersed, then they outbid each other to the point that the expected price paid by the winning bidder is close to its value. In other words, given the mean of its valuation, bidder B prefers to have the highest variance. The effect is caused by the convexity of bidder B's payoff function in its valuation of the target, so that a higher posterior variance $\sigma^2_{B|A}$ leads to higher expected payoffs.

With the assumption of this subsection that v_A is observable, neither the informational externality effect nor the competition effect dominates for all levels of similarity. The derivate of the expected payoff of bidder B from entering (given in (4)) with respect to ρ includes both effects and is given by

$$\frac{\sigma}{\sqrt{1-\rho^2}}\left[-\rho\phi(z_A)+(1-\rho)z_A\left(1-\Phi(z_A)\right)\right]. \tag{6}$$

It is easy to establish that this expression is positive for relatively small positive ρ (the positive informational externality effect dominates the negative competition effect), and is negative for large positive ρ (the negative competition effect dominates the positive informational externality effect).

The preceding discussion clearly conveys the intuition for the two effects of similarity, but the separating strategy of bidder A that fully reveals its valuation cannot be sustained by an equilibrium. The next section analyzes strategies of both bidders that can form equilibrium.

2.3. Bidders' strategies and equilibrium

2.3.1. Bidder A: to preempt or to accommodate

We restrict our attention to cut-off pure strategies in which bidder A with valuations within a certain set places a specified bid. These strategies have a clear interpretation in our bidding game: preemption and accommodation. With a preemptive bid, the expected payoff for the second bidder is sufficiently low so that it is deterred from entering. An accommodating bid does not attempt to limit participation of the follower. If bidder A preempts with a bid *b*, its expected payoff is given by

$$E[\pi_A(v_A, \tilde{v}_B, b, 0)] = v_A - b - c_A. \tag{7}$$

If bidder A accommodates, it cannot gain anything from bidding above the reservation value, so its bid is equal to v_0 and its expected payoff is

$$\begin{aligned} E[\pi_A(v_A, \tilde{v}_B, v_0, 1)] &= \int_{-\infty}^{\infty} \pi_A(v_A, v, v_0, 1) f_{B|A}(v) dv = \int_{-\infty}^{v_0} (v_A - v_0 - c_A) f_{B|A}(v) dv \\ &+ \int_{v_0}^{v_A} (v_A - v - c_A) f_{B|A}(v) dv + \int_{v_A}^{\infty} -c_A f_{B|A}(v) dv \\ &= \sigma\sqrt{1-\rho^2}\left[\phi(z_A) - \phi(z_0) + z_A \Phi(z_A) - z_0 \Phi(z_0)\right] - c_A, \end{aligned} \tag{8}$$

where $z_A = (v_A - \mu_{B|A}) / \sigma_{B|A}$ and $z_0 = (v_0 - \mu_{B|A}) / \sigma_{B|A}$.

Bidder A will be willing to preempt with a bid b if the expected payoff from preemption exceeds or equals the expected payoff from accommodation, that is if

$$V(v_A, b) \equiv E[\pi_A(v_A, \tilde{v}_B, b, 0)] - E[\pi_A(v_A, \tilde{v}_B, v_0, 1)] \geq 0. \tag{9}$$

Conversely, if $V(v_A, b) < 0$, then bidder A is better off with accommodation. Denote by $\bar{b}(v_A)$ the maximum bid that bidder A with value v_A is willing to offer to preempt bidder B. This means that with a bid at $\bar{b}(v_A)$, the condition in (9) holds in equality. Substituting (7) and (8) into (9), we obtain that

$$\bar{b}(v_A) = v_A - \sigma\sqrt{1-\rho^2}\left[\phi(z_A) - \phi(z_0) + z_A \Phi(z_A) - z_0 \Phi(z_0)\right]. \tag{10}$$

For a given preemptive bid b, bidder A's incentive for accommodation or preemption depends on the realized value of v_A . If $b \leq \bar{b}(v_A)$, then the expected payoff from preemption is larger than that from accommodation, and the opposite relation holds if $b > \bar{b}(v_A)$. In the Appendix we prove that the following result holds given that $\rho \geq 0$.

Lemma 1. $\bar{b}(v_A)$ increases in $v_A \geq v_0$.

The implication of the lemma is that for a given preemptive bid b, such that $b = \bar{b}(\underline{v})$, bidder A with valuation larger than or equal to $\underline{v}$ prefers to preempt rather than to accommodate. This observation justifies our focus on cut-off accommodation and preemption strategies of bidder A.

2.3.2. Bidder B: to participate or to stay out

We consider here bidder B's expected payoff when bidder A uses a cut-off strategy. Suppose a bid b is chosen if the realized valuation of bidder A lies in between some $\underline{v}$ and $\bar{v}$. Denote by $W(\underline{v}, \bar{v})$ bidder B's expected payoff if it decides to enter the contest (as long as bid b is lower than $\underline{v}$, which is the case in equilibrium, this value depends only on the implied valuations of bidder A, not on the bid itself). Then

$$W(\underline{v}, \bar{v}) = \frac{1}{F_A(\bar{v}) - F_A(\underline{v})} \int_{\underline{v}}^{\bar{v}} E[\pi_B(v_A, \tilde{v}_B, b, 1)] f_A(v_A) dv_A \ . \tag{11}$$

Bidder B is deterred by the set of bidder A with valuations in $(\underline{v}, \bar{v})$ if $W(\underline{v}, \bar{v}) \leq 0$. If this is the case, then bidder B's payoff from entering falls below its payoff from staying out, which is equal to zero.

From Section 3.1 we know that for $\rho \geq 0$, bidder A's incentives to preempt increase in its own valuation. Therefore bidder A uses a preemptive strategy if its valuations are above some $\underline{v}$. A preemptive strategy works only if it implies that bidder B does not enter, that is, that the expected payoff of bidder B from entering W is non-positive. The following lemma shows that the cheapest such strategies (with W equal to zero) are unique.

Lemma 2. There exists at most one $\underline{v} \geq v_0$ that solves $W(\underline{v}, \infty) = 0$.

Let us define v_L such that $W(v_L, \infty) = 0$. v_L is the lowest value such that information that $v_A \geq v_L$ deters bidder B from the contest.

The incentives of bidder B to enter are influenced by the informational externality and competition effects. If the negative effects of similarity dominate, bidder B may easily be deterred. In particular, in some cases, bidder B may be deterred by information that v_A exceeds the reservation value, $v_A \geq v_0$, inferred from observing bidder A placing *any* bid. The following lemma specifies when this is the case.

Lemma 3. Let $R = \sqrt{2\pi} c_B / \sigma$ and assume that $2R < 1$. If bidder B believes that $v_A \geq v_0$, then bidder B does not enter the contest whenever $\rho < \rho_1 = R - \sqrt{1-2R}$ or $\rho > \rho_2 = R + \sqrt{1-2R}$.

We assume from now on that $2R < 1$ to focus on interesting cases. If this condition is not satisfied, then bidder B does not participate after a bid from A for any possible value of ρ.[11] Lemma 3 states that if bidder B's only information is that bidder A's valuation exceeds the reservation price v_0, it may still be sufficient as a deterrent if the valuations

[11] The condition is a result of the requirement that $W(v_0, \infty)$ is positive at least for some values of ρ.

are interdependent with a low correlation coefficient, $\rho < \rho_1$, or if the valuations are strongly positively correlated, $\rho > \rho_2$. Intuitively, a high value of v_A together with a low correlation promises a low expected value of v_B. For example, consider the extreme case with $\rho = -1$. Then $v_A > v_0$ implies $v_B < v_0$ and bidder B makes sure losses with any positive entry cost. On the other hand, a high value of v_A with a high correlation leaves little profit to be earned in the subsequent auction, because values of both bidders are expected to be similar. At the extreme point as $\rho = 1$, v_B is equal to v_A with probability one, and after entry the price paid is equal to the value, which leaves no profit. At very low and very high correlation, expected payoffs do not compensate the entry cost. We note that for positive c_B and $2R < 1$, both ρ_1 and ρ_2 are inside the domain for a correlation coefficient and are such that $-1 < \rho_1 < 0.5 < \rho_2 < 1$.

2.3.3. Equilibrium

Equilibrium strategies consist of bidder A's initial bidding strategy b and bidder B's entry strategy e_B. In the previous subsections, we outlined the derivation of the strategies in the signaling equilibrium involving the most profitable outcome for bidder A. These strategies can be interpreted as accommodation with a bid at the reservation price that induces entry of the competitor and as preemption with a bid at a premium over the reservation price that deters the other contestant. In some cases, a deterring bid is placed that, while low at the reservation price, effectively deters the competitor.

For example, in the case of the preemptive outcome, the equilibrium is constructed as follows. We have shown that there is a threshold v_L such that bidder A with $v_A \geq v_L$ places a preemptive bid and deters bidder B. For this bid not to be imitated by bidder types with $v_A < v_L$, it must be at least $\bar{b}(v_L)$. Bidder A with valuations $v_A < v_L$ cannot match this bid and offers the lowest price v_0 which invites the second bidder. These results are gathered in the following proposition.[12]

Proposition 4. In the game after bidder A enters, there exists equilibrium (b^*, e_B^*) in cut-off strategies with the following properties. If $v_A \geq v_0$, then bidder A places a bid and there are two cases.

1. If $0 \leq \rho < \rho_2$, then

$$b^*(v_A) = \begin{cases} \bar{b}(v_L) & \text{if} \quad v_A \geq v_L \\ v_0 & \text{if} \quad v_0 \leq v_A < v_L, \end{cases}$$

$$e_B^*(b) = \begin{cases} 1 & \text{if} \quad b < \bar{b}(v_L) \\ 0 & \text{if} \quad b = \bar{b}(v_L); \end{cases}$$

2. If $\rho \geq \rho_2$, then $b^*(v_A) = v_0$ and $e_B^*(b) = 0$.

Figure 2.1 presents how the equilibrium strategies depend on the level of correlation between the valuations. There are four possible scenarios depending on the correlation ρ and the first bidder's valuation v_A. In Region 1 at intermediate levels of correlation, bidder A preempts bidder B with a high bid. This happens for sufficiently high values v_A such that $v_A \geq v_L$. In Region 2 at intermediate levels of correlation and at low valuations (but

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[12] For transparency, Proposition 4 is stated for the case $\rho_1 < 0$. Using Lemma 3, it holds if $R < \sqrt{2} - 1$. The proposition can be adapted to the other case in the obvious way.

above v_0), bidder A accommodates. With increasing correlation, the accommodation strategy is first supported by increasing valuations (preemption is difficult due to the informational externality effect). Then with increasing correlation, preemption becomes easier (due to the competition effect) and accommodation is used only by bidder A with relatively low values.[13] In Region 3, the bidders are so similar that it does not pay for bidder B to engage in a costly bidding contest. In Region 4, the bidders are so dissimilar that if the target is sufficiently attractive for the initial bidder to place a bid, then bidder B's expected payoff is too low to participate.

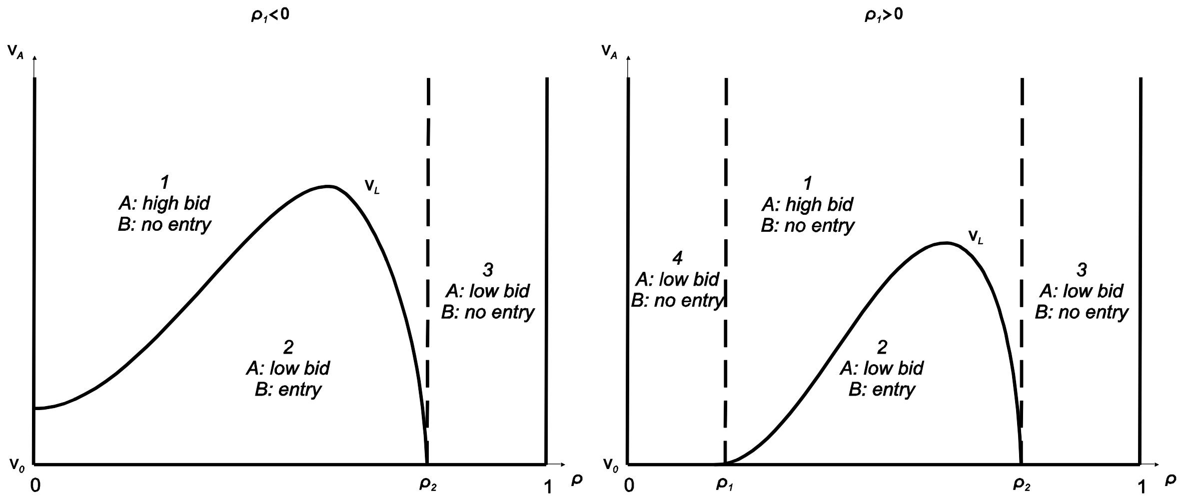

Figure 2.1. Equilibrium strategies in the bidding game (with bidder A participating) for various correlations ρ and bidder A's valuations v_A . The figure on the left presents the case of $\rho_1 \leq 0$ and the one on the right presents the case of $\rho_1 > 0$. Regions 1-4 specify qualitatively different strategy pairs.

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[13] See the Appendix for a proof that v_L is always non-monotonic in ρ, increasing for low correlation and decreasing for high correlation.

2.4. Model implications

Similarity between bidders generates the trade-off between the informational externality of the initial bid and competition intensity. The interaction of these two forces leads to a non-monotonic relationship of the correlation coefficient on acquisition strategies and returns. Figure 2.2 presents numerical comparative statics with respect to the correlation coefficient between bidders' valuations. Other exogenous parameters are set at $\sigma = 20$, $c_B = 2$, and $v_0 = 50$. These parameters are later used in our experiments. Figures 2.2.A and 2.2.B present the probabilities of observing either a single-bidder contest or a multiple-bidder contest conditional on observing a takeover. The probability of single-bidder contests is non-monotonic and has a U-shape. The complementing probability of two-bidder contests is then also non-monotonic and has an inverted U-shape. The two-bidder contests are mostly observed at intermediate positive correlation. The intuition is that it is most difficult to deter the second bidder at these levels of correlation—the information externality is strong enough to attract followers and the post-entry competition is not yet to fierce—and only the highest valuations of the first bidder can serve as an effective deterrent.

Figures 2.2.C and 2.2.D plot the expected prices paid for the target in single-bidders contests and multiple-bidder contests. Contingent on observing a single-bidder contest, the offered price has an inverted U-shape in bidder similarity. This non-monotonic effect is driven by the fact that low initial bids may deter competition if the potential competitors are very similar (post-entry bidding competition makes entry unattractive) or very dissimilar (the initial bid does not convey much of positive information to potential followers about their valuation of the target). Similarly, contingent on observing a two-bidder contest, the expected price paid by the winning bidder has an inverted U-shape in bidder similarity. The prices are the lowest for very similar and very dissimilar bidders because multiple-bidder contests arise in these cases only when bidders have low valuations for the target (the first bidder cannot afford to place relatively low preemptive bids).

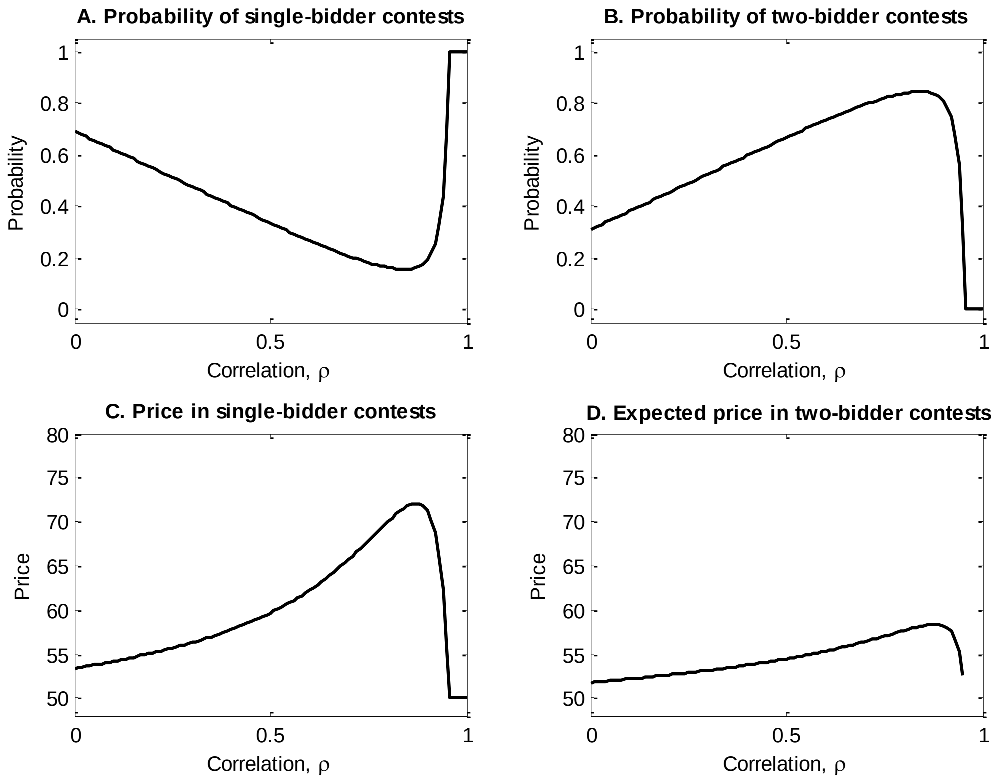

Figure 2.2. Non-monotonic effects of correlation ρ . The figures present the probability of single-bidder contests (A), the probability of two-bidder contests (B), the price in single-bidder contests (C), and the expected price paid in a two-bidder contest (D) for different levels of the correlation coefficient between the bidders' valuations. All the values are calculated for $\sigma = 20$, $c_B = 2$, and $v_0 = 50$.

The expected final price in two-bidder contests is lower that the preemptive bid in single-bidder acquisitions for any given correlation. This is because accommodating bids are offered by bidder A only when it has a relatively low valuation or when it expects weak competition. However, two-bidder contests are most likely when the expected prices in two-bidder contests are high, and single-bidder contests are most likely when the prices in single-bidder contests are low. This may explain why empirical evidence of the effects of competition measured by the number of bidders on target returns is inconclusive and frequently demonstrates a puzzling lack of any significant relation. The analysis indicates that the effect of the number of bidders should be controlled for the level of similarity.

2.5. The experimental setup

As discussed in the introduction, testing the model's predictions with historical field data is difficult because the identity of preempted bidders, and so their similarity with acquirers, is not observable to researchers. To address this problem and to offer a first test of the model's trade-offs, we use experimental data in which we can control the combinations of competing bidders and other characteristics of the environment. Specifically, we design a computerized laboratory experiment in which we recreate the exact setting of the model. In different treatments, we change only the level of interdependence between bidders' valuations and keep all other variables constant.

2.5.1. Treatments and hypotheses

The parameters in the experiment are chosen to replicate a takeover opportunity with uncertain value and with sufficient potential profits to make the investment attractive. The mean target value is set at $v_0 = 50$, the standard deviation of the bidders' valuation, σ, equals 20, and the entry cost, c, equals 2. When there is no rival, this parameter setting leads to an expected payoff of about 30 to a bidder if he or she enters. With competing bidders, the expected payoff of the initial bidder will vary depending on the intensity of competition and the strategies bidders adopt.

We set up three treatments that differ in the level of correlation between bidders' valuations. The correlations are 0, 0.5, and 0.95. These levels are sufficiently different to represent three typical takeover contests. In the low similarity treatment (with correlation equal to 0), bidders' valuations are independent. This is as in the standard Fishman (1988) model and we interpret this case as a contest between a strategic bidder and a financial bidder. The intermediate similarity treatment (with correlation equal to 0.5) represents the case of two strategic bidders. The high similarity treatment (with correlation equal to 0.95) represents the case in which bidders' valuation are highly dependent with each other as in bidding between two financial bidders.

The three treatments generate qualitatively distinctive equilibrium strategies. Table 2.1 reports the theoretical predictions for equilibrium strategies and outcomes. At low similarity, the minimum bid that can preempt bidder B is 53 and when bidder A's value is above 58, he chooses to offer this preemptive bid. This implies that single-bidder contests are expected in 66% of observed takeovers and that the average price in two-bidder contests is about 51. At intermediate similarity, bidder A makes a preemptive bid equal to 60 when his value is above 69 and the proportion of single-bidder contests is significantly lower at 30%, while prices in two-bidder contests are higher at 54. At high similarity, the proportion of single-bidder contests increases to 70%, bidder A will make a preemptive bid of 56 when his value is above 58, and the average price in two-bidder contests decreases slightly to 53. The model predicts a non-monotonic pattern in the proportion of single-bidder contests and acquisition prices. This leads to three testable hypotheses.[14]

[14] We do not specify a separate hypothesis for preemption values. First, preemption values used by bidder A are not directly observable in the experiment. Second, in the theory, preemption values measure the same behavior as the proportion of single-bidder contests. The proportion of single-bidder contests is the proportion of bidder A's distribution that falls above preemption value.

Hypothesis 1. The proportion of single-bidder contests is higher in the low and high treatments than in the intermediate treatment.

Hypothesis 2. Acquisition prices in single-bidder contests in the low and high similarity treatments are lower than in the intermediate treatment.

Hypothesis 3. Acquisition prices in two-bidder contests in the low and high similarity treatments are lower than in the intermediate treatment.

Table 2.1. Theoretical predictions in the three treatments.
Single-bidder contests denotes the proportion of contests in which bidder B does not participate; *Price in single-bidder contests* denotes the level of the first bid that deters bidder B from entering (preemptive bid); *Price in two-bidder contests* denotes the average price in cases where bidder B enters; and *Preemption value* denotes the level of the first bidder valuation above which he decides to place a preemptive bid. The numbers are rounded to integer values.

Similarity treatment	Single-bidder contests[a]	Price in single-bidder contests	Price in two-bidder contests	Preemption value
Low	66%	53	51	58
Intermediate	30%	60	54	69
High	70%	56	53	58

[a] Based on the generated data used in this experiment. The predictions based on the exact theoretical distribution are 67%, 34%, and 67% for Low, Intermediate and High treatments, respectively.

2.5.2. Experiment implementation

We carried out the experiment in the Erasmus University Behavioural Lab with subjects that are master-level students in economics and finance. 36 subjects took part in the experiment in two identical sessions with different subjects: 20 in a first session and 16 in a second session.

In each session, the bidding game was repeated in 30 rounds. Additionally, the subjects first played six unpaid practice rounds to learn about the experimental setup and the game. Our experiment comprised 540 rounds in total. At the beginning of each session, participants were randomly assigned to play a role throughout the entire session: either "first bidder" or "second bidder". Each first bidder was randomly paired with a second bidder in each round to avoid learning bidder characteristics. This was aimed to facilitate the perception of a series of one-shot games.

The sequence of the game was as follows. At the beginning, both bidders were informed about the level of their similarity. The first bidder was assigned his or her valuation of the target and the entry fee was deducted from its account. Next, the first bidder submitted a bid. After observing the first bid and similarity level, the second bidder chose whether to enter or not. If he entered, the entry fee was deducted from his current account and his valuation of the target was revealed. Then the outcome of the auction was automatically determined by an English auction rule – the bidder with the highest valuation bought the target for the second highest bid.[15] If instead the second bidder chose not to enter, the game ended and the first bidder bought the target with his first bid.

Each bidder's valuation of the target was private information. The similarity level and the distribution of bidders' valuations were known to both bidders. It was also known that the target would not sell below a reservation price of 50. In every round, the first bidder was assigned a new random valuation drawn from normal distribution with a mean of 50 and a standard deviation of 20. The first bidder will only observe his value if it is no less than 50, because otherwise no contest is initiated.[16] The value for the second bidder was drawn from another normal distribution with a mean of 50 and a standard deviation of 20.

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[15] The second highest bid is defined as the second highest value in {the first bidder's valuation, the second bidder's valuation, the first bid}.

[16] Alternatively, we could have used a full normal distribution and removed half of the rounds which involved no actions and had no information.

The second bidder's valuation was correlated with the normal distribution underlying the first bidder's valuation with a coefficient equal to the similarity level. To ensure that participants understood the distribution of bidders' valuations and their interdependent nature, numerical examples were given for different similarity levels.[17]

Each pair of bidders in each round was assigned with a new similarity level drawn from the set {0, 0.5, 0.95} with equal probability. To control for learning across different similarity levels, the sequence of similarity levels was selected randomly. The experimental sessions lasted about two hours and the final payoffs in the experiment were determined by the performance of the participants and by their roles. The accumulated payoffs were recorded by points they earned or lost, with a conversion rate of €1 for every 20 points. Because of the entry fee, the bidders that lost an auction incurred a net loss. To prevent bankruptcy, each bidder was given 60 initial points, which was just sufficient to cover the entire entry fee if he bid in every round. Furthermore, the second bidders were given an additional fixed payment of €5 to compensate for their disadvantaged initial position compared to the first bidders. The range of actual earnings paid to the first bidder was €5.90-17.00, with a mean of €9.00; the range of actual earnings paid to the second bidder was €7.70-10.90, with a mean of €9.00[18].

[17] The full experiment instructions can be found at the online appendix.

[18] The payment level in our experiment is not high. As experimental literature shows that subject performance can be affected by compensation level (Smith, Walker, 1993; Gneezy, Rustichini, 2000), we add one more session by increasing conversion rate between experimental points and euro from 20:1 to 8:1. Sixteen subjects participated in this new session, and the payment ranges from €13.9 to € 33.6 with an average of € 22.3. Results are similar to the original sessions, which suggest non-monotonic patterns in entry and bidding behaviour. Because of the different compensation structure, experiment outcome from high payment session is not reported here. Extra analysis on these additional data will be provided upon request.

2.6. Experimental results

We start with an overview of aggregate bidder behavior in different treatments. Table 2.2 presents descriptive statistics of the results. Panel A shows that the first bid in the single-bidder contests is higher than that in the two-bidder contests. The differences are highly significant in all treatments. We take this finding as reassurance that first bids can be preemptive and most subjects were responding sensibly within our experiment.

Table 2.2. Descriptive statistics of the experimental results.
Statistics are calculated from 540 experimental observations. In Panel A, the data are split into two subgroups depending on the number of bidders active in the contest. Columns report the percentage of the two types of contests (*Proportion*) and the mean of the first bids (*First bid*) and prices across the three treatments. The last two columns present the difference in first bids across the two types of contests and t-statistics for differences between means. Panel B reports t-statistics for differences between means of the proportion of and prices paid in two types of contests across the three treatments. Parentheses report number of observations or standard errors.

Panel A: Statistics for each contest outcome

Similarity treatment	Single-bidder contests		Two-bidder contests			First bid difference	
	Proportion	First bid [=Price]	Proportion	First bid	Price	Mean	t-stat
Low	27% (N=48)	56 (0.93)	73% (N=132)	52.48 (0.33)	55.97 (0.56)	3.52 (0.79)	4.47
Intermediate	22% (N=39)	58.79 (1.28)	78% (N=141)	53.81 (0.43)	57.82 (0.73)	4.99 (1.05)	4.73
High	39% (N=70)	60.8 (1.42)	61% (N=110)	56.04 (0.71)	61.78 (0.95)	4.76 (1.44)	3.31

Panel B: Differences between treatments

Comparison pair	Proportion of single-bidder contests		Price in single-bidder contests		Price in two-bidder contests	
	Mean	t-stat	Mean	t-stat	Mean	t-stat
Low – Intermediate	5% (4.50%)	1.11	-2.79 (1.54)	-1.81	-1.85 (0.92)	-2.01
High – Intermediate	17% (4.80%)	3.56	2.01 (2.13)	0.94	3.96 (1.17)	3.38

Panel B of Table 2.2 provides some support to the theoretical predictions for the proposed effects of similarity between bidders. The proportion of single-bidder contests is moderately lower in the intermediate similarity treatment compared to the low similarity treatment, while the percentage of single-bidder contests in the high similarity treatment is significantly higher than that in the intermediate treatment. The U-shape across the three treatments is in line with Hypothesis 1. The mean price paid in single-bidder contests is lower in the low treatment than in the intermediate treatment (significant at the 5% level), which is consistent with Hypothesis 2. The mean price paid in the high similarity treatment is higher than in the intermediate treatment, at odds with Hypothesis 2; the difference is, however, not significant. The mean prices paid in two-bidder contests exhibit similar pattern. Compared to the intermediate treatment, the low treatment is characterized with lower mean price, which confirms the prediction in Hypothesis 3, while the high treatment has the highest mean price, deviating from Hypothesis 3.

2.6.1. H1: proportion of single-bidder contests

The second bidder knows only the first bid and the similarity level before he decides whether to participate in the contest. To explain the binary participation decision in a regression analysis, we use these two variables as explanatory variables. Furthermore, considering that the participation decision may also be affected by individual characteristics, we adopt a random-effect probit regression with an individual specific term included in the disturbance. Specifically, we estimate the following model:

$$y_{jt}^* = \gamma_0 + \gamma_1 First\ Bid_t + \gamma_2 Low_t + \gamma_3 High_t + \eta_j + \varepsilon_{jt}$$
$$y_{jt} = \begin{cases} 1 & \text{if} \quad y_{jt}^* \geq 0 \\ 0 & \text{if} \quad y_{jt}^* < 0 \end{cases}$$

where y_{jt}^* is a latent variable, and y_{jt} is the observed participation decision of j^{th} second bidder in round t (with 1 denoting non-participation and 0 participation). Variable $First\ Bid_t$ is the first bid of the first bidder in round *t*. Variables Low_t and $High_t$ are two dummies indicating the low similarity and the high similarity treatments, respectively. We take intermediate similarity as a reference treatment. If the proportion of single-bidder contests indeed exhibits a U-shape, both γ_2 and γ_3 are expected to be positive. Finally, η_j is an individual random effect of subject *j* and ε_{jt} is a residual error term; both are assumed to be normally distributed with a mean zero.

Table 2.3. Random-effects probit regression on proportion of single-bidder contests.

Regression is done on all experimental data, with a sample size equal to 540. The dependent variable takes a value 1 if the second bidder does not participate in the contest and 0 otherwise. *First Bid* is the first bid of the first bidder. *Low* and *High* are dummies for the similarity treatments. The second column reports estimated coefficients and standard errors. The third column reports predicted signs and t-statistics.

Variable	γ estimate (std. err.)	Predicted sign (t-stat)
First Bid	0.06 (0.01)	$H_0:\ \gamma_1 > 0$ (6.53)
Low	0.31 (0.17)	$H_0:\ \gamma_2 > 0$ (1.86)
High	0.52 (0.16)	$H_0:\ \gamma_3 > 0$ (3.19)
Constant	-4.55 (0.61)	--

Estimation results are presented in Table 2.3. The positive sign of the coefficient of FirstBid confirms that the probability of successful preemption is increasing in the first bid. Furthermore, the positive signs of the coefficients of Low and High indicate that the probabilities of being preempted in the low and high similarity treatments are higher than in the intermediate similarity treatment. All the estimates of γ are significantly positive. Therefore, the response of the second bidder is consistent with Hypothesis 1. It seems that the second bidders respond to the tradeoff between similarity effects. Low information externality in the low similarity treatment apparently discourages the second bidder from entering. The strong competition effect in the high similarity treatment can also be discouraging. On the contrary, the second bidder is less likely to be preempted in the intermediate treatment because the information externality is relatively large while the competition is not very high.

2.6.2. H2: prices in single-bidder contests

If the second bidder is preempted, prices in single-bidder contests are equal to the first bidder's preemptive bids; if the second bidder enters, prices in two-bidder contests are equal to the highest among bidders' valuations. That is, the determination of final price essentially switches between two pricing regimes depending the successfulness of preemption:

$$Price_{ijt} = \begin{cases} Price1_{ijt} = \beta' X_t + v_{ij} + \epsilon_{ijt} & \text{if} \quad \gamma' Z_t + \eta_j + \varepsilon_{ijt} \geq 0 \\ Price2_{ijt} = \theta' X_t + v_{ij}' + \epsilon_{ijt}' & \text{if} \quad \gamma' Z_t + \eta_j + \varepsilon_{ijt} < 0 \end{cases}$$

Where X_t is the vector of explanatory variables in round t, v_{ij} (v_{ij}')is a random effect of the group consisting of i^{th} first bidder and j^{th} second bidder assumed normal with a mean of 0. Z_t is a vector of explanatory variables in the model of participation of from Section 6.1. Due to the correlation between the second bidder's participation decision and the price formation, estimation of coefficients (β and θ) can be biased because $E(\epsilon_{ijt} \mid \gamma' Z_t + \eta_j + \varepsilon_{ijt} \geq 0) \neq 0$, and $E(\epsilon_{ijt} \mid \gamma' Z_t + \eta_j + \varepsilon_{ijt} < 0) \neq 0$.

To eliminate this selection bias, we apply the Heckman two-step estimation method (Heckman, 1979; Li and Prabhala, 2007). The first step is to conduct a probit regression on the preemption outcomes to estimate γ, which is already done in the previous section.

Denote the inverse Mills ratio by λ_{jt}. $\lambda_{jt} = \phi(\hat{\gamma}' Z_t) / \Phi(\hat{\gamma}' Z_t)$ in single-bidder contests, and $\lambda_{jt} = -\phi(\hat{\gamma}' Z_t) \ /[1-\Phi(\hat{\gamma}' Z_t)]$ in two-bidder contests. The second step is to introduce the inverse Mills ratio as a regressor and run a panel data regression to control for individual effect and time varying error:

$$Price1_{ijt} = \beta_0 + \beta_1 Low_t + \beta_2 High_t + \beta_3 \lambda_{jt} + v_{ij} + \epsilon_{ijt}$$

According to Hypothesis 2, the intermediate treatment should facilitate the highest prices in single-bidder contests. That is, both β_1 and β_2 are expected to be negative. The estimation results are reported in Table 2.4. Both β_1 and β_2 are significantly negative. The first bids in preempted contests exhibit non-monotonic patter, as Hypothesis 2 predicted, with the intermediate treatment yielding the highest price. The experiment outcome, therefore, confirms the comparative statics prediction of Hypothesis 2 across different similarity treatments.

Table 2.4. Linear regression on prices in single-bidder contests.
Only data in single-bidder contests are included, with a sample size equal to 157 observations. The dependent variable is the price paid for the target in single-bidder contests. *Low* and *High* are dummies for the similarity treatments. *Inverse Mills ratio* is estimated based on regression outcomes in Table 2.3, and is negative if the second bidder enters and positive otherwise. The second column reports estimated coefficients and the third column reports standard errors.

Variable	β estimate (std. err.)	Predicted Sign (t-stat)
Low	-5.42 (0.36)	$H_0 : \beta_1 < 0$ (-14.87)
High	-8.41 (0.37)	$H_0 : \beta_2 < 0$ (-22.8)
Inverse Mills ratio	-24.54 (0.35)	--
Constant	92.56 (0.56)	--

2.6.3. H3: prices in two-bidder contests

The next step is to check prices in two-bidder contests. According to Hypothesis 3, the intermediate treatment boasts the highest average price compared to low and high treatments. To test it, we run a similar self-selection regression as above, but the dependent variable changes to prices in two-bidder contests and we use only observations with two-bidder contests. The regression equation is as follows:

$$Price2_{ijt} = \theta_0 + \theta_1 Low_t + \theta_2 High_t + \theta_3 \lambda_{jt} + v_{ij}' + \epsilon_{ijt}$$

$Price2_{ijt}$ denotes prices in two-bidder contests, and Low_t and $High_t$ are two similarity indicators. Again, we control an random effect of group *ij*, v_{ij}', assumed to be normal with a mean of 0.

Table 2.5. Linear regression on prices in two-bidder contests.

Only data in two-bidder contests are analyzed, which include 383 observations. The dependent variable is the price paid for the target in two-bidder contests. *Low* and *High* are dummies for the similarity treatments. *Inverse Mills ratio* is estimated based on regression outcomes in Table 2.3, and is negative if the second bidder enters and positive otherwise. The second column reports estimated coefficients and standard errors. The third column reports predicted signs and t-statistics.

Variable	θ estimate (std. err.)	Predicted Sign (t-stat)
Low	-3.67 (0.86)	$H_0: \theta_1 < 0$ (-4.28)
High	-3.13 (1.06)	$H_0: \theta_2 < 0$ (-2.95)
Inverse Mills ratio	-24.08 (1.92)	--
Constant	51.40 (0.81)	--

As Hypothesis 3 predicts that prices in two-bidder contests in the low and high treatments are lower than in the intermediate treatment, both θ_1 and θ_2 are expected to be negative. Regression results in Table 2.5 provide confirmative evidence to this prediction. Both θ_1 and θ_1 are significantly negative. Again, non-monotonic pattern in prices is supported in two-bidder contests. In addition, coefficients of inverse Mills ratio are both significant at 1% level in Table 2.4 and Table 2.5, which indicate the self-selection effect plays a role in determining prices.

2.6.4. Dynamic session-effects

There are two sessions in our experiment. Observations across subjects of a given session might be more correlated than observations across subjects from different sessions. One possible source of the higher correlation can be that subjects adjust their strategy according to the feedbacks from their previous actions. For example, a successful low bid in a previous round can make the first bidder more likely to submit a low bid in the following round, and a successful entry decision can induce the second bidder to enter. If this is the case, there can be some interdependence among observations within one session, which is named as "dynamic session effects" in experimental economics (Frechette, 2012). [19]

Ignoring dynamic session effects can bias the variance computation of estimators, resulting in incorrect conclusion on accepting or rejecting null hypothesis. To mitigate this session effects problem, we employ two solutions suggested by Frechette (2012), one by clustering, and the other by identifying the source of interdependence among observations.

Because the interdependence among observations is within sessions, one simple solution is to cluster the variance computation at the session level. Table 2.6 presents the new estimates by clustering. All of our previous findings hold with the new regression

---

[19] The discussion on dynamic session effects is inspired by the comment from an anonymous referee.

outcomes. Both the proportion of single-bidder contests and acquisition prices follow non-monotonic pattern, consistent with all the hypotheses. However, because the clustered standard error places no restriction on the correlation structure of the residuals within a cluster, the limited number of clusters in our experiment can result in an underestimation of the variance[20]. As an alternative, we cluster the standard errors at both subject and period level. The two-dimension clustering produces similar results, confirming that acquisition prices and entry decisions changes non-monotonically in similarity level[21].

Table 2.6. Regression outcomes by clustering at session level.
This table reports new regression outcomes by clustering variance estimation at session level. First Bid is the first bid of the first bidder. Low and High are dummies for the similarity treatments. Inverse Mills ratio is estimated based on regression outcomes on the proportion of single-bidder contests, and is negative if the second bidder enters and positive otherwise. For each estimate, we report estimated coefficients and predicted sign. Standard errors and t-statistics are listed in parentheses.

Variable	Proportion of single-bidder contests		Price in single-bidder contests		Price in two-bidder contests	
	γ estimate	Predicted sign	β estimate	Predicted sign	θ estimate	Predicted sign
	(std. err.)	(t-stat)	(std. err.)	(t-stat)	(std. err.)	(t-stat)
First Bid	0.05	$H_0:\ \gamma_1 > 0$				
	(0.00)	(20.76)				
Low	0.25	$H_0:\ \gamma_2 > 0$	-5.57	$H_0: \beta_1 < 0$	-4.18	$H_0: \theta_1 < 0$
	(0.18)	(1.39)	(0.01)	(-681.50)	(0.14)	(-29.31)
High	0.39	$H_0:\ \gamma_3 > 0$	-8.16	$H_0: \beta_2 < 0$	-3.47	$H_0: \theta_2 < 0$
	(0.10)	(3.71)	(0.08)	(-104.05)	(0.21)	(-16.80)
Inverse Mills ratio			-31.69	--	-30.32	--
			(0.38)	(-83.76)	(0.43)	(-69.70)
Constant	-3.52	--	98.37	--	47.35	--
	(0.27)	(-12.81)	(0.54)	(181.97)	(0.08)	(629.49)
N	540		157		383	

Compared to clustering, modeling the source of dynamic session effects in regression is less robust but more efficient. Following Aoyagi and Frechette (2009) and Rojas (2012),

[20] See Camerer et al (2008) and Petersen (2009) for a more recent discussion on clustered errors.

[21] For the sake of brevity, we report the estimate by 2D clustering in Appendix B.

we modify previous regression in several ways to capture the characteristics of dynamic session effects. The first modification is to assume the individual random effect η_j follow an independent normal distribution $N(\psi_\eta \varsigma_j, \sigma_\eta)$. ς_j is equal to the entry choice of second bidder j in the first round of each similarity treatment, which serves as a proxy for bidder j's tendency to enter. ψ_η and σ_η are common parameters across subjects, and can be estimated from the data. Similarly, v_{ij} and v_{ij}' follow independent normal distribution $N(\psi_v \tau_{ij}, \sigma_v)$ and $N(\psi_v' \tau_{ij}', \sigma_v')$, respectively. τ_{ij} (τ_{ij}') is set to be equal to the first acquisition price in single-bidder contests (two-bidder contests) in a paired bidder group in each similarity treatment. This specification is introduced to deal with the initial-conditions problem (Chamberlain, 1980; Heckman, 1981; Wooldridge, 2002). Moreover, we add two variables, namely *Successful entry in previous round*, and *Successful first bid in previous round*, to reflect the idea that previous successful experience can influence consequent decision-making. Variable *Period* is introduced to see whether there is evolution of bidding outcomes over time, and variable *First Round* is added to check what's in common in subjects' first action.

New estimates are presented in Table 2.7. Most of our findings remain under the new specification, except that θ_2 becomes insignificantly positive. Considering the predicted difference in acquisition prices in two-bidder contests is very small between intermediate and high similarity treatment[22], this estimate of θ_2 can still be viewed as consistent with model prediction.

[22] The predicted price in two-bidder contests in intermediate treatment is 54, while it is 53 for high treatment.

Table 2.7. Regressions incorporating the potential source of dynamic session effects.

This table presents new regressions to investigate potential dynamic session effect in the experiment. *First Bid* is the first bid of the first bidder. *Low* and *High* are dummies for the similarity treatments. *Inverse Mills ratio* is estimated based on regression outcomes on the proportion of single-bidder contests, and is negative if the second bidder enters and positive otherwise. If the first bidder buys the target in most recent round where the similarity level is the same as the current round, *Successful first bid in previous round* is equal to the first bid in that round and 0 otherwise. If the second bidder buys the target in the most recent round where the similarity level is the same as the current round, *Successful entry in previous round* is equal to 1 and 0 otherwise. *First round* is an indicator which takes value of 1 if the round is the first round in that session and 0 otherwise. For each estimate, we report estimated coefficients and predicted sign. Standard errors and t-statistics are listed in parentheses.

Variable	Proportion of single-bidder contests		Price in single-bidder contests		Price in two-bidder contests	
	γ estimate (std. err.)	Predicted sign (t-stat)	β estimate (std. err.)	Predicted sign (t-stat)	θ estimate (std. err.)	Predicted sign (t-stat)
First Bid	0.06	$H_0: \gamma_1 > 0$				
	(0.01)	(6.11)				
Low	0.27	$H_0: \gamma_2 > 0$	-2.43	$H_0: \beta_1 < 0$	-1.83	$H_0: \theta_1 < 0$
	(0.17)	(1.54)	(1.08)	(-2.25)	(0.93)	(-1.97)
High	0.29	$H_0: \gamma_3 > 0$	-4.73	$H_0: \beta_2 < 0$	0.53	$H_0: \theta_2 < 0$
	(0.17)	(1.68)	(1.12)	(-4.24)	(1.05)	(0.51)
Inverse Mills ratio			-16.76	--	-11.83	--
			(1.19)	(-14.09)	(1.73)	(-6.83)
Period	0.01	--	0.00	--	0.01	--
	(0.01)	(0.70)	(0.05)	(-0.01)	(0.05)	(0.27)
Successful entry in previous round	-0.37	--	7.62	--	2.80	--
	(0.18)	(-2.05)	(1.36)	(5.60)	(0.98)	(2.86)
Successful first bid in previous round			0.01	--	-0.02	--
			(0.02)	(0.62)	(0.02)	(-1.02)
First Round	-0.06	--	0.67	--	1.55	--
	(0.44)	(-0.13)	(2.29)	(0.29)	(2.40)	(0.65)
Constant	-4.77	--	64.56	--	39.44	--
	(0.66)	(-7.23)	(4.93)	(13.10)	(3.73)	(10.59)
ψ	-0.88	--	0.23	--	0.25	--
	(0.16)	(-5.49)	(0.07)	(3.16)	(0.06)	(4.16)
ρ	0.30		0.15		0.00	
N	540		157		383	

With regards to the dynamic session effects, significant estimates of ψ indicate that initial outcome has persistent influence on the following decisions. A successful entry decision in previous round is more important than a successful first bid, as the coefficients of the former are all significant while the coefficients of the later are not significant at all. Evolution of bidding over time is not supported as all of the coefficients of *Period* are not significant. In addition, insignificant coefficients of *First Round* suggest that bidders do not behave differently in the first round from what they do in other rounds.

In sum, the new estimates in Table 2.7 indicate the existence of dynamic session effects, and the hypotheses of non-monotonic entry and bidding cannot be rejected after controlling for dynamic session effects.

2.7. Conclusions

This paper has shown that interdependence (or similarity) in bidders' private valuations has significant effects on the strategies and outcomes in sequential-entry takeover contests. With interdependent valuations, the initial bid not only conveys information about the first bidder's valuation but also about other potential bidders' valuations. Besides this information externality, similarity levels indicate the intensity of bidding competition if both bidders enter the contest. The information externality and the intensity of competition determine the chances of preemption and equilibrium acquisition prices. Our theory for takeover contests predicts that the information externality effect dominates at low levels of similarity and the competition effect dominates at high levels of similarly. The interplay of these two forces generates a non-monotonic effect of similarity: the proportion of multiple-bidder versus single-bidder contests and the level of acquisition prices are the highest at intermediate levels of similarity.

To verify whether these predictions hold, we carried out a controlled laboratory experiment. Subjects participated in three treatments that differed in the level of interdependence between valuations. The comparative statics prediction with respect to the proportion of single-bidder contests and acquisition prices are strongly supported by the data, indicating that subjects reacted strategically to the effects of information externality and competition intensity in the way predicted by our model. Our findings on the differences between takeover contests with different similarity levels between bidders can be summarized as follows. Contests between dissimilar potential acquirers (e.g., a strategic bidder against a financial bidder) have low prices and are relatively often single-bidder contests. Contests between intermediately similar bidders (e.g., two strategic bidders) generate high prices and are frequently competitive with two bidders placing bids. Contests in which potential acquirers are very similar (e.g., two financial bidders) have low prices and are seldom with more than one bidder.

In conclusion, this paper reveals a strong influence of bidders' similarity on takeover strategies. The theory and the experiment imply that, in addition to the number of bidders, the similarity in bidders' characteristics is an important measure of competition intensity which should be accounted for in empirical studies of returns in takeovers.

Appendix 2.A. Proofs

Proof of Lemma 1: Taking the derivative of (10) with respect to v_A we obtain

$$
\begin{aligned}
\overline{b}'(v_A) &= 1-\Phi(z_0)-\left(1-\rho\right)(\Phi(z_A)-\Phi(z_0)) \\
&\geq 1-\Phi(z_0)-(\Phi(z_A)-\Phi(z_0)) = 1-\Phi(z_A) \geq 0.
\end{aligned}
\tag{12}
$$

In the first inequality we use that $z_A \geq z_0$ and $\rho \geq 0$. □

Proof of Lemma 2: Let $\underline{v} \in \left\{v : W(v,\infty)=0\right\}$. We will show that $\underline{v}$ is unique if it exists. By (11) $W(\underline{v},\infty)=0$ is equivalent to

$$
\int_{\underline{v}}^{\infty} E\left[\pi_B(v_A,\tilde{v}_B,b,1)\right] f(v_A)dv_A = 0. \tag{13}
$$

Note that $E\left[\pi_B(v_A,\tilde{v}_B,b,1)\right]$ (given in (4)) is negative for large v_A, $E[\pi_B(\infty,\tilde{v}_B,b,1)] = -c_B < 0$. Since $f(v_A)$ is always positive, $E\left[\pi_B(v_A,\tilde{v}_B,b,1)\right]$ must be positive for some $v_A \geq \underline{v}$, for the root $\underline{v}$ in (13) to exist. Because $E\left[\pi_B(v_A,\tilde{v}_B,b,1)\right]$ is decreasing in v_A:

$$
\begin{aligned}
\frac{\partial E[\pi_B(v_A,\tilde{v}_B,b,1)]}{\partial v_A} &= \sigma\sqrt{1-\rho^2}\left[-z_A f(z_A)-1+\Phi(z_A)+z_A f(z_A)\right]\frac{dz_A}{dv_A} \\
&= \sigma\sqrt{1-\rho^2}\left[\Phi(z_A)-1\right]\frac{(1-\rho)}{\sigma_{B|A}} \leq 0,
\end{aligned}
$$

it must be then that

$$
E[\pi_B(\underline{v},\tilde{v}_B,b,1)] > 0. \tag{14}
$$

Suppose now that $\underline{v}$ exists so that (14) holds. Then the derivative of $W(v,\infty)$ with respect to v evaluated at $\underline{v}$ is negative:

$$
\begin{aligned}
\frac{d}{dv}W(v,\infty)\Big|_{v=\underline{v}} &= \frac{f(\underline{v})}{\left(1-F(\underline{v})\right)^2}\int_{\underline{v}}^{\infty} E\left[\pi_B(v_A,\tilde{v}_B,b,1)\right] f(v_A)dv_A - \frac{f(\underline{v})}{1-F(\underline{v})}E\left[\pi_B(\underline{v},\tilde{v}_B,b,1)\right] \\
&= \frac{f(\underline{v})}{1-F(\underline{v})}\left(W(\underline{v},\infty)-E\left[\pi_B(\underline{v},\tilde{v}_B,b,1)\right]\right) \\
&= -\frac{f(\underline{v})}{1-F(\underline{v})}E\left[\pi_B(\underline{v},\tilde{v}_B,b,1)\right] \\
&< 0.
\end{aligned}
$$

Since $W(v,\infty)$ is a continuous function, it follows that it must have at most one root. Therefore the solution to $W(\underline{v},\infty)=0$ is unique if it exists. □

Proof of Lemma 3: We will use the following integrals for some constants m, n, and h:

$$
\begin{aligned}
&\int_m^n \phi(hx)\phi(x)dx = \frac{\Phi(Hn)-\Phi(Hm)}{H\sqrt{2\pi}}, \\
&\int_m^n x\Phi(hx)\phi(x)dx = \frac{h}{H\sqrt{2\pi}}\left(\Phi(Hn)-\Phi(Hm)\right)+\phi(m)\Phi(hm)-\phi(n)\Phi(hm),
\end{aligned}
\tag{15}
$$

where $H=\sqrt{1+h^2}$. Then

$$
\begin{aligned}
W(\underline{v},\overline{v}) &= \frac{1}{F_A(\overline{v})-F_A(\underline{v})}\int_{\underline{v}}^{\overline{v}} E[\pi_B(v_A,\tilde{v}_B,b,1)]f_A(v_A)dv_A \\
&= \frac{1}{F_A(\overline{v})-F_A(\underline{v})}\int_{\underline{v}}^{\overline{v}}\left[\sigma\sqrt{1-\rho^2}\left(\phi(z_A)-z_A(1-\Phi(z_A))\right)-c_B\right]f_A(v_A)dv_A \\
&= \frac{\sigma-\sigma\rho}{\Phi(\overline{y})-\Phi(\underline{y})}\left[\frac{H}{h\sqrt{2\pi}}(\Phi(H\overline{y})-\Phi(H\underline{y}))-\phi(\underline{y})(1-\Phi(h\underline{y}))+\phi(\overline{y})(1-\Phi(h\overline{y}))\right]-c_B,
\end{aligned}
$$

(16)

where $\underline{y} = (\underline{v} - v_0)/\sigma$, $\bar{y} = (\bar{v} - v_0)/\sigma$, $h = (1-\rho)/\sqrt{1-\rho^2}$ and $H = \sqrt{1+h^2}$. In the second line of (16) we use (4) and the third line follows from (15).

If bidder A's valuation is above v_0, then bidder B's expected payoff from entering is equal to

$$W(v_0, \infty) = \frac{1}{\sqrt{2\pi}}\left[\sigma\sqrt{2(1-\rho)} - \sigma(1-\rho)\right] - c_B.$$

The expression follows from (16). Bidder B does not enter if $W(v_0, \infty) \le 0$. Solving this quadratic inequality for ρ, yields ρ_1 and ρ_2 given in the proposition. They exist and are distinct under the assumption that $2R < 1$. □

Proof of the non-monotonic shape of v_L in ρ: We show that v_L increases in ρ at low ρ and decreases in ρ at high ρ. Since v_L is defined by $W(v_L, \infty) = 0$, we have that $dv_L / d\rho = -\partial W / \partial\rho \big/ \partial W / \partial v_L$. As shown in the proof of Lemma 2, $\partial W / \partial v_L$ is negative, so $dv_L / d\rho$ has the same sign as $\partial W / \partial\rho$. Differentiating (16), we obtain

$$\frac{\partial W(v_L, \infty)}{\partial\rho} = \frac{-\sigma}{1-\Phi(y_L)}\left[\frac{H}{2h\sqrt{2\pi}}\left(1-\Phi(Hy_L)\right) - \phi(y_L)\left(1-\Phi(hy_L)\right)\right], \tag{17}$$

where $y_L = (v_L - v_0)/\sigma$.

Suppose first that $\rho_1 \ge 0$. Then the lowest ρ that supports preemption is ρ_1. At $\rho = \rho_1$, $v_L = v_0$ and so $y_L = 0$. We have

$$\left.\frac{\partial W(v_0,\infty)}{\partial \rho}\right|_{\rho=\rho_1} = \frac{\sigma}{\sqrt{2\pi}}\frac{\sqrt{2(1-\rho_1)}-1}{\sqrt{2(1-\rho_1)}} > 0.$$

The inequality holds because $\rho_1 < 0.5$ and thus $2(1-\rho_1)>1$.

Suppose next that $\rho_1 < 0$. Then preemption is possible at $\rho = 0$. At $\rho = 0$, $v_L > v_0$ and so $v_L > 0$. When $\rho = 0$, $h = 1$ and $H = \sqrt{2}$, and (17) becomes

$$\left.\frac{\partial W(v_L,\infty)}{\partial \rho}\right|_{\rho=0} = \frac{\sigma}{1-\Phi(y_L)}\left[\phi(y_L)\left(1-\Phi(y_L)\right) - \frac{1}{2\sqrt{\pi}}\left(1-\Phi(\sqrt{2}y_L)\right)\right].$$

which has the same sign as $G(y_L)$, where

$$G(y_L) = \phi(y_L)\left(1-\Phi(y_L)\right) - \frac{1}{2\sqrt{\pi}}\left(1-\Phi(\sqrt{2}y_L)\right).$$

Because $y_L > 0$,

$$G'(y_L) = -y_L\phi(y_L)\left(1-\Phi(y_L)\right) - \phi^2(y_L) + \frac{\phi(\sqrt{2}y)}{\sqrt{2\pi}} = -y_L\phi(y_L)\left(1-\Phi(y_L)\right) < 0.$$

In addition, $G(0) = 1/(2\sqrt{2\pi}) - 1/(4\sqrt{\pi}) > 0$ and $G(\infty) \to 0^+$. It follows that the sign of function $G(y_L)$ is always positive, which means that $\partial W / \partial \rho \,|_{\rho=0}$ is positive. The signs of the derivatives at $\rho = \rho_1$ (if $\rho_1 \geq 0$) and $\rho = 0$ (if $\rho_1 < 0$) show that the preemptive value first increases in similarity level.

The highest ρ that supports preemption is ρ_2. At $\rho = \rho_2$,

$$\left.\frac{\partial W(v_0,\infty)}{\partial \rho}\right|_{\rho=\rho_2} = \frac{\sigma}{\sqrt{2\pi}} \frac{\sqrt{2(1-\rho_2)}-1}{\sqrt{2(1-\rho_2)}} < 0.$$

The sign is negative because $2(1-\rho_1)$ >1. This shows that the preemptive value v_L decreases in ρ at high ρ.

Appendix 2.B. 2-D clustering

Table 2.A. Regression outcomes by 2-Dimension clustering
This table reports new regression outcomes by clustering variance estimation both at subject and period level. *First Bid* is the first bid of the first bidder. *Low* and *High* are dummies for the similarity treatments. *Inverse Mills ratio* is estimated based on regression outcomes on the proportion of single-bidder contests, and is negative if the second bidder enters and positive otherwise. For each estimate, we report estimated coefficients and predicted sign. Standard errors and t-statistics are listed in parentheses.

Variable	Proportion of single-bidder contests		Price in single-bidder contests		Price in two-bidder contests	
	γ estimate (std. err.)	Predicted sign (t-stat)	β estimate (std. err.)	Predicted sign (t-stat)	θ estimate (std. err.)	Predicted sign (t-stat)
First Bid	0.05 (0.01)	$H_0:\ \gamma_1 > 0$ (4.58)				
Low	0.25 (0.16)	$H_0:\ \gamma_2 > 0$ (1.55)	-5.57 (0.15)	$H_0: \beta_1 < 0$ (-36.20)	-4.18 (0.88)	$H_0: \theta_1 < 0$ (-4.77)
High	0.39 (0.28)	$H_0:\ \gamma_3 > 0$ (1.38)	-8.16 (0.24)	$H_0: \beta_2 < 0$ (-34.24)	-3.47 (2.26)	$H_0: \theta_2 < 0$ (-1.53)
Inverse Mills ratio			-31.69 (0.81)	-- (-39.33)	-30.32 (2.75)	-- (-11.01)
Constant	-3.52 (0.61)	-- (-5.77)	98.37 (0.96)	-- (102.62)	47.35 (1.09)	-- (43.26)
N	540		157		383	

Chapter 3

The Learning Effect in Takeovers with Toeholds[23]

3.1. Introduction

In corporate takeovers, "toeholds" refer to the ownership of target's shares before initiating a takeover. Theoretically, the acquisition of a toehold in a target can grant its owner several advantages in acquiring full control. It can mitigate the free-rider problem[24] (Shleifer and Vishny, 1986); it signals the acquirer's valuation and facilitates the efficient allocation of targets to acquirers owning high value of the targets (Hirshleifer and Titman, 1990); it increases the probability of the owner of a toehold stake winning a takeover contest even when competing with a stronger rival bidder (Burkart 1995, and Singh 1998); and, in

[23] This draft is based on Dai, Gryglewicz, and Smit (2013).

[24] Free-rider problem was firstly discussed in Grossman and Hart (1980). Given a tender offer, the target's shareholders must balance between two possible payoffs – one is what they can gain by selling their shares to an acquirer, the other is to enjoy the post-takeover synergy if the tender offer is accepted by the majority. As every shareholder wants to free-ride the synergy value created by a successful takeover, the tender offer will only be accepted when it offers the whole synergy value, which is likely to make takeovers unprofitable for acquirers.

common value auctions, it also enables toehold-owners to win auctions cheaply because of their information advantage and their potential position as sellers (Bulow *et al.,* 1999).

Probably due to a combination of these benefits, the toehold acquisition strategy was popular in the early 1980s, when over 60% of tender offers were acquired via toehold strategies. However, the proportion of toehold strategies to total acquisitions has decreased rapidly over time to below 10% in the past decade (Betton *et al.*, 2009a). The declining popularity and scare adoption of the strategy in the market for corporate control contradicts sharply with its attractive merits as noted in takeover literature. This constitutes a "toehold puzzle": If the use of toeholds improves acquisition performance, why do fewer acquirers buy them?

The current literature on the toehold puzzle provides several alternative explanations for the infrequent adoption of staged toehold strategies. Chowdhry and Jegadeesh (1994) view toeholds as a signal of acquirers' value and show that it is not optimal for "low value" acquirers to purchase toeholds, while Ravid and Spiegel (1999) show that market liquidity and merger legislation decrease toehold bids. The decision to acquire a toehold can be greatly affected by its information externality (Bris, 2002; Goldman and Qian, 2005), and Betton *et al.* (2009a) focus on merger negotiation processes, and show toeholds can only be effective when their sizes exceed certain thresholds. The contribution of this paper to these studies is the detection of learning in the evolution of efficiency in toehold strategies, which adds a new and truly dynamic perspective to the existing explanations to the toehold puzzle.

In our proposed learning explanation, toehold owners need to posses certain qualifications to achieve a better outcome from a toehold strategy. If it is the case, acquirers can be categorized into two types: "qualified" bidders, who can use toeholds to their benefit, and “unqualified” bidders, who cannot benefit from such strategies. Because of its public context,[25] and its similarity to sunk costs, toeholds in the hands of the “unqualified” bidders can lead to acquisition pitfalls such as over-commitment or escalation errors[26]. After their initial investment, managers can become insensitive to new inflows of bad news (Haunschild *et al.,* 1994) or may deliberately stick to bad investments to hinder their release of private information about their human capital (Kanodia *et al.,* 1989). If pitfalls associated with the execution of a toehold strategy become increasingly understood by market participants, acquirers will walk away from toehold strategies to avoid their adverse impacts: only “qualified” acquirers, with high levels of rationality or whose decisions are well-monitored, will stay. So, by mitigating these pitfalls and increasing the efficiency, self-selection gradually improves, resulting in a declining proportion of toehold strategies being adopted, but – at the same time – in their increasing performance over time.

Testing the dynamic learning hypothesis of the toehold puzzle calls for detailed investigation of 1) the evolution of toehold performance over time and 2) self-selection of the qualified acquirers. First, we look into four measures to analyze toehold performance: the return to acquirers, the acquisition premium, the combined return, and the completion rate – in aiming to provide a thorough description of a toehold’s role in the success of mergers and acquisitions. We divide our sample into two periods to see whether toehold strategies perform consistently overtime. Our results confirm that toeholds are not always

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[25] Under the 1968 Williams Act, toehold acquisitions that exceed 5% threshold are required for mandatory disclosure. The 1976 Hart-Scott-Radino Antitrust Improvements Act also requires that share purchases over a certain threshold trigger notification to the anti-trust agency.

[26] For general discussion about how sunk cost can result in over-commitment or escalation errors, refer to Staw (1976), Thaler (1980), Laughhunn and Payne (1984), Arkes and Blumer (1985), and Staw and Ross (1986).

beneficial to acquirers – and in fact can work against the interest of their owners, by lowering their return, leading them to select worse targets, and decreasing the completion rate of deals. However, as time passes by, we find that toehold strategies perform better in all four measures, implying an improvement in their efficiency over time. The adverse impact of toehold strategies in all aspects in the early period seems to disappear in the later period.

Second, we propose an improved self-selection procedure – which we refer to as a "learning effect" – as a possible explanation of the co-existence of declining popularity and efficiency improvement of toehold strategies. We use the Heckman two-step estimation process to confirm that such self-selection is an important factor in determining toehold strategies' performance, but also that their efficiency improved over time, which is consistent with our learning hypothesis. To identify which forces contribute to learning about toehold strategies, we use monitoring strength – proxy by institutional holdings – to separate the market-wide improvement of toehold performance and the efficiency improvements associated with high-quality acquirers. Our regression results show that acquirers' quality is a better explanation, and also identifies qualified acquirers as those with better monitoring.

The rest of this paper is organized as follows. Section 3.2 describes our sample construction, deal characteristics and efficiency measures in our data. Section 3.3 reports separate regression results on four efficiency measures and identifies a time pattern in the toehold performance. Section 3.4 divides the sample into two sub-samples to verify the existence of a learning effect in toeholds' performance with self-selection models. Section 3.5 checks whether monitoring can explain this learning effect. Section 3.6 performs robustness check and section 3.7 concludes.

3.2. Data description

3.2.1. Sample construction

To construct our sample, we begin with all the Mergers and Acquisitions announced by US public acquirers for US public targets between 1990 and 2006[27] extracted from the Security Data Corporation (SDC) database. We require all bids to be aimed at obtaining major control of a target, so acquirers are restricted to those who own less than 50% of the target's shares before the takeover and intend to gain control (i.e., have more than 50%) after the transaction. Financial acquirers and financial targets are removed, so that measurements of combined returns[28] are comparable across all takeovers. Special transactions marked as spinoffs, exchange offers, self-tenders, repurchases, recapitalizations, acquisitions of remaining interest, minority stake purchases, and privatizations are excluded, and we delete all the deals announced as rumors. We also require data about both targets and acquirers to be available from the Center for Research in Security Prices (CRSP), to insure takeover performance is measurable. To make sure the transactions have substantial impact on acquirers' performance, targets are required to have a market valuation no less than 5% of that of acquirers 42 days before announcement date. Meeting all these requirements resulted in a sample of 2118 bids.

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[27] In mid-1980s, the widespread adoption of takeover defenses such as 'poison pill' tactics led to a decline in hostile takeovers, where toehold is much more common in hostile takeovers than in friendly takeovers. (Betton *et al.*, 2008). To leave this structural change out of our sample, we only collected deals from 1990 onwards.

[28] Combined returns can serve as a measure of the synergy created by merging target and acquirer if both parties are operating firms, but the meaning of combined return in cases where a financial firm acquires an operating target is not clear, as financial acquirers usually focus on a target's financial aspects, aiming to benefit from higher prices when exiting via IPO, or by selling the target to second buyer, i.e. synergy value is not a major motivation for financial acquirers initiating a takeover.

Table 3.1 presents the yearly distribution of deals in our sample. We observe a surge of takeovers from the mid 1990s to the early 2000s, which is consistent with merger waves recorded in the takeover literature. The percentage of toehold strategies is low over the whole of our sample period, at an average of 6.33% of all takeovers. Their frequency is relatively high in early 1990s (at about 15% of all deals), but the strategy loses popularity over time, accounting for less than 5% of deals later in the period.

Table 3.1. Corporate takeovers over time, 1990-2006.

Our sample consists of 2118 deals announced during the period from 1 Jan, 1990 to 31 Dec, 2006, extracted from SDC. All the deals are announced for public US targets by public US acquirers, and are required to have available data on CRSP. Rumored deals are excluded, and targets should have a market valuation no less than 5% of that of acquirers at 42 days before announcement date. This table gives the yearly distribution of deals, and further reports the number and frequency of deals with toeholds in each year.

Year	No. of Deals	No. of Toehold strategies	Percent of Toehold strategies (%)
1990	66	10	15.15
1991	58	9	15.52
1992	52	10	19.23
1993	87	8	9.20
1994	140	18	12.86
1995	170	16	9.41
1996	176	10	5.68
1997	238	13	5.46
1998	239	12	5.02
1999	214	6	2.80
2000	167	6	3.59
2001	128	5	3.91
2002	65	1	1.54
2003	74	2	2.70
2004	83	3	3.61
2005	84	4	4.76
2006	77	1	1.30
Total	2118	134	6.33

3.2.2. Sample Characteristics

To ensure comparability, we choose the same determinant variables as those adopted by Betton *et al.* (2009a), except for three variables - *Horizontal*, *Poison pill* and *Analyst*. We replace *Horizontal* with *Diversification*, which should not affect the results because both measures capture the industry relatedness between target and acquirer. We do not include

Poison pill in our regressions, as data from RiskMetrics is only available for fewer than half of our sample deals.[29] We include an additional variable, *Analyst*, recording the number of analysts following a target's stock, which can indicate the availability of information about a target on the stock market.

Table 3.2 Descriptive statistics

This table presents the overview of deal characteristics in the whole sample, non-toehold strategies, and toehold strategies, separately. *Analyst* refers to the numbers of analysts following target, which is collected from I/B/E/S. *Target MVE* measures the market value of target, and is recorded in millions and adjusted to 2006 price level. *Target runup* measures cumulative abnormal return to target over runup period [-41,-2] using a value-weighted market return model estimated over [-293, end]. *Penny stock* is a dummy variable, taking value of 1 if the stock price on day -42 is less than one dollar, and 0 otherwise. *Turnover* is calculated as the average daily trading volume of target stock as a fraction of its total shares outstanding over time window [-293, -42]. *NYSE|Amex* denotes whether the target is listed on NYSE or AMEX. *Diversification* is a dummy taking value of 1 if target and acquirer differ at 2-digit SIC, and 0 otherwise. *Tender offer, All cash, Hostile* are indicator variable equal to one if the deal is in the form of tender offer, 100% with cash payment, or deal attitude is hostile. *Number of acquirers* reports the numbers of acquirers bidding for the same target.

	N	Full sample	Non-toehold strategies	Toehold strategies	Difference	t-stat
Analyst	2118	25.21	25.47	21.47	4.00	1.21
		0.80	0.84	2.49	3.30	
Target MVE ($millions, 2006)	2118	1408.44	1446.48	845.09	601.39	1.28
		114.32	121.58	150.01	469.53	
Target runup	2118	0.06	0.06	0.02	0.04	1.40
		0.01	0.01	0.02	0.03	
Penny stock	2118	0.05	0.05	0.04	0.01	0.44
		0.00	0.01	0.02	0.02	
Turnover (%)	2118	0.68	0.69	0.48	0.21	2.57
		0.02	0.02	0.06	0.08	(***)
NYSE|Amex	2118	0.30	0.30	0.34	-0.04	-0.89
		0.01	0.01	0.04	0.04	
Diversification	2118	0.34	0.33	0.42	-0.09	-2.06
		0.01	0.01	0.04	0.04	(**)
Tender offer	2118	0.14	0.13	0.31	-0.18	-5.70
		0.01	0.01	0.04	0.03	(***)
All cash	2118	0.15	0.14	0.29	-0.15	-4.65
		0.01	0.01	0.04	0.03	(***)
Hostile	2118	0.05	0.04	0.22	-0.19	-9.67
		0.01	0.00	0.04	0.02	(***)
Number of acquirers	2118	1.12	1.11	1.16	-0.05	-1.44
		0.01	0.01	0.04	0.04	

29 In addition, Betton *et al.* (2009a) do not find that this tactic has significant impact on returns to acquirers: although their study shows it has a significantly negative impact on the probability of the initial acquirer winning bidding contests. In fact, our results show that removing this variable does not affect the significance of the estimates, as we find similar estimates as in Betton *et al.* (2009a).

Table 3.2 provides an overview of the deal characteristics of the full sample of non-toehold and acquisitions with toeholds separately. There are about 25 analysts (on average) following stock activity in targets taken over by acquirers without using toehold strategies, slightly more than in acquisitions following toeholds (21 analysts on average). The average target size is larger for acquisitions without toeholds, about US$1,446m (at 2006 values), but only US$ 845m for targets acquired using toeholds. Cumulative abnormal return to the targets over the run-up period [-41, -2] are higher for non-toeholds than for acquisitions with toeholds (0.06 compared to 0.02), and average daily turnovers of target shares before takeovers without toeholds is 0.69%, which is significantly higher than for takeovers with toeholds (with an average turnover is 0.48%). Other liquidity measures of target stocks, such as whether they are ‘‘penny stocks’ (i.e., priced at less than $1), and whether they are listed on major exchanges (such as NYSE and Amex) seem not to differ across takeover types. About 42% of takeovers using toeholds are cross-industry, but only 33% of takeovers without toeholds are for diversification purposes. Acquirers buying with toeholds are more likely to place their bids in the form of tender offers, and pay 100% in cash. Toehold strategies are also more frequently associated with hostile takeovers. Twenty-two percent of the takeovers with toeholds are hostile, while the figure is only four percent for takeovers without toeholds. Finally, most of the takeovers in our sample are single bidder contests: the proportions of multiple acquirers are low for both takeovers with or without toeholds. In general, based on significance, we find toehold strategies are commonly used for acquiring targets of lower turnover, more frequently for diversification purposes, in the form of tender offers, with 100% cash payment, and with hostile attitudes.

3.2.3. Takeover efficiency measures

We explore takeover efficiency using four measures: *returns to acquirers*, *acquisition premiums*, *combined returns to target and acquirer*, and *completion rates*. The first two measures aim to evaluate acquirers' benefits and costs in takeovers; combined returns serves as measures of the synergy created by takeovers, and also reflects acquirers' ability for select targets; completion rate, checks whether adopting a toehold strategy can help an acquirer win a takeover contest.

In particular, we measure returns by cumulative abnormal returns over total contest window [-41, end], where the end date is defined as the earlier of the bid's effective date and the target stock delisting date, plus 126 trading days. The total contest window can be further divided into three event periods - the run-up period [-41,-2]; the announcement period [-1, 1]; and the post-announcement period [2, end]. We estimate daily abnormal returns, AR_{jk}, for each event period, by the method described in Betton *et al.* (2008).

$$r_{jt} = \alpha_j + \beta_j r_{mt} + \sum_{k=1}^{K} AR_{jk} d_{kt} + \varepsilon_{jt}, \quad t = day\{-293,...,end\}$$

where r_{jt} is the excess return to firm j at day t; r_{mt} is the value-weighted market return adjusted by risk-free rate; and d_{kt} is a dummy variable that takes a value of one if day t is in the kth event window and zero otherwise. Stock returns are obtained from CRSP, and market return and risk-free rates from the Fama French & Liquidity Factor provided by Wharton Research Data Services (WRDS). To be included in the sample, a firm should have at least 100 return observations over the whole event window. Our estimation method applies ordinary least squares with White's heteroskedastic-consistent covariance matrix.

The cumulative abnormal return (CAR) to firm j over event period k is $CAR_{jk} = \omega_k AR_{jk}$,where ω_k is the number of trading days in the event window.

Table 3.3 lists the overview of our four efficiency measures in the full sample and the two sub-samples (with and without toeholds), respectively. The total returns to the acquirer, *acquirer CAR (-41, end)*, are measured by the sum of CARs in three event windows, and the acquisition premiums are defined as $\ln(p_{final} / p_{-42})$, where p_{final} refers to the final price per target share offered by acquirer and p_{-42} is the target share price 42 days before takeover announcement. Combined returns are the sum of returns to acquirers and targets, weighted by their market valuation at day -42, while completions are an indicator equal to one if the deal is completed, and zero otherwise.

Table 3.3 Overview of takeover efficiency

We measure takeover efficiency by four measures, namely, return to acquirers, final premium, combined returns and completion rate. Panel A provides an overview about these four measures in the whole sample. Panel B reports data before 1995, and Panel C reports data after 1995. Abnormal returns are estimated using the following regression specification in Betton *et al.* (2008).

$$r_{jt} = \alpha_j + \beta_j r_{mt} + \sum_{k=1}^{K} AR_{jk} d_{kt} + \varepsilon_{jt}, \quad t = day\{-293,...,end\}$$

where r_{jt} is the return to firm j over day t, r_{mt} is the value-weighted market return, and d_{kt} is a dummy variable that takes a value of one if day t is in the kth event window and zero otherwise. The end date in the sample is defined as the earlier date between bid's effective date and target stock delist date plus 126 trading days. The cumulative abnormal return (CAR) to firm j over event period k is $CAR_{jk} = \omega_k AR_{jk}$, where ω_k is the number of trading days in the event window. The combined acquirer and target abnormal returns are determined by weighting the acquirer and target abnormal returns by the market capitalization on day -42. *Acquisition premium* is calculated as $\ln(p_{final} / p_{-42})$, where p_{final} refers to the final price per target share offered by acquirer and p_{-42} is target share price on day -42. Completion is an indicator which is equal to one if the deal is completed.

	N	Full sample	Non-toehold strategies	Toehold strategies	Difference	t-stat
Acquirer CAR	1640	-0.88	-0.93	0.06	-0.99	-1.35
(-41,end)		0.16	0.16	0.46	0.74	
Combined	1614	-0.72	-0.76	0.16	-0.92	-1.55
CAR (-41,end)		0.13	0.13	0.38	0.60	
Acquisition	1816	0.28	0.28	0.28	0.00	0.08
premium		0.01	0.01	0.04	0.04	
Completion	2118	0.78	0.79	0.60	0.19	5.19
Rate		0.01	0.01	0.04	0.04	(***)

Over the whole sample, takeovers executed with the use of toeholds generate higher returns to acquirers. Acquirer CARs (-41, end) are negative for takeovers executed without toeholds, but positive for those with toeholds (-0.93 v.s. 0.06). Combined CARs (-41, end) are negative for acquisition without toehold strategies, but positive in acquisitions with toehold strategies (-0.76 compared to 0.16). Acquisition premiums are almost the same (about 0.28) for both types of takeovers. Toehold strategies also have lower average completion rates – at about 60% of deals, while about 79% of takeovers without toeholds are completed. Although none of the differences are significant except for the completion rate, this rough comparison shows the use of toehold strategies does not significant enhance takeover efficiency: on the contrary, their adoption can be a clue of bad performance, being associated, for instance, with lower completion rates.

3.3. Efficiency change in toehold strategies

Table 3.4 presents regression results on the four efficiency measures with three different specifications. The first specification is the same as used in Betton *et al.* (2009a), where year dummies are not included as explanatory variables. In the second specification, we add year dummies into the regression to control for year effects, while in the third specification, an interaction term, *Toehold size*Time*, is also added to see whether there is a consistent time trend in toehold performance.

The first efficiency measure we investigate is cumulative abnormal returns to acquirer during the event window [-41, end]. Without control for year effects, toehold strategies seem to have no significant impact on acquirers' returns, which are negatively correlated with turnover rate of targets' stocks, and higher if the target's run-up is larger, its stock price is less than one dollar, or it is listed on NYSE or Amex. In contrast, target size, daily turnover of its stock, and takeovers with diversification purpose are associated with lower returns: all these findings are consistent with those in Betton *et al.* (2009a). We also find that the existence of multiple bidders leads to higher acquirer returns. However, since all these estimates only concern completed deals, acquirers in the regression are actually “winning acquirers” in takeover contests. Winning a takeover contest by defeating others can be viewed as a strong market signal of acquirers’ competiveness, which explains why the indicator of multiple acquirers has a positive coefficient on the acquirers’ returns.

The introduction of year dummies in the second specification does not change the estimates much – they remain much as before, in terms of coefficient signs, magnitude and significant levels. The only exceptions are that the coefficients for Toehold size and Tender offer increase in significance levels to become significantly positive. This new evidence on the positive influence of toehold size on acquirers’ return is significant, as the efficiency of toehold is the focus of our paper. When controlling for year effects, toehold seems beneficial to acquirers, bringing them higher abnormal returns. This change in significance suggests that there is a time pattern in toehold performance, implying that ignoring it can lead to inaccurate conclusions about toeholds’ impacts.

The addition of the estimation of Toehold size*Time in the third specification further confirms the importance of time patterns in measuring the efficiency of toehold strategies. The term has a coefficient of 0.006 at the 1% significance level, which shows that this time pattern not only exists, but also follows a consistent trend. In the early sample period, the use of toeholds has an adverse impact on acquirer’s return – as suggested by the significantly negative coefficient of Toehold size (which is equal to -0.035) – but, as time passes, the toehold strategy performs better and better. The positive coefficient of the

Table 3.4 Regressions on toehold efficiency

The table reports WLS estimates of cumulative abnormal returns (CAR) to acquirers and combined CAR in event window [-41, end], respectively, using σ_{CAR} as weights. Column 7 to 9 present OLS estimates on acquisition premium, and column 10 to 12 report probit estimates on completion rate. The first three efficiency measures are calculated only for completed deals, and the last one uses all the observations regardless of its completion status. Time is defined as the year difference between observation year and base year of 1990. Target size equals to natural logarithm of target MVE. Multiple acquirers are an indicator equal to one if a takeover involves multiple acquirers. Targets' industry is defined by their primary SIC as manufacture, service, trade and others. Acquirer CAR (-1, 1) is the three-day cumulative abnormal return for acquirers around the takeover announcement. All other variables are defined as in Table 3.2. For each variable, its coefficient and p-value (in brackets) are reported.

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
Toehold size	0.006	0.010	-0.035	0.005	0.015	-0.026	-0.004	-0.004	-0.006	-0.013	-0.011	-0.004
	(0.213)	(0.054)	(0.001)	(0.473)	(0.022)	(0.058)	(0.053)	(0.086)	(0.127)	(0.048)	(0.095)	(0.712)
Toehold size*Time			0.006			0.005			0.000			-0.001
			(0.000)			(0.001)			(0.483)			(0.480)
Analyst	0.003	0.002	0.003	0.003	0.003	0.003	0.000	0.000	0.000	0.003	0.003	0.003
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.898)	(0.719)	(0.706)	-(0.006)	-(0.013)	(0.014)
Toehold size*Analyst	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.666)	(0.469)	(0.672)	(0.925)	(0.603)	(0.903)	(0.804)	(0.869)	(0.698)	-(0.155)	-(0.126)	(0.164)
Target size	-0.132	-0.141	-0.151	-0.121	-0.152	-0.154	0.002	0.002	0.002	0.062	0.044	0.044
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.710)	(0.733)	(0.748)	(0.009)	(0.076)	(0.074)
Target runup	0.664	0.715	0.709	0.996	0.906	0.896	0.665	0.667	0.668	0.220	0.220	0.222
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.046)	(0.049)	(0.048)
Penny stock	1.193	1.298	1.267	0.506	0.844	0.848	0.012	0.023	0.023	-0.161	-0.196	-0.195
	(0.000)	(0.000)	(0.000)	(0.112)	(0.008)	(0.008)	(0.821)	(0.672)	(0.678)	(0.308)	(0.221)	(0.224)
Turnover	-0.409	-0.480	-47.862	-37.941	-42.797	-42.657	-0.002	-0.005	-0.460	-0.038	-0.054	-5.329
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.849)	(0.650)	(0.654)	(0.291)	(0.136)	(0.139)
NYSE|Amex	0.329	0.376	0.377	0.364	0.378	0.374	-0.032	-0.036	-0.036	-0.122	-0.106	-0.107
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.151)	(0.112)	(0.112)	(0.150)	(0.214)	(0.210)
Diversification	-0.142	-0.149	-0.181	-0.109	-0.119	-0.138	-0.023	-0.023	-0.023	-0.142	-0.151	-0.153
	(0.014)	(0.011)	(0.002)	(0.074)	(0.054)	(0.026)	(0.206)	(0.215)	(0.214)	(0.041)	(0.031)	(0.030)
Tender offer	-0.002	0.220	0.201	0.097	0.336	0.332	0.044	0.044	0.043	0.871	0.901	0.905
	(0.976)	(0.008)	(0.017)	(0.246)	(0.000)	(0.000)	(0.111)	(0.117)	(0.126)	(0.000)	(0.000)	(0.000)

Table 3.4 (continued)

All cash	0.589	0.295	0.309	0.595	0.296	0.309	0.023	0.016	0.016	-0.154	-0.212	-0.214
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.397)	(0.570)	(0.564)	(0.137)	(0.051)	(0.049)
Hostile	-0.265	-0.217	-0.192	-0.377	-0.242	-0.226	0.161	0.156	0.157	-1.561	-1.527	-1.527
	(0.166)	(0.258)	(0.318)	(0.070)	(0.249)	(0.281)	(0.011)	(0.014)	(0.013)	(0.000)	(0.000)	(0.000)
Multiple Acquirers	0.609	0.597	0.607	0.565	0.460	0.464	0.027	0.030	0.030	-1.101	-1.140	-1.141
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.493)	(0.438)	(0.438)	(0.000)	(0.000)	(0.000)
Acquirer CAR (-1,1)										0.039	0.089	0.091
										(0.881)	(0.738)	(0.732)
Toehold size*Acquirer CAR (-1,1)										0.060	0.059	0.058
										(0.374)	(0.383)	(0.392)
Constant	0.528	0.444	0.607	0.533	0.599	0.726	0.167	0.168	0.173	0.870	0.768	0.767
	(0.000)	(0.041)	(0.006)	(0.000)	(0.030)	(0.009)	(0.001)	(0.023)	(0.020)	(0.000)	(0.002)	(0.002)
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	no	yes	yes	no	yes	yes	no	yes	yes	no	yes	yes
Method	WLS	WLS	WLS	WLS	WLS	WLS	OLS	OLS	OLS	Probit	Probit	Probit
N	1640	1640	1640	1614	1614	1614	1542	1542	1542	2113	2113	2113
chi2	464.60	808.88	835.80	396.28	746.92	758.20				313.47	341.98	342.46
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							30.72	16.16	15.68			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.236	0.240	0.239	0.140	0.152	0.153

interaction term between *Toehold size* and *Time* implies a yearly improvement of 17.14% (=0.006/0.035), which is economically significant. In sum, the above finding suggests a negative impact of the toehold strategy on acquirers' return at the beginning of our sample (year 1990) as the stand-alone *Toehold size* has a negative coefficient of -0.035. However, at the end of sample period (year 2006), toehold acquisitions generate beneficial outcomes to acquirers, with a positive impact of 0.057 (calculated as stand-alone toehold performance + yearly change * time, -0.035+ 0.006*(2006-1990)).

While return to acquirers measures net benefits to acquirers, combined return can be viewed as a measure of takeover synergy between target and acquirer. Columns 4 to 6 in Table 3.4 present regressions in which the dependent variable is the combined return. Without year dummies (Column 4), the link between toeholds and synergy value is weak and insignificant. It becomes effective in identifying better targets and is positively correlated with higher combined returns after introducing year dummies (Column 5). Furthermore, the coefficient of *Toehold size*Time* in the regression in Column 6 again confirms an upward trend in toehold performance: while toehold size alone is negative correlated with combined returns, the interaction term loads a positive and significant coefficient so that, as above, this upward yearly change results in positive impacts of toeholds by the end of our sample period.

Next, we look at the effect of toeholds on acquisition premiums. The regression excluding year effects in Column 7 reports a significantly negative impact of toehold size on acquisition premium (as found in Betton *et al.*, 2009a). This impact remains significant after controlling for year effects in the second pooled regression, but after introducing the interaction term between toehold size and time, estimates of this impact become insignificant. The coefficient of *Toehold size*Time* is also indistinguishable from zero, which shows the time pattern in acquisition premium is not as strong as in return measures.

The final efficiency measure of toehold strategies that we tested is the completion rate of takeovers: we use a probit regression to estimate determinants of completion rates. As Chen *et al.* (2007) suggested, acquirers can update their belief in targets' quality with perceived announcement CAR (i.e. CAR over announcement window [-1, 1]), which can change their determination to complete a takeover deal. According to their argument, higher announcement returns to acquirers reflect better market perceptions of such deals, which are good signals of project quality. Witnessing market reaction during announcement period, acquirers will re-evaluate their target selection and is likely to withdraw from bad projects (i.e. those with low announcement return) and complete good ones (i.e. those with high announcement return). To accommodate this information updating, we introduce two additional determinants of completion rate (*Acquirer CAR (-1,1)*, and *Toehold size * Acquirer CAR (-1,1)*) in related regressions. The first variable is the cumulative abnormal return to acquirers over the announcement window [-1, 1], and tracks sensitivity of completion rate to deal quality, and the second is an interaction term which records additional sensitivity of completion rate to deal quality when a toehold is involved. If the toehold strategy facilitates the updating of information, the coefficient of *Toehold size * Acquirer CAR (-1,1)* is expected to be positive.

The estimates in column 10 to 12 suggest a weak time pattern in completion rates. In general, toeholds lower the probability of completing a deal: but this negative impact loses its significance at the 5% significance level after introducing year dummies. The coefficient of *Toehold size*Acquirer CAR (-1,1)* is not significant at all, which indicates the use of a toehold strategy does not help acquirers to withdraw from bad takeover projects.

The term *Toehold size*Analyst* is not significant in any estimate of the four efficiency measures, which implies acquirers cannot use toeholds to compensate for the lack of availability of information about targets on public market.

To summarize, we find that toehold strategies have time-varying impacts on takeover performance. In particular, their efficiency in terms of enhancing acquirers' returns and success in choosing targets with higher synergistic value improves over time. However, this improvement cannot be explained by better information or its updating during the announcement period.

3.4. The learning effect with a self-selection model

As is shown in the previous section, toehold efficiency improves in generating higher returns to acquirers and enabling them to select better targets over time, though the number of acquirers who use toehold strategies is still declining at the same time. This phenomenon is puzzling if we assume that acquirers are homogeneous with regards to their ability to implement toehold strategies. Under that assumption, the improvement in the efficiency of such strategies would apply to all acquirers, and the natural outcome of the improving efficiency of toehold strategies should be an accompanying increase in their use. However, empirical evidence points to a contradictory result – the co-existence of improving toehold's efficiency and their declining popularity. This indicates that the impact of toeholds varies across different acquirers – i.e., acquirers are heterogeneous in their ability to benefit from using toehold acquisition strategies.

To put this puzzle in a dynamic framework, the heterogeneity of acquirers and the efficiency improvements in toehold's performance suggest a self-selection process in toehold strategy. Suppose there are two types of acquirers with respect to their ability to use toeholds, qualified acquirers and unqualified acquirers. At first, if acquirers (especially unqualified ones) are not conscious about the qualifications needed to produce favorable outcomes with toeholds, both qualified and unqualified acquirers may buy toeholds, attracted by their theoretical appeal. This would result in a pooling effect, where toeholds' efficiency when used by qualified acquirers is moderated by the inefficiency generated by their use by unqualified acquirers. Over time, it becomes clear that successful implementation of toehold strategies requires certain qualities in acquirers, so unqualified acquirers start to withdraw from using them, while qualified acquirers stick with them. Gradually, this self-selection process transforms the pooled population of toehold bidders into separate populations, where most toehold acquirers are qualified, which is reflected by enhanced toehold performance in later periods. The learning effect of this self-selection process successfully explains the co-existence of toehold strategies' improving performance and declining popularity.

3.4.1. Subsample division

As improving self-selection can be a possible explanation of improved efficiency improvement in toehold performance, the next step is to check whether there is indeed a difference in selection outcomes. To facilitate this comparison, we divide our sample into two sub-samples, using year 1995 as the cutting point. The first sub-sample includes observations prior to and including 1995, and the second all observations after 1995. 1995 was chosen as the cut-off point because the percentage of acquisitions using toehold strategies is always above the sample average before 1995 (6.33%), and always below that average afterwards.

Table 3.5 Toehold distribution in subsamples

The table shows the toehold held by acquirers in 2118 takeovers before and after 1995 (1995 is included in the first subsample). A toehold refers to target shares owned by acquirers before the announcement of their takeover bids. Information about toehold existence and toehold size is attained from SDC. Percentage of toeholds reports the proportion of takeovers where acquirers own a toehold. Average toehold size is calculated using takeovers with positive toeholds. Number of toeholds reports the number of cases with positive toeholds.

	Before 1995	After 1995	Difference	t-stat
Percentage of toeholds	12.39	4.08	8.31	7.06
(%)	1.38	0.50	1.18	(***)
Average toehold size	14.55	16.65	-2.11	-0.84
(%)	1.72	1.83	2.51	
Number of toeholds	71	63		

*,**,*** represent statistical significance at the 10, 5, and 1% level, respectively.

Table 3.5 describes toeholds in the sub-samples. In the first sub-sample, 12.39% of the total deals are toehold strategies, while only 4.08% of deals in the second sub-sample utilize toeholds. The numbers in the two sub-samples are roughly balanced - 71 observations in the first and 63 observations in the second. The average toehold size in the first sub-sample is 14.55%, while it is 16.65 in the second sub-sample, and the difference is insignificant. It is important that the two sub-samples are similar in terms of numbers of toeholds and average toehold size, and only differ in the proportion of deals involving the use of toehold strategies, so that the following analysis reflects only the impact of the difference in this characteristic rather than the influence of changes in toehold size or observation numbers.

Table 3.6 gives estimates of toehold efficiency in the two sub-samples and across the whole sample, respectively. We use the same control variables as in Table 3.4, and control for both industry and year effects in each regression. We also define a new dummy variable *Recent* (which takes the value of 1 if the deal takes place after 1995, and 0 otherwise) to separate the two sets of deals in the pooled regression.

Table 3.6 Regressions on toehold efficiency in sub-samples

The table reports estimates of toehold efficiency in two subsamples and the whole sample, respectively. According to the statistics in Table 3.5, we use year 1995 as the cut-off point to define sub-samples. The same regressions, controlling industry and year fix effects, are carried out with control variables defined the same as in Table 3.4. Instead of variable "*Time*", we define a dummy variable "*Recent*" to separate observations before and after 1995. It is equal to one if the deal is announced after 1995, and zero otherwise. To save space, we do not report estimates of control variables, which do not change a lot from results in Table 3.4. P-values are reported (in brackets) below each coefficient.

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled
Toehold size	-0.033	0.024	-0.018	-0.030	0.023	-0.013	0.000	-0.006	-0.001	-0.020	-0.006	-0.011
	(0.002)	(0.000)	(0.046)	(0.077)	(0.001)	(0.338)	(0.953)	(0.032)	(0.720)	(0.058)	(0.537)	(0.249)
Toehold size*Recent			0.037			0.033			-0.003			0.000
			(0.000)			(0.021)			(0.380)			(0.979)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	Yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Method	WLS	WLS	WLS	WLS	WLS	WLS	OLS	OLS	OLS	Probit	Probit	Probit
N	398	1242	1640	387	1227	1614	358	1184	1542	571	1542	2113
chi2	169.67	715.20	823.75	166.74	669.85	752.24				85.97	250.89	341.98
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							9.06	14.84	15.69			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.322	0.233	0.239	0.123	0.165	0.152

On the whole, we find the same efficiency improvements in toehold performance with respect to both acquirer's return and target quality. Before 1995, toehold strategies appear to have adverse impacts in takeover outcomes, lowering acquirers' benefits (with a significantly negative coefficient of -0.033), and tending to be associated with the selection of worse targets (its impact on combined return is negative and significant at 10% level). But the situation changes after 1995: when toehold size is associated with higher returns to acquirers and combined returns: both these effects are positive and highly significant at 1% level. This efficient improvement is further confirmed by the coefficients of *Toehold size*Recent*, which are significantly positive. Looking at acquisition premiums and completion rates in the two subsamples, we find additional evidence of improvement in toehold performance. Toehold's impact on acquisition premium is indistinguishable from zero before 1995, but becomes significantly negative after (with a coefficient of -0.006 and p-value of 0.032), showing that they help to lower the prices paid by acquirers in the 'recent' period. Furthermore, the use of toehold strategies in acquisitions bids decreases the probability of the deal being completed successfully before 1995, but this negative effect loses its significance thereafter. But the time differences in acquisition premiums and completion rates are slight, as their insignificant estimates in the pooled regression indicate.

3.4.2. Self-selection model

To test the learning hypothesis empirically, we introduce a self-selection model as in Betton *et al.* (2009b), where the acquisition of a toehold is modeled as an endogenous decision which is determined by a mix of both publicly available information (such as acquirer's characteristics) and private information (such as CEO's self-restrain from empire building, which is unobservable). The following specification describes the interplay between the self-selection of a toehold strategy and toehold performance.

$$Performance_{toe>0} = \beta' X + \varepsilon \text{ iff } \gamma' Z + \eta \geq 0$$
$$Performance_{toe=0} = \beta' X + \varepsilon' \text{ iff } \gamma' Z + \eta < 0$$

where X is the vector of explanatory variables for toehold performance, which are the same as in Table 3.4. The following conditions describe the decision to adopt a toehold strategy. An acquirer buys a toehold if the sum of $\gamma' Z$ and η is positive, and not otherwise. The vector Z contains factors known to influence toehold strategy. η represents any unmeasured characteristics and is assumed to be jointly normally distributed with ε (ε'). The correlation between η and ε (ε') mean that the estimation of β can be biased because $E(\varepsilon | \gamma' Z + \eta \geq 0) \neq 0$ and $E(\varepsilon | \gamma' Z + \eta < 0) \neq 0$. To eliminate this selection bias, we introduce the inverse Mills ratio, using the "Heckman two-step" method (Heckman, 1979; Li and Prabhala, 2007; Betton *et al.,* 2009b).

The first step is to conduct a probit regression on the decision to adopt a toehold strategy (Table 3.7) to estimate $\hat{\gamma}' Z$, which defines the inverse Mills ratios as λ. $\lambda = \phi(\hat{\gamma}' Z) / \Phi(\hat{\gamma}' Z)$ in toehold strategies, and $\lambda = -\phi(\hat{\gamma}' Z) / [1 - \Phi(\hat{\gamma}' Z)]$ in non-toehold strategies. In particular, we introduce two instruments- *Target age* and *Acquirer's equity investment* - to mitigate the potential multi-collinearity issue in self-selection models[30]. *Target age* denotes the number of years between the target list date as a public company and announcement date: the longer a target has been listed on exchange, the more time the acquirer has had to accumulate its shares. *Acquirer's equity investment* refers to the ratio of an acquirer's equity holdings in investment assets to its total assets. If an acquirer is prone

[30] Strictly speaking, extra instruments are not necessary in the Heckman selection model, because the inverse Mills ratio is a nonlinear function of variables. But if the selection variables Z and explanatory variables in the second step X are identical, it's likely that the inverse Mills ratio λ has very little variation relative to X, which may lead to multicollinearity problems.

to invest a lot in other firms' equities, its probability of owning target's share is higher than those who undertake less equity investments. Since these two variables can affect the probability of an acquirer making a toehold purchase, but seems to have little link with our efficiency measures, including them in Z helps to enhance the quality of our λ estimates.

Table 3.7 Probability of toehold strategies

The table reports estimate about the probability of acquiring toehold by probit model. Besides the explanatory variables used in explaining toehold performance, two additional variables are introduced: Target age and Acquirer's equity investment. Target age denotes the number of years between target list date and announcement date. Acquirer's equity investment refers to the ratio of equity holding in investment asset to acquirer's total asset. These regressions are conducted to provide an estimate for inverse Mills ratio in Table 3.8. Coefficients and p-values (in brackets) are reported for each regression.

	year≤1995	year>1995	pooled
Target Age	-0.002	0.010	0.006
	(0.881)	(0.143)	(0.272)
Acquirer's Equity Investment	4.064	0.532	1.744
	(0.043)	(0.677)	(0.025)
Analyst	0.006	-0.005	-0.002
	(0.070)	(0.027)	(0.239)
Target size	-0.007	0.069	0.047
	(0.910)	(0.122)	(0.172)
Penny stock	-0.486	0.059	-0.234
	(0.161)	(0.870)	(0.349)
Turnover	-0.283	-0.055	-0.104
	(0.121)	(0.512)	(0.202)
NYSE|Amex	0.093	-0.106	-0.032
	(0.611)	(0.494)	(0.784)
Diversification	0.254	0.044	0.118
	(0.088)	(0.729)	(0.214)
Industry dummy	yes	yes	yes
Year dummy	yes	yes	yes
N	573	1545	2118
LR Chi2	30.930	23.400	81.080
	(0.014)	(0.323)	(0.000)
Pseudo R-squared	0.072	0.044	0.081

The second step is to introduce the inverse Mills ratio into the regressions as an explanatory variable to control for heterogeneity (Table 3.8). New regression outcomes confirm selection bias is important in measuring toehold efficiency. Except for acquisition premiums, coefficients of *Inverse Mills ratio* are significant in most estimation. For the other three efficiency measures, self-selection process seems to produce a different impact on the two sub-samples. In the early period, selection is accompanied with lower returns to acquirer and lower synergy values, but brings favorable outcomes in the later period, where its generates higher acquirer returns and is associated with the selection of better targets, as suggested by the significant coefficient of *Inverse Mill's ratio*Recent*. This improvement in selection efficiency is consistent with a transformation from a pooling of toehold strategies to a separated situation, where only qualified acquirers buy toeholds. But when it comes to completion rates, selection is associated with a higher probability of failure: it does not affect completion rates before 1995 (with an insignificant coefficient of -0.210) but reduces them after 1995, with a significant estimate of -0.438. This difference is further confirmed by the interaction term between *Inverse Mill's ratio* and the dummy variable *Recent* in the pooled regression, whose coefficient is -0.384 and significant at 5% level.

But caution is needed in interpreting this as evidence of the inefficiency of self-selection on the probability of deal completion. As toehold strategies are much more common in hostile takeovers than in friendly ones (Betton *et al.*, 2008), it is natural to expect that completion rates are lower in takeovers with toeholds. Some empirical studies, such as Jennings and Mazzeo (1993), claim toehold strategies have a two-fold impact on completion rates: they find that their existence increases the possibility of target resistance, but also that the size of toehold is negatively associated with the likelihood of such resistance. We make similar findings seeing a positive correlation between completion rates and toehold size, regardless of the negative correlation between completion rates and Inverse Mill's ratio (which represents the hidden information involved in the toehold).

Table 3.8 Toeholds performance by selection model

The table reports estimates on four measures of toehold's efficiency by selection model. Inverse Mills ratio is calculated with estimates in Table 3.9. Control variables include Analyst, Toehold size*Analyst, Target size, Target runup, Penny stock, Turnover, NYSE|Amex, Diversification, Tender offer, All cash, Hostile, Multiple Acquirers, and two additional variables, Acquirer CAR3 and Toehold size*Acquirer CAR3, for Panel D. Regression specifications and methods are the same as those used in previous section, i.e. WLS model for return analysis, OLS for acquisition premium and probit model for completion rate. Coefficients and p-values (in brackets) are reported for each regression.

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled
Toehold size	-0.021	0.023	-0.005	-0.011	-0.004	0.013	-0.003	-0.009	-0.003	-0.009	0.025	-0.007
	(0.091)	(0.013)	(0.657)	(0.581)	(0.702)	(0.442)	(0.456)	(0.027)	(0.448)	(0.471)	(0.091)	(0.562)
Toehold size*Recent			0.022			-0.016			-0.005			0.034
			(0.095)			(0.410)			(0.347)			(0.069)
Inverse Mill's ratio	-0.293	0.019	-0.306	-0.355	0.468	-0.388	0.061	0.058	0.039	-0.210	-0.438	-0.134
	(0.033)	(0.867)	(0.016)	(0.035)	(0.003)	(0.012)	(0.124)	(0.264)	(0.332)	(0.135)	(0.002)	(0.300)
Inverse Mill's ratio*Recent			0.323			0.761			0.019			-0.384
			(0.052)			(0.000)			(0.770)			(0.036)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	398	1242	1640	387	1227	1614	358	1184	1542	571	1542	2113
chi2	174.23	715.23	829.56	171.16	678.71	764.89				88.22	260.99	357.82
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							8.79	14.34	14.86			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.324	0.233	0.239	0.126	0.172	0.159

After controlling for self-selection, toehold has a greater impact on completion rates in the recent period than in the early one. The positive estimate of *Toehold size**Recent* indicates such strategies become much more beneficial over time in facilitating acquirers to complete deals. On the whole, as Table 3.8 shows, the efficiency improvement in toehold performance can be explained to some extent by self-selection procedure. Except for completion rates[31], the coefficient of the interaction term between *Toehold size* and the dummy variable *Recent* becomes less significant after controlling for self-selection outcomes.

3.5. Is monitoring an important qualification for an efficient toehold strategy?

According to the M&A literature, the takeover field is severely affected by agency problems (Mueller, 1969; Amihud and Lev, 1981; Berkovitch, and Narayanan, 1993). However, concentrated ownership, especially institutional holdings, helps monitor managers' actions and bring good outcomes for takeovers (Shleifer, and Vishny, 1986; Schranz 1993; Allen *et al.*, 2000; Gaspar *et al.*, 2005; Chen *et al.*, 2007). Inspired by these studies, we start to wonder: whether the better monitoring provided by institutional investors qualifies acquirers to use toeholds efficiently.

One possible explanation could be as follows. The adverse impact of toeholds in the early period can be viewed as evidence of agency problems in takeovers, but the involvement of institutional investors can mitigate such adverse impacts by monitoring managers to act in shareholders' interest. As time pass, the inappropriate usage of toeholds

[31] As discussed above, the relation between toehold and completion rate is complicated, which is greatly affected by the endogenous interaction between management resistance and toehold strategy, so it's hard to use self-selection procedure alone to identify all the impacts of toehold strategies on completion rate.

is reduced because of increased monitoring power. If this explanation holds, the introduction of institutional holdings into our previous regressions could capture the improvement of toehold's efficiency performance over time.

We define *Institutional holdings* as the percentage of shares held by institutional investors, and collect this data from Thomson Reuters. Table 3.9 shows new estimates of our four efficiency measures after introducing this new variable and its interaction term with toehold size. Again, a two-step method that controls for selection bias and heterogeneity is conducted. Compared to results in the previous section, the greatest changes occur on estimates for the recent period (after 1995) and the interaction term between toehold size and the recent dummy. For returns to acquirers in the recent period, the coefficient of Toehold size decreases from significantly positive (0.023 in Table 3.5) to significantly negative (-0.047), i.e., even worse than in the early period (-0.030). This adverse impact of stand-alone toehold strategies is further confirmed by the insignificant coefficients of the interaction term, *Toehold size*Recent*, in the last two pooled regressions. Similar changes happen to estimation results for combined returns, acquisition premiums, and completion rates. The relative better performance of toehold strategies in the recent period disappears in the presence of institutional holdings and its interaction terms. Apart from completion rates, where all coefficients of Toehold size are insignificant, stand-alone toeholds load with estimates of the same sign both before and after 1995. This change further helps to exclude the alternative explanation for the learning effect, i.e., a growing market acknowledgement of toehold's impact over time. If improvement in toehold's efficiency was attributed to better market perception of toehold strategies, coefficients of stand-alone Toehold size should remain time varying, rather than have the same sign across the two sub-samples. Toeholds owned by acquirers without institutional investors

Table 3.9 Toeholds performance by selection model with institutional holdings

The table reports estimates on four measures of toehold's efficiency by selection model with institutional holdings and its interaction terms as explanatory variables. *Institutional holdings* is defined as the percentage of shares held by institutional investor, which is collected from Thomson Reuters. Control variables and regression specifications are the same as in Table 3.8. We use same probit regression in Table 3.7 to calculate Inverse Mill's ratio and add institutional holdings as an additional explanatory variable in determining the probability of toehold strategy. The regression outcome for generating Inverse Mill's ratio are similar to that in Table 3.7, so we do not report it here for the concern of page limit. Coefficients and p-values (in brackets) are reported for each regression after introducing institutional holdings.

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled
Toehold size	-0.030	-0.047	-0.016	-0.017	-0.074	0.002	-0.004	-0.013	-0.005	-0.003	0.019	-0.009
	(0.017)	(0.003)	(0.133)	(0.376)	(0.000)	(0.902)	(0.412)	(0.009)	(0.233)	(0.826)	(0.251)	(0.487)
Toehold size*Recent			-0.018			-0.067			-0.007			0.033
			(0.237)			(0.003)			(0.212)			(0.085)
Inverse Mill's ratio	-0.354	0.222	-0.411	-0.429	0.680	-0.554	0.059	0.058	0.035	-0.190	-0.437	-0.120
	(0.012)	(0.056)	(0.001)	(0.021)	(0.000)	(0.000)	(0.139)	(0.261)	(0.374)	(0.182)	(0.003)	(0.357)
Inverse Mill's ratio*Recent			0.584			1.118			0.021			-0.395
			(0.001)			(0.000)			(0.734)			(0.032)
Institutional holdings	-1.017	0.049	-0.081	-0.763	-0.038	-0.116	0.143	0.066	0.074	1.059	0.408	0.520
	(0.000)	(0.577)	(0.317)	(0.012)	(0.681)	(0.184)	(0.033)	(0.039)	(0.010)	(0.000)	(0.003)	(0.000)
Toehold size*Institutional holdings	0.075	0.160	0.123	0.076	0.154	0.136	0.005	0.014	0.013	-0.041	0.034	0.015
	(0.066)	(0.000)	(0.000)	(0.206)	(0.000)	(0.000)	(0.655)	(0.147)	(0.067)	(0.422)	(0.439)	(0.603)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	398	1242	1640	387	1227	1614	358	1184	1542	571	1542	2113
chi2	193.45	746.29	857.49	178.11	701.27	789.27				104.53	270.89	377.46
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							8.39	13.67	14.47			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.332	0.237	0.244	0.149	0.179	0.168

persist in being inefficient over time, indicating that market do not perceive toehold strategies in a more positive light as time passes.

Compared to Table 3.8, the efficiency improvement indicated by coefficients of *Toehold size*Recent* become even weaker after adding Institutional holdings into the regression. The positive change in acquirer's return becomes insignificantly negative, and the period difference in combined return changes from insignificant to significantly negative. Efficiency improvements in these two return measures cease to exist after controlling for monitoring power. Estimates of *Toehold size*Institutional holdings* are more significant for deals taking place after 1995 than those for earlier deals, especially for Acquirer CAR (-41,end) and Combined CAR (-41,end), showing that Institutional holdings function better in improving toehold performance in the recent period. As with the pervious findings, time-variance in acquisition premiums is indistinguishable from zero, and better monitoring does not help to reduce the costs paid by acquirers (coefficients of *Toehold size*Institutional holdings* are insignificant in two subsamples, and significantly positive for the pooled regression). Institutional holdings also increase takeover completion rates - as all the estimates of *Institutional holdings* are significant at 1% level - but it does not help to improve toehold's performance in this respect, as none of their interaction terms are significant.

In sum, efficiency improvement in toehold performance ceases to exist after controlling for institutional holdings, as indicated by its similar impact on deals in the two sub-samples. It implies that better monitoring power can be a candidate to help toehold-owners to use such strategies properly to benefit them.

3.6. Robustness check

3.6.1. Different specifications of institutional holdings

As *Institutional holdings* is a general measure of shares owned by all institutional investors, it cannot reflect concentration of share ownership. To address this issue, we repeat our regressions in Table 3.10 using *shares held by top five institutional investors* in acquirer firms (defined as variable *Top five*) and its interaction terms with *Toehold size* and *Recent* to replace *Institutional holdings* and corresponding interaction terms.

Table 3.10 presents the same result as in Table 3.9, and shows that concentrated holdings by top five institutional investors reduces time-variance in toehold efficiency. The impacts of the size of stand-alone toeholds are of the same sign in two sub-samples, strengthening the evidence that firms with higher institutional holdings are the more qualified toehold acquirers.

As well as the concentration of share ownership, the type of institutional investors also matters. Previous studies show that public pension funds are more active in monitoring their portfolios than other investors (Del Guercio and Hawkins, 1999; Gompers and Metrick, 2001) and use the percentage of a firm's shares owned by public pension fund as a measure of corporate governance (Atanassov, 2012; Dittmar and Mahrt-Smith, 2007). We follow these studies in using public pension fund ownership as an alternative measure, and use the list assembled by Dittmar and Mahrt-Smith (2007) to identify them from the pool of institutional investors in our data. Table 3.11 shows similar results as the robustness check with shares held by top five institutional investors, confirming that good corporate governance can enhance toehold performance, and mitigate differences in toehold efficiency over time.

Table 3.10 Toeholds performance and shares held by top five institutional investor

The table reports estimates on four measures of toehold's efficiency with shares held by top five institutional investor as an explanatory variable. *Top five* refers to the percent of shares hold by the five largest institutional investors in an acquirer firm. Control variables are the same as in Table 3.8. Regression models remain the same as before. Inverse Mills ratios are from similar probit models as before, except that *Institutional holdings* is replaced by *Top five*. Coefficients and p-values (in brackets) are reported for each regression.

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled
Toehold size	-0.033	-0.053	-0.017	-0.018	-0.078	0.000	-0.003	-0.012	-0.005	-0.004	0.016	-0.011
	(0.012)	(0.001)	(0.134)	(0.363)	(0.000)	(0.986)	(0.529)	(0.022)	(0.261)	(0.777)	(0.346)	(0.423)
Toehold size*Recent			-0.021			-0.067			-0.005			0.034
			(0.177)			(0.003)			(0.319)			(0.074)
Inverse Mill's ratio	-0.341	0.261	-0.398	-0.409	0.687	-0.527	0.061	0.059	0.038	-0.197	-0.432	-0.121
	(0.015)	(0.027)	(0.002)	(0.023)	(0.000)	(0.001)	(0.123)	(0.253)	(0.342)	(0.168)	(0.003)	(0.354)
Inverse Mill's ratio*Recent			0.596			1.096			0.019			-0.393
			(0.001)			(0.000)			(0.768)			(0.033)
Top five	-1.442	0.614	0.309	-0.781	0.322	0.146	0.235	0.147	0.164	2.148	0.874	1.134
	(0.006)	(0.004)	(0.115)	(0.236)	(0.155)	(0.493)	(0.083)	(0.038)	(0.009)	(0.000)	(0.003)	(0.000)
Toehold size*Top five	0.151	0.268	0.197	0.123	0.255	0.222	-0.002	0.019	0.014	-0.057	0.102	0.032
	(0.024)	(0.000)	(0.000)	(0.226)	(0.000)	(0.000)	(0.892)	(0.365)	(0.269)	(0.470)	(0.370)	(0.562)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	398	1242	1640	387	1227	1614	358	1184	1542	571	1542	2113
chi2	184.22	756.12	859.94	173.41	702.58	787.21				104.60	271.23	378.74
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							8.23	13.60	14.38			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.327	0.236	0.243	0.149	0.179	0.169

Table 3.11 Toeholds performance and shares held by public pension funds

The table reports estimates on four measures of toehold's efficiency with shares held by public pension funds. *Pension fund* refers to the percentage of shares held by public pension funds, where the list of public pension funds is obtained from Dittmar and Mahrt-Smith (2007) . Control variables are the same as in Table 3.8. Regression models remain the same as before. Inverse Mills ratios are from similar probit models as before, except that *Institutional holdings* is replaced by *Pension fund*. Coefficients and p-values (in brackets) are reported for each regression.

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Price premium			Completion rate		
	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled	year≤1995	year>1995	pooled
Toehold size	-0.020	-0.036	-0.013	-0.012	-0.053	0.001	-0.003	-0.013	-0.004	-0.006	0.021	-0.007
	(0.095)	(0.017)	(0.226)	(0.547)	(0.004)	(0.959)	(0.438)	(0.006)	(0.361)	(0.654)	(0.193)	(0.588)
Toehold size*Recent			-0.015			-0.052			-0.008			0.029
			(0.310)			(0.017)			(0.179)			(0.136)
Inverse Mill's ratio	-0.300	0.227	-0.346	-0.341	0.658	-0.389	0.056	0.068	0.037	-0.214	-0.417	-0.128
	(0.031)	(0.050)	(0.007)	(0.055)	(0.000)	(0.012)	(0.157)	(0.189)	(0.355)	(0.129)	(0.003)	(0.326)
Inverse Mill's ratio*Recent			0.550			0.983			0.033			-0.361
			(0.001)			(0.000)			(0.608)			(0.050)
Pension fund	3.836	8.950	7.230	4.765	8.036	7.375	0.752	0.968	0.797	6.589	4.337	4.570
	(0.171)	(0.000)	(0.000)	(0.156)	(0.000)	(0.000)	(0.315)	(0.084)	(0.076)	(0.053)	(0.103)	(0.025)
Toehold size*Pension fund	0.374	0.496	0.471	0.182	0.395	0.417	0.131	0.077	0.075	-0.723	0.125	0.065
	(0.507)	(0.001)	(0.000)	(0.840)	(0.015)	(0.005)	(0.383)	(0.108)	(0.093)	(0.558)	(0.783)	(0.842)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	398	1242	1640	387	1227	1614	358	1184	1542	571	1542	2113
chi2	177.300	773.030	890.810	173.460	709.220	802.360				92.120	265.130	364.440
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							8.170	13.640	14.300			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.325	0.237	0.242	0.132	0.175	0.162

3.6.2. Merger wave

Our sample contains observations during the recent merger wave between the mid-1990s and the early 2000s. Although both of our sub-samples cover a portion of this merger wave, more years belong to the merger wave period in the recent sub-sample than in the early sub-sample. To separate the impact of market abnormalities associated with the merger wave, we exclude data from the wave period from our sample and divide the rest into two subsamples, i.e. before the merger wave (1990-1993), and after it (2002-2006). Using observations before the wave as the benchmark, we define one dummy variable *'after'* to denote those made after the wave.

Panel A in Table 3.12 presents estimates similar to Table 3.6, where we compare differences in toehold performance before and after the merger wave. In general, the changes in toeholds' efficiency in Table 3.6 still persist in the sample without the presence of a merger wave. Toehold strategies perform better in the later period than they did in the early period, especially in terms of increasing acquirers' returns and success in selecting good targets. There is little change in acquisition premiums. Before the merger wave, toeholds reduce the probability of completing deals, but this negative correlation disappears after the wave, although the insignificant coefficient of *Toehold size*After* indicates this time variance is not significant, which is consistent with previous findings.

Panel B in Table 3.12 reports new estimates after introducing the self-selection procedure and institutional holdings as additional regressors. Due to fewer observations, most estimates are less significant as before, but we can still observe that the self-selection model has similar explanatory power as it had before. Time differences in toehold efficiency disappear, indicated by insignificant estimates of all the interaction terms

Table 3.12 Toeholds performance by selection model in different periods defined by merger wave

The table reports estimates on four measures of toehold's efficiency by selection model in different periods excluding data in merger wave. Merger wave is defined as from 1994 to 2001, when the numbers of deals are much higher than other years. Panel A reports estimates from regressions without selection procedure. Variable "After" is a dummy variable, which takes value of 1 if a deal happens after merger wave and 0 otherwise. Panel B reports estimates by self-selection model with institutional holdings as an additional regressor. Inverse Mill's ratios are estimated separately for each subsample, using probit model similar to Table 3.7. Control variables are the same as in Table 3.8. For each variable, its coefficient and corresponding p-value (in brackets) are reported.

Panel A: normal regression without selection procedure

	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
	before merger wave	after merger wave	without merger wave	before merger wave	after merger wave	without merger wave	before merger wave	after merger wave	without merger wave	before merger wave	after merger wave	without merger wave
Toehold size	-0.031	0.114	-0.023	-0.036	0.106	-0.020	0.002	0.001	0.004	-0.037	-0.036	-0.022
	(0.023)	(0.041)	(0.058)	(0.059)	(0.058)	(0.247)	(0.765)	(0.905)	(0.391)	(0.021)	(0.305)	(0.102)
Toehold size* After			0.057			0.050			-0.003			-0.030
			(0.005)			(0.023)			(0.629)			(0.275)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	180	319	499	172	317	489	152	305	457	263	382	645
chi2	128.77	178.13	245.09	108.15	137.17	208.40				51.27	75.19	112.70
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							3.66	7.94	6.81			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.251	0.313	0.242	0.156	0.220	0.163

Table 3.12 (continued)

Panel B: self-selection model	Acquirer CAR (-41,end)			Combined CAR (-41,end)			Acquisition premium			Completion rate		
	before merger wave	after merger wave	without merger wave	before merger wave	after merger wave	without merger wave	before merger wave	after merger wave	without merger wave	before merger wave	after merger wave	without merger wave
Toehold size	-0.031	0.123	-0.017	-0.025	0.109	-0.001	-0.004	0.003	-0.004	0.007	0.371	-0.007
	(0.050)	(0.400)	(0.216)	(0.265)	(0.445)	(0.963)	(0.613)	(0.929)	(0.534)	(0.793)	(0.525)	(0.767)
Toehold size* After			0.052			0.054			0.002			0.293
			(0.591)			(0.584)			(0.912)			(0.334)
Inverse Mill's ratio	-0.459	1.391	-0.256	-0.715	1.061	-0.511	0.119	-0.381	0.094	-0.321	-5.379	-0.236
	(0.017)	(0.683)	(0.137)	(0.015)	(0.755)	(0.033)	(0.092)	(0.608)	(0.050)	(0.172)	(0.225)	(0.250)
Inverse Mill's ratio * After			0.066			0.101			-0.106			-3.682
			(0.945)			(0.920)			(0.637)			(0.126)
Institutional holdings	-2.786	-0.210	-0.481	-2.397	-0.053	-0.244	0.313	0.034	0.086	1.700	0.612	0.692
	(0.000)	(0.224)	(0.000)	(0.000)	(0.759)	(0.063)	(0.028)	(0.412)	(0.046)	(0.000)	(0.057)	(0.003)
Toehold size *Institutional holdings	0.190	-0.122	0.040	0.162	-0.089	0.048	-0.002	0.023	0.009	-0.159	-0.106	-0.052
	(0.001)	(0.447)	(0.403)	(0.044)	(0.567)	(0.435)	(0.919)	(0.633)	(0.458)	(0.092)	(0.920)	(0.539)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	180	289	469	172	288	460	152	279	431	263	346	609
chi2	171.98	148.29	248.79	132.89	135.80	216.73				69.07	94.13	138.74
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
F-value							3.67	8.33	7.29			
							(0.000)	(0.000)	(0.000)			
Adjusted / Pseudo R-squared							0.280	0.356	0.298	0.211	0.304	0.211

between Toehold size and After. Apart for completion rates, the impact of the self-selection procedure - as reflected by the coefficient of Inverse Mill's ratio - is adverse for the rest of the efficiency measures before the merger waves, but this negative effect ceases to exist afterwards. The overall result shows that the existence of a merger wave does not introduce significant bias into our original analysis.

3.7. Conclusion

By investigating performance of toehold strategies in terms of return to acquirers, acquisition premiums, combined returns and completion rates, we find their efficiency improves over time, which indicates there is a time difference in the performance of acquisitions which use such strategies. This is in sharp contrast with the decline in popularity of minority stake acquisitions. We believe that – in addition to existing explanations – a dynamic perspective is required to understand the evolution of this puzzle. This explanation can be an improving self-selection outcome from learning the qualifications needed to use toehold strategies properly in executing acquisitions. We test this by building a self-selection model, and our outcomes support this argument. Furthermore, we show the better monitoring provided by institutional investors helps to overcome pitfalls in implementing toehold strategies, and can be seen as part of an acquirer's qualification to use them successfully.

This interplay between toehold performance and monitoring quality has practical implications, especially in mitigating agency problems in corporate investment. Driven by incentives to control more resources, managers can be highly motivated to expand their firms without maximizing shareholder's interest, which can lead to zero - or even negative - takeover payoffs. The adverse impacts of toehold strategies can be one consequence of this distorted incentive. Good corporate governance can be an effective mechanism to mitigate this principal-agent problem. Improvements in toehold performance show the rewards of strengthening monitoring: as a measure of external monitoring strength, institutional holdings demonstrate their important role in enhancing takeover performance, and suggest a similar role for internal monitoring mechanisms such as, for example, board independence.

This interplay between toehold performance and monitoring quality has theoretical and empirical implications. A dynamic model under agency considerations can more rigorously and realistically explain the suboptimal execution of minority stake, where unqualified bidders execute their acquisitions before the optimal threshold. An in-depth exploration of the relationship between internal monitoring and toehold performance is left for future work.

Chapter 4

Are Corporate Governance Mechanisms Complements? Evidence from Failed Takeovers

4.1. Introduction

Corporate governance is a set of disciplinary forces that is used to control companies and reduce agency cost. Takeover threats from potential acquirers are usually considered a very strong external governance mechanism in the management team. In the context of failed takeovers, this chapter investigates the interplay among different corporate governance mechanisms, which aims at shedding some light on the following questions. Are different corporate governance mechanisms complements or substitutes? In particular, is the quality of a firm's response to takeover threat positively correlated to the quality of other aspects of the firm's corporate governance? Previous studies have generated a lot of results and insights on this topic, but not yet reached a conclusive answer.

Some research supports the complements view. Hadlock and Lumer (1997) and Mikkelson and Parch (1997) find that the internal disciplinary pressure on the top managers is weaker when the threat of takeover is low. Denis and Serrano (1996) show that the post-contest internal restructuring is more value enhancing in the presence of an outside blockholder. Giroud and Mueller (2010) and Atanassov (2013) speak for the substitutes view. Their papers show that the adverse impact of the anti-takeover legislation is weaker in the presence of better internal governance. Other studies find neither complementary nor substitutional effect between the internal and external governance. Huson, Parrino, and Starks (2001) find that the intensity of the takeover threats does not affect the sensitivity of forced CEO turnover to firm performance, and conclude that takeover does not influence the internal corporate control. Denis and Kruse (2000) also find no change in CEO turnover and a firm's restructuring after the great decline in takeover activities in the late 1980s.

In this article, I focus on three aspects of corporate governance: monitoring by institutional investors, product market competition, and takeover threats. Monitoring by institutional investors is an internal and direct disciplinary mechanism that can actively affect corporate operation by proxy voting (Gillan and Stark, 2000; Hartzell and Stark, 2003). Product market competition is an external and relatively weak governance mechanism that facilitates a comparison of managerial performance (Nickell et al, 1997). Takeover threat poses a strong dismissal threat to management, and is therefore a powerful external disciplinary mechanism (Shleifer and Vishny, 1997; Bertrand and Mullainathan, 2003). The investigation into the interplay among these three governance mechanisms aims at providing a comprehensive understanding of their interactions. In particular, I want to address the following two questions:

Question (1): Can monitoring by institutional investors promote the effectiveness of the target firms' response to takeover threats? (Are monitoring by institutional investors and takeover threats complements?)

Question (2): Can competition in product markets enhance the effectiveness of firms' response to takeover threats? (Are competition in product markets and takeover threats complements?)

In particular, I consider failed takeovers as the ground to identify the relationship between different governance mechanisms. The key advantage of using the data on failed takeovers is that although the failed takeover creates a concrete control threat to the target firm, it does not actually shift in corporate control in the end. However, the threat is so strong that target firms may respond with substantial restructuring. Denis and Serrano (1996) report high management turnover among poorly performing firms after unsuccessful control contests. Franks and Mayer (1996) observe a high board turnover and an increase in asset disposals in target firms after unsuccessful hostile takeovers. Safieddine and Titman (1999) find that the target firms significantly increase leverage after the termination of takeovers.

Furthermore, I restrict the failed takeovers to those with a hostile or an unsolicited deal attitude. As argued by Morck *et al* (1989), Lambrecht and Myers (2007), and Servaes and Tamayo (2013), hostile takeovers are more likely to occur in troubled industries than in healthy industries. This grants hostile takeovers with the information externality, as it can signal poor performance of the whole industry. Since the inefficiency occurs industry wide, peer firms are expected to take similar corrective actions as the target firms (Servaes and Tamayo, 2013). They find significant changes in peer firms' investment and financing policies. Relative to target firms, control threats facing the peer firms are weaker and less direct. As a result, peer firms' responses to control threats may vary with the quality of their governance. Examining peer firms' responses enables me to investigate whether corporate governance can enhance firms' sensitivity to inefficiency signals embedded in failed takeovers.

The effectiveness of firms' responses is measured from two perspectives. The first is the changes in firms' investment and financing decisions. As discussed in Servaes and Tamayo (2013), as hostile takeovers identify industries with overinvestment problems, peer firms respond to this signal by cutting down their investment and increasing leverage. To make the analysis comparable to their study, I follow Servaes and Tamayo (2013) to focus on the changes in the capital spending and debt levels. The second perspective is to look at stock performance. It reflects a market's view on firms' profitability. By examining both operational decisions and market expectations, my result can provide a comprehensive picture of the influence of corporate governance on the effectiveness of firms' responses in failed takeovers.

The findings suggest that these three corporate governance mechanisms are, at most, weak complements. Although monitoring from institutional investors helps decrease target firms' free cash, it does nothing in improving firms' financing decisions or stock performance. Competition in product markets does not have a strong impact either. Although it brings higher abnormal returns to peer firms, its impact disappears after matching target and peer firms by their probability of being taken over. This means that the influence of product market competition is derived from its implication of the strength of takeover threat, rather than its disciplinary power. Overall, the quality of firms' responses to failed takeovers (the effectiveness of takeover threats as an external governance mechanism) does not have a strong correlation with either the monitoring by institutional investors (internal governance) or competition in the product market (anther external governance).

This article contributes to the literature on the interplay among different corporate governance mechanisms. Hadlock and Lumer (1997), Mikkelson and Parch (1997), Giroud and Mueller (2010), Atanassov (2013), Huson, Parrino, and Starks (2001), and Denis and Kruse (2000) investigate this topic under the context of declined takeover threat, whereas I complement the evidence by examining the interactions in the presence of strong takeover threats. The inclusion of both target and peer firms further decomposes takeover threats into two levels: strong and concrete threats to target firms, and indirect signals of industry-wide inefficiency to peer firms. This decomposition enables me to investigate the role of corporate governance under different strengths of control threats, which is a unique feature of failed takeovers.

The rest of this article is organized as follows. Section 4.2 develops the hypotheses. Section 4.3 describes the sample construction, variable definitions, and hypotheses to test. Section 4.4 reports the results, and section 4.5 is the conclusion.

4.2. Hypotheses development

Target firms and peer firms are subject to different strengths of takeover threats. Therefore, their responses are expected to be different in terms of the magnitudes. The target firms directly receive takeover bids. Although they successfully defend themselves, the takeover attempts indicate external recognition of inefficiency in their operations. As a reaction, they can either improve their performance or adopt takeover defenses. Whether the post-takeover restructuring is value enhancing or increasing management entrenchment will depend on the quality of other aspects of corporate governance. If the other aspects of governance mechanisms are complements to takeover threats, the target firms' post-takeover performance should be higher for firms that are better in those aspects of corporate governance. This leads to hypothesis 1 and 2:

Hypothesis 1: Firms with higher monitoring from institutional investors make better responses to takeover threats, and perform better in the stock market.

Hypothesis 2: Firms facing more competition in the product market make better responses to takeover threats, and perform better in the stock market.

Peer firms are not directly involved in takeovers. However, takeovers have information externality, implying industry-wide inefficiency (Morck *et al*, 1989; Lambrecht and Myers, 2007; Servaes and Tamayo, 2013). Peer firms can respond to this inefficiency signal by adopting similar actions as target firms. Since this signal is weaker than the shock received by target firms, whether peer firms can fully recognize it is not guaranteed. If other governance mechanisms are complements to takeover threats, they should improve peer firms' sensitivity to the inefficiency signal sent by takeover threats. After the failed takeover attempts, peer firms with better governance in other aspects are more likely to consider takeover threat a signal of operational inefficiency. Corporate governance is further expected to determine how well the peer firms can do after takeovers. Based on these arguments, I formulate the following testable hypotheses:

Hypothesis 3: Peer firms with higher monitoring from institutional investors make better financial and investment decisions after the takeover threats on the target firm, and perform better in the stock market.

Hypothesis 4: Peer firms facing more competitive pressure in the product market make better financial and investment decisions after the takeover threats on the target firm, and perform better in the stock market.

Finally, since the takeover threat influences the target firm directly, and the peers of the target firms only indirectly, I hypothesize that the magnitude of the response by the peer firms is to a lesser extent than the target firm, and if that leads to improved stock market performance, the improvement on the peers' stocks should be smaller than the target's improvement.

Hypothesis 5: The response to the takeover threat by the peer firms should be of a smaller magnitude than the target firms. The change/improvement of stock performance (if any) should also be smaller for the peer firms than for the target firms.

4.3. Data

4.3.1. Sample construction

Two samples of firms are constructed: a group of targets and a group of peers. The target sample is collected from the Security Data Corporation (SDC). To be included in the sample, a takeover attempt should meet the following criteria:

- The deal is announced for U.S. public non-financial targets during the period from 1 January 1987[32] to 31 December 2008;
- The deal status is withdrawn, and the deal attitude is hostile or unsolicited[33];

[32] I choose 1987 as the starting year, because this article uses historical SIC codes from Compustat to identify peer firms, and the earliest historical SIC codes provided by Compustat start from 1987.

- Acquirers are seeking to own more than 50% of target shares, and the percentage owned by acquirers before the takeover attempts is less than 50%;
- The following deal types are excluded: privatization, spinoffs, recapitalizations, exchange offers, repurchases, debt restructuring, target bankrupt, and acquirer involves management;
- The deal is announced at least one year after the last completed bid and one year before the next completed bid;
- The target has available accounting data from Compustat and available stock data from CRSP in the announcement year.

If one target received multiple withdrawn bids satisfying the earlier criteria, it is counted as one single takeover attempt with the announcement equal to that of the earliest bid and the withdrawn date equal to that of the last bid. In the end, there are 270 failed takeover attempts in the target sample.

The sample of industry peers is identified by historical 4-digit SIC codes from Compustat.[34] To exclude the impact from other takeovers, firms receiving takeover bids within 3 years around the corresponding failed takeover are removed. This requirement also effectively removes targets from the sub-sample of peer firms. Furthermore, to be included in the peer sample, firms should have available data on both Compustat and CRSP. These requirements result in 1849 firms in the peer sample.

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[33] Servaes and Tamayo (2013) focus only on hostile takeovers, whereas I also include unsolicited takeovers because of the limited number of unsuccessful hostile takeovers (only 125 deals meeting the selection criteria are hostile). Furthermore, unsolicited takeovers are expected to be similar to hostile takeovers, as they are not invited by target firms and reflect external investors' opinions on the efficiency of target firms' operation.

[34] According to Guenther and Rosman (1994) and Kahle and Walkling (1996), Compustat SIC codes are more reliable than CRSP SIC codes.

Table 4.1 gives an overview of targets and peers by year. The peak of failed (hostile or unsolicited) attempts is in 1988, of 52 deals; whereas the year 2006 has the least failed takeover attempts, only of 1 deal. The distribution of the target sample is a bit skewed to the 1980s (where 114 deals occurred), as the hostile takeover is more frequent during this period (Betton et al, 2008; Holmstrom and Kaplan, 2001; Servaes and Tamayo, 2013). Furthermore, the average size of targets is smaller than their peers, except for the years 1993 and 2004, which indicates that small firms are more likely to face takeover threats.

Table 4.1

Yearly distribution of targets in failed takeovers and their peers

Our sample consists of 270 failed takeovers announced during the period from 1 Jan 1987 to 31 Dec 2008, extracted from SDC. All the deals are announced for public U.S. targets with a status as withdrawn and a deal attitude as hostile or unsolicited. Multiple bids on a single target are aggregated as one takeover attempt. Peers are recognized by 4-digit historical SIC of targets during the announcement year. To be included in the sample, targets and peers are required to have available data on both CRSP and Compustat. This table presents the yearly distribution of targets and peers, and their average size. MV denotes the market value of firms, and it is in millions of 1987 dollars.

Year	Number of Targets	Average Target Size (millions $)	Number of Peers	Average Peer Size (millions $)
1987	38	634.38	225	906.52
1988	52	589.84	406	7174.87
1989	24	370.34	163	907.57
1990	15	380.23	128	3058.12
1991	13	33.27	91	418.52
1992	3	28.51	5	1480.89
1993	9	799.86	41	129.03
1994	15	282.47	73	2623.08
1995	14	969.70	91	6672.86
1996	5	517.89	32	2041.36
1997	6	86.18	53	1591.79
1998	8	875.04	42	1511.78
1999	8	181.27	49	1759.16
2000	6	106.01	63	1064.25
2001	3	872.78	29	720.83
2002	2	271.09	31	957.95
2003	4	66.03	40	2302.02
2004	9	3592.74	70	2215.54
2005	5	634.67	14	22415.89
2006	1	920.87	6	13857.66
2007	6	163.97	37	3955.04
2008	24	1340.65	160	8381.73
Total	270		1849	

Most of the firms in the target sample are involved in only one failed takeover. The maximum number of failed takeover attempts for a target firm is two, and only eight target firms appeared twice in the sample. The average number of peer firms per deal is 7.12, ranging from zero for 22 deals to 40 for two deals.

With regard to the distribution of the deal sample across industries, Table 4.2 shows that 27 deals occurred in the business service sector according to Fama-French 48-industry categories, whereas the retail sector scored the second with 20 deals in the sample. All the other industries have less than 20 deals.

Table 4.2

Distribution of deals in Fama-French 48-industry categories

This table gives the distribution of deals in our sample by Fama-French 48-industry categories.

Fama-French 48-industry categories	Number of deals
Business service	27
Retail	20
Constrution materials	15
Restaurants, hotels, motels	14
Computers	13
Electronic equipment	13
Healthcare	11
Apparel	10
Other	147

4.3.2. Definition of variables and summary statistics

To provide a comprehensive picture of the interplay between different corporate governance mechanisms, I use two measures of corporate governance. One is the percentage shares held by institutional investors, *institutional holdings*. They are well grounded in the corporate governance theory that the institutional investors as blockholders can strengthen the monitoring power on corporate management. (Shleifer and Vishny, 1986; Brickley, Lease, and Smith, 1988; Agrawal and Mandelker, 1990). The institutional holdings are computed from Thomson Reuters as the sum of the percentage of shares held by institutional investors. Greater institutional holdings of a target firm imply more active monitoring from shareholders.

The other measure of corporate governance is the Herfindahl–Hirschman index (HHI). The HHI captures the intensity from product market competition. As shown by Giroud and Mueller (2010) and Atanassov (2013), product market competition can mitigate weakened discipline of management resulted from the enactment of antitakeover laws. The HHI is defined as the sum of squared market shares of all firms in a given three-digit SIC industry,[35] where market shares are calculated from firms' sales. A higher HHI implies weaker competition.

The firms' performance in failed takeovers is measured at two levels. The first level is the corporate level. Previous studies show that corporate takeover plays an important role in correcting managerial failure. In particular, it has a disciplining function on managers' tendency to overinvest. In failed takeovers, firms often reduce investments and increase the amount of debt in their capital structure (Franks and Mayer 1996; Safieddine and Titman, 1999; Servaes and Tamayo, 2013**)**. Following previous studies, I mainly look at firms' responses to takeover threats in terms of investment and capital structure policies. The main measures of investment policies are the capital spending and the level of free cash flow relative to assets. The capital spending is measured as the ratio of capital expenditure to assets. The level of free cash flow is defined as "operating income – interest payments – tax payments – dividend payments" (Lehn and Poulsen, 1989; Servaes and Tamayo, 2013), and its ratio to total assets can be viewed as a proxy for post-tax cash flow

[35] To make results comparable to Giround and Mueller (2010), I define the industry by a three-digit SIC code similar to the one in their paper.

that is not distributed to stakeholders. If firms view takeover attempts as signals of their overinvestment, they will reduce their capital spending and the levels of free cash flow. The main measure of capital structure policy is the ratio of long-term debt to total assets. As argued widely in earlier literature, high leverage helps align the interests of managers and shareholders, as it increases the probability that the manager is fired for poor performance (Grossman and Hart, 1982; Jensen, 1986). If the firms want to signal their commitment to correct overinvestment, they will borrow more debt to increase leverage.

Second, I use stock performance to depict investors' expectations on firms' profitability. If the changes in firms' financial policies are correct and effective, the stock of the firm should experience high abnormal returns around the takeovers. Considering the uncertainty and noise in choosing the proper event window, I calculate two measures of abnormal returns, *CAR(-1,1)* and *CAR(-42, end)*, to describe stock performance in both short and long horizons. Furthermore, I use analysts' forecasts on EPS to show how professionals, who are assumed to have better investment knowledge, view the efficiency of firms' reactions in failed takeovers.

Table 4.3 presents the summary statistics of all the performance measures. In addition to aggregating observations by the firms' identity (targets or peers), each firm group is further divided into four subgroups according to the level of institutional holdings and HHI, respectively. I use the differences between two-year averages of each accounting measure before and after the takeovers to measure the changes in investment and capital structure policies. Targets experienced greater changes in investment and capital structure policies, higher abnormal returns, and larger decreases in EPS forecast than their peers. Scaled by total assets, targets on average reduce their capital spending by 1%, increase long-term debt by 4%, and increase free cash flow by 3.4% after failed takeovers; whereas the corresponding changes for peers are only 0.6%, 3.7%, and 2%, respectively. Moreover, the takeover events result in positive and significant abnormal returns for targets, whereas the CARs for peers are insignificantly negative. For an inter-subgroup comparison, t-statistics are insignificant for all but two of the differences. Targets with high institutional holdings only suffer a slight decrease in EPS forecast, of 0.75%; whereas those with low institutional holdings experience a decrease of 2.88%. Furthermore, peers with high institutional holdings reduce their capital expenditures by 1.07%, whereas those with low institutional holdings only cut their capital spending by 0.23%.

Table 4.3

Summary statistics of performance measures

This table presents the overview of the performance measures. Panel A reports the descriptive statistics for targets, and panel B reports the descriptive statistics for peers. For each panel, the statistics for all targets (peers) and for subsamples defined by HHI and institutional holdings are listed, respectively. Institutional holdings denote the percentage of shares held by institutional investors. It is computed from Thomson Reuters based on shares held by institutional investors. HHI refers to Herfindahl–Hirschman index. It is computed as the sum of squared market shares of all firms in a given three-digit SIC industry. Market shares are computed from firms' sales, which comes from Compustat. The subgroups by institutional holdings (HHI) are defined by the yearly average of institutional holdings (HHI) in the sample. The variables Δ CAPX/Asset, Δ FCF/Asset, and Δ Long-term Debt/Asset are the difference between two-year average of CAPX/Asset, free cash flow / asset, and long-term debt / Asset after the takeover attempts and their corresponding two-year average before the takeovers. The variable CAR(-1,1) is the 3-day cumulative abnormal return around the announcement day, based on market model parameters. The variable CAR(-42,end) is the market-adjusted cumulative abnormal return from 42 trading days before the announcement of the first bid to the end date, which is defined as the earliest between 126 trading days after the withdrawn date and the delist date. Δ EPS forecast is calculated as the difference between the first average earning forecast in the six-month period after the takeover attempt is withdrawn (normalized by the stock price at the 42nd trading day after the withdrawn date) and the last average forecast in the six-month period before takeover announcement (normalized by the stock price at the 42nd day before the announcement date). All the performance measures are recorded in percentage. For each variable, the mean, standard errors (in parentheses), and the number of observations are reported. Furthermore, the t-statistics of difference in subgroups by HHI and s are reported.

Panel A: Targets

	All	Institutional holdings				HHI			
		Low	High	Difference	t-statistics	Low	High	Difference	t-statistics
Δ CAPX/Assets	-1.02	-0.90	-1.16	0.26	0.32	-1.53	-0.47	-1.06	-1.29
%	(0.41)	(0.64)	(0.47)	(0.83)		(0.66)	(0.47)	(0.82)	
	[N=160]	[N=87]	[N=73]			[N=84]	[N=78]		
Δ FCF/Assets	3.40	5.27	1.26	4.00	1.22	2.28	4.63	-2.35	-0.72
%	(1.64)	(2.75)	(1.52)	(3.28)		(2.60)	(1.92)	(3.28)	
	[N=159]	[N=85]	[N=74]			[N=83]	[N=76]		
Δ Long term debt / Assets	4.11	2.38	6.16	-3.79	-1.29	3.86	4.37	-0.50	-0.17
%	(1.47)	(1.96)	(2.21)	(2.95)		(2.13)	(2.03)	(2.95)	
	[N=162]	[N=88]	[N=74]			[N=84]	[N=78]		
CAR(-1,1)	17.22	17.89	16.01	1.88	0.86	17.99	15.98	2.00	0.93
%	(1.05)	(1.39)	(1.55)	(2.20)		(1.35)	(1.68)	(2.17)	
	[N=270]	[N=174]	[N=96]			[N=167]	[N=103]		
CAR(-42, end)	26.50	29.06	21.87	7.19	0.94	29.38	21.84	7.54	1.00
%	(3.67)	(4.82)	(5.53)	(7.68)		(4.16)	(6.89)	(7.57)	
	[N=270]	[N=174]	[N=96]			[N=167]	[N=103]		
Δ EPS forecast	-1.84	-2.88	-0.75	-2.13	-1.91	-2.19	-1.38	-0.81	-0.71
%	(0.56)	(0.95)	(0.56)	(1.11)		(0.81)	(0.75)	(1.13)	
	[N=143]	[N=73]	[N=70]			[N=81]	[N=62]		

Table 4.3 (continued)

Panel B: Peers

	All	Institutional holdings				HHI			
		Low	High	Difference	t-statistics	Low	High	Difference	t-statistics
Δ CAPX/Assets	-0.61	-0.23	-1.07	0.84	2.40	-0.53	-0.75	0.22	0.61
%	(0.17)	(0.27)	(0.19)	(0.35)		(0.24)	(0.20)	(0.37)	
	[N=1664]	[N=913]	[N=751]			[N=1084]	[N=580]		
Δ FCF/Assets	2.02	2.17	1.83	0.33	0.19	2.17	1.74	0.44	0.24
%	(0.85)	(1.49)	(0.54)	(1.72)		(1.20)	(1.03)	(1.78)	
	[N=1678]	[N=924]	[N=754]			[N=1079]	[N=599]		
Δ Long term debt / Assets	3.73	5.19	1.95	3.24	1.12	2.50	6.02	-3.52	-1.17
%	(1.44)	(2.58)	(0.54)	(2.89)		(0.60)	(3.97)	(3.01)	
	[N=1723]	[N=944]	[N=779]			[N=1122]	[N=601]		
CAR(-1,1)	-0.33	-0.30	-0.37	0.07	1.14	-0.37	-0.26	-0.11	-1.63
%	(0.03)	(0.04)	(0.05)	(0.06)		(0.03)	(0.06)	(0.07)	
	[N=1808]	[N=990]	[N=818]			[N=1173]	[N=635]		
CAR(-42, end)	-0.21	1.05	-1.77	2.82	0.64	0.50	-1.51	2.01	0.44
%	(2.20)	(3.67)	(1.93)	(4.42)		(2.93)	(3.18)	(4.60)	
	[N=1823]	[N=1005]	[N=818]			[N=1178]	[N=645]		
Δ EPS forecast	-1.22	-2.25	-0.94	-1.31	-1.21	-1.41	-0.83	-0.58	-0.62
%	(0.44)	(1.66)	(0.35)	(1.08)		(0.48)	(0.91)	(0.93)	
	[N=876]	[N=184]	[N=692]			[N=578]	[N=298]		

4.4. Results

4.4.1. Changes in investment and capital structure policies

In this section, I examine how a firm changes its capital spending, free cash flow, and long-term debt after a failed takeover, and the influence of institutional holdings and industry competition (HHI) on the changes.

The yearly observations of CAPX/Assets, FCF/Assets, and Long-term debt/Assets are accumulated for a window ranging from three years before the takeover announcement to three years after the takeover withdrawal. The variable "After" is introduced to separate observations before and after takeovers. It is a dummy variable that uses a value of one for the years after the year of withdrawn, and zero otherwise. Its interactions with "institutional holdings" and "HHI" are the key variables in this section. These interactions describe the interplay between takeover threat and corporate governance. In particular, the following panel data regression is performed:

$$\begin{aligned} Ratio_{it} &= a_1 * After_{it} + a_2 * Institutional \quad holding_{it} * After_{it} + a_3 * HHI_{it} * After_{it} \\ &\quad + a_4 * Institutional \quad holding_{it} + a_5 * HHI_{it} + b * X_{it} + \eta_i + e_{it} \end{aligned} ,$$

where X_{it} is a vector of control variables, b is a vector of regression coefficients on the control variables, and η_i is an unobservable individual effect that is estimated by the fixed effect. To make the results comparable, I use the same sets of control variables as in Sevaes and Tamayo (2013) and list them explicitly for each ratio in the Appendix. Along with control variables, the noise in measuring the firms' policy changes is reduced, as the impact of changes on firms' fundamentals is identified. Furthermore, the fixed-effect specification in panel regression captures the unobserved time-invariant heterogeneity in firms' investment and capital structure policies, which makes the estimates more efficient.

Panel A of Table 4.4 contains the main results for target firms. Column 1 shows the effect of failed takeovers on target firms' capital spending, and whether the change in CAPX/Assets is different for firms with high and low institutional holdings, and for firms in competitive and non-competitive industries. The coefficient of the After dummy is -2.12 (with a standard error of 0.68). It is significant at the 1% level, implying that CAPX/Assets drop by 2.12% points on average. Given that the average CAPX/Assets of target firms is 8.62%, it implies a drop in CAPX/Assets by 24.6% for the average firm, which is very large economically. The interaction term between the After dummy and the institutional holdings has a coefficient of 0.74 (with a standard error of 0.95), which implies that the change in CAPX/Assets is not affected by the percentage of shares held by institutional investors. For the impact of industry competition, the interaction term between the After dummy and the HHI has a coefficient of 2.61 (standard error of 1.46), and it is significant at the 10% level. It implies that the drop in CAPX/Assets is larger for firms in competitive industries. As for the economic magnitude of the effect, a decrease in the HHI by one standard deviation is associated with a drop in CAPX/Assets by 2.61%*0.156=0.407%, or a drop in CAPX/Asset of 4.72% for the average firm. Both the stand-alone institutional holdings and HHI have insignificant coefficients, meaning they do not influence a target firm's capital spending without the takeover threat.

Table 4.4

Financial policies and corporate governance in failed takeovers

This table presents the impact of corporate governance on firms' investment and capital structures in failed takeovers. Panel A reports the regression outcomes on the target sample, and panel B reports the regression outcomes on the peer sample. The variables CAPX/Asset, FCF/Asset, and Long-term Debt/Asset are capital expenditure, free cash flow, and long-term debt, respectively, for each firm, scaled by total assets. All these performance measures are recorded in percentage. *After* is a dummy variable that assumes a value of 1 in the years after the withdrawal of the takeover and 0 otherwise. Institutional holdings denote the percentage of shares held by institutional investors. It is computed from Thomson Reuters based on the shares held by institutional investors. *HHI* refers to Herfindahl–Hirschman index. It is computed as the sum of squared market shares of all firms in a given three-digit SIC industry. Market shares are computed from firms' sales, which comes from Compustat. Control variables are described in the Appendix. Regression outcomes are based on fixed-effect panel regression. Standard errors are in brackets and are clustered at the firm level. Coefficients denoted with ***, **, or * are significant at the 1%, 5%, or 10% level, respectively.

Panel A: Targets

	CAPX/Assets	FCF/Assets	Long-term debt / Assets
After	-2.12***	3.52	-0.37
	(0.68)	(2.66)	(2.40)
Institutional holdings * After	0.74	-7.69**	0.92
	(0.95)	(3.57)	(4.62)
HHI * After	2.61*	6.45	4.58
	(1.46)	(6.80)	(5.34)
Institutional holdings	0.09	-0.68**	2.67***
	(0.19)	(0.35)	(0.27)
HHI	0.66	-5.72	1.56
	(2.65)	(6.54)	(11.00)
Control variables	Yes	Yes	Yes
Coefficient estimate	FE panel	FE panel	FE panel
N	1399	1415	778
R-squared	0.000	0.045	0.230

Panel B: Peers

	CAPX/Assets	FCF/Assets	Long-term debt / Assets
After	-0.40	-0.18	0.64
	(0.41)	(1.20)	(1.96)
Institutional holdings * After	0.16	1.78	-0.64
	(0.32)	(1.46)	(0.99)
HHI * After	-1.01	-2.57	-1.23
	(0.87)	(5.57)	(2.55)
Institutional holdings	0.49	1.33	0.73
	(0.34)	(1.31)	(0.69)
HHI	-0.60	-4.46	6.06
	(0.73)	(7.70)	(3.88)
Control variables	Yes	Yes	Yes
Coefficient estimate	FE panel	FE panel	FE panel
N	12395	12427	7086
R-squared	0.008	0.012	0.332

Column 2 in Panel A of Table 4.4 studies target firms' free cash flows. As claimed by Servaes and Tamayo (2013), hostile takeovers signal industry-wide overinvestment. If target firms think in this manner, the correct response is to reduce the level of free cash flows. The coefficient of the After dummy does not support this argument, as it is insignificant and positive. However, consistent with the over-investment story, high institutional holdings decrease the level of free cash flow after takeover, as the coefficient of the interaction term between the After dummy and the institutional holdings is significantly negative. An increase in the institutional holdings by one standard deviation is associated with a reduction in FCF/Assets by 7.69%*0.188=1.45%. Since the average FCF/Assets in the target sample is 2.36%, it equals a decline of 61.4% in FCF/Assets for the average target firm, which is highly economically significant. Furthermore, the stand-alone institutional holdings appear effective in cutting the level of free cash flow. Its coefficient is -0.68, which implies that high institutional holdings can mitigate the over-investment problem in target firms.

The third column in Panel A of Table 4.4 examines the debt levels in target firms. Neither the After dummy nor its interaction terms with the institutional holdings or the HHI has significant coefficients. It seems that neither monitoring from institutional investors nor the discipline from product competition can encourage target firms to increase their leverage more after a failed takeover. When it comes to stand-alone institutional holdings, they are positively associated with debt level, as it has a positive coefficient of 2.67, which is significant at a 1% level. If a target firm increases its institutional holdings by one standard deviation, the ratio between long-term debt and total assets will increase by 2.67%*0.188=0.50%. The coefficient of the HHI is insignificant.

Panel B of Table 4.4 presents the regression outcomes for peer firms. None of the variables in concern has a significant coefficient. It seems that the peer firms do not consider failed takeover attempts to industry counterparts as a concrete control threat, or, at least, they are not sensitive to this threat. The insignificant coefficient of the interaction terms between the After dummy and the institutional holdings (the HHI) shows that the corporate governance cannot enhance the peer firms' response to weak potential control threats. We can summarize these findings in Result 1:

Result 1: The estimation results provide some support for Hypothesis 1, and weak support for Hypothesis 2. Higher institutional holding is a complement to takeover threat in terms of reducing free cash flows; there is weak evidence that more competition in the product market is a complement (the coefficient is only significant at a 10% level) to takeover in terms of cutting down capital expenditure. The result does not support neither Hypothesis 3 nor 4. The financial decision by the peer firms does not seem to be affected by the takeover threat, and it is, therefore, possible to identify interaction terms of takeover threat and institutional holding, or competition in the product market. This result is supportive of Hypothesis 5, namely, since the takeover threat has a direct impact on the target firm, but only indirect impact on the peers, it improves the financial decision by the targets, whereas it generates barely any influence on the financial decision of the peers.

Table 4.5

Stock performance and corporate governance in failed takeovers

This table presents the impact of corporate governance on stock performance in failed takeovers. Panel A reports the regression outcomes on the target sample, and panel B reports the regression outcomes on the peer sample. The variable CAR(-1,1) is the 3-day cumulative abnormal return around the announcement day, based on market model parameters. The variable CAR(-42,end) is the market-adjusted cumulative abnormal return from 42 trading days before the announcement of the first bid to the end date, which is defined as the earliest between 126 trading days after the withdrawn date and the delist date. Δ EPS forecast is calculated as the difference between the first average earning forecast in the six-month period after the takeover attempt is withdrawn (normalized by the stock price at the 42nd trading day after the withdrawn date) and the last average forecast in the six-month period before takeover announcement (normalized by the stock price at the 42nd day before the announcement date). All these three measures of stock performance are recorded in percentage. Institutional holdings denote the percentage of shares held by institutional investors. They are computed from Thomson Reuters based on the shares held by institutional investors. HHI refers to Herfindahl–Hirschman index. It is computed as the sum of squared market shares of all firms in a given three-digit SIC industry. Market shares are computed from firms' sales, which comes from Compustat. Control variables are described in the Appendix. Standard errors are in brackets and are clustered at the firm level. Coefficients denoted with ***, **, or * are significant at the 1%, 5%, or 10% level, respectively.

Panel A: Targets

	CAR(-1,1)	CAR(-42,end)	Δ EPS forecast
Institutional holdings	1.10	0.39	-2.22
	(4.17)	(17.74)	(3.80)
HHI	2.74	-3.69	-2.02
	(6.75)	(22.60)	(4.04)
Control variables	Yes	Yes	Yes
Coefficient estimate	OLS	OLS	OLS
N	270	270	143
R-squared	0.362	0.283	0.568

Panel B: Peers

	CAR(-1,1)	CAR(-42,end)	Δ EPS forecast
Institutional holdings	0.03	-0.43	3.25
	(0.03)	(2.89)	(3.32)
HHI	0.62**	33.70**	3.53
	(0.27)	(16.60)	(2.49)
Control variables	Yes	Yes	Yes
Coefficient estimate	OLS	OLS	OLS
N	1805	1819	876
R-squared	0.229	0.125	0.151

4.4.1. Stock performance around failed takeovers

In this section, I investigate the impact of corporate governance on firms' stock performance around failed takeovers. In particular, firms' abnormal returns and the changes in analysts' EPS forecast are studies that examine how the market expects the profitability of the firm to develop after a failed takeover, and how the presence of an institutional investor and the competition in the product market affect this expectation.

Panel A of Table 4.5 presents the results for target firms. None of the estimated coefficients is significant. This suggests that investors and professional analysts do not expect different performance of target firms after failed takeovers, irrespective of the level of the institutional holding in the firm, or the competitiveness in the product market. Panel B of Table 4.5 reports the result for peer firms. Similar to an earlier finding, the institutional holdings do not affect CARs or changes in the forecast of EPS after in failed takeovers. However, the intensity of product market competition is negatively associated with abnormal stock returns of peer firms, as the coefficients of the HHI are significantly positive. For CAR(-1,1), the HHI has a coefficient of 0.62, with a standard error of 0.27. As for the economic magnitude of the effect, an increase in the HHI by one standard deviation is associated with an increase in CAR(-1,1) by 0.62%*0.156=0.097%. Since the average CAR(-1,1) in the sample of the peer firms is 0.59%, it equals an increase of 16.44% in CAR(-1,1) for the average firm. This positive correlation between the market competition and abnormal returns also holds for a longer event window. For CAR(-42,end), the HHI has a coefficient of 33.70 (standard error of 16.60); that is, an increase in the HHI by one standard deviation will increase CAR(-42,end) by 33.70%*0.156=5.257%. Given the average CAR(-42,end) in the sample of the peer firm is -0.212%, the impact of the HHI is large both statistically and economically. Nevertheless, one should be cautious in interpretation of the relationship between product market competition and CARs for peer firms. The HHI is highly determined by the number of firms in the same product industry. In addition to product market competition, it also reflects the size of the potential target pool in a certain industry. Within a highly concentrated market, a failed takeover may result in high attention toward peer firms, as they are likely to be the next target if the acquirer aims at buying assets from the same industry. If this is the case, the positive correlation between the HHI and CARs cannot be treated as the positive correlation between market competition and CARs. Instead, it only demonstrates a stronger spill-over effect of failed takeover in a more concentrated market. The results can be summarized in Result 2:

Result 2: The result of simple regression suggests that institutional holding has no impact on post-failed-takeover stock performance of either the target or the peers. Competition in the product market does not influence the post-failed-takeover stock performance of the target, but it lowers the stock return of the peers, which is quite counter-intuitive.

4.4.2. After matching

In the earlier sections, the samples of target and peer firms are separated, and the relationship between corporate governance and firms' performance in failed takeovers is examined separately for each sample, because the sizes of the target sample and peer sample differ a lot, 270 targets vs. 1849 peers. In this section, I match peer firms with target firms by their takeover probability, and use the pooled sample to re-investigate the hypotheses.

Matching is introduced for two reasons. First, it can create a balanced pooled sample in which the groups of target and peer firms have a similar size. Second, by leveling the possibility of being acquired, it can be more certain that the impact of HHI and institutional holdings comes from their roles as a measurement of corporate governance, rather than other alternative implications such as the industry concentration or the similarity with the target firms. Peer firms are identified by the industry classification of target firms, and there can be huge heterogeneity in industry characteristics, which will affect firms' sensitivity to takeover threats. For instance, the industry concentration varies in different industries. It is natural that a peer firm in a wide-spread industry is less sensitive to a failed takeover targeted at a remote target firm, compared with a peer firm in a concentrated industry facing the same signal, because the concentration of an industry can affect both the dissemination and perception of the signal conveyed by failed takeover threats. In a concentrated industry, the likelihood of a peer firm to become the next target is higher than in the case of a wide-spread industry, which will lead to different responses of peer firms in industries with different levels of concentration. This concern can cause serious problems if not treated well, because one key variable in this article, HHI, is a common measure of the industry concentration and indicates the intensity of product market competition. The previous finding shows that HHI has a significant impact on peer firms' stock performance, but it is doubtful as to whether this impact comes from the effect of corporate governance or the industry concentration measured by HHI. In order to reduce the noise brought about by multiple implications of HHI, I include HHI as one of the dependent variables to calculate the propensity score of firms. Moreover, peer firms sharing the common characteristics with target firms are more likely to become the next target, and, thus, respond more strongly to takeover threats. Since ownership structure is a critical characteristic, institutional holdings are also included as a dependent variable in the estimation of propensity score, to control for its impact on the likelihood of a peer firm becoming the next target.

The model I used to pair target and peer firms is propensity score matching (PSM). It was first introduced by Rosenbaum and Rubin (1983), and further developed by Heckman *et al* (1997). It is a widely applied approach that is used to estimate causal treatment effects (Dehejia and Wahba, 1999; Perkins et al, 2000; Hitt and Frei 2002; Davies and Kim, 2003; Brand and Halaby 2006; Caliendo and Kopeinig, 2008). Based on firms' asset characteristics, I calculate the probability of being the target in failed takeovers for each firm in the sample. Specifically, the propensity score is estimated from a probit regression with the control variables in section 4.1 (those for CAPX/Assets, FCF/Assets, and Long-term debt/Assets) as independent variables and the target dummy as the dependent variable. In particular, I use nearest-neighbor matching by using a propensity score. Table 4.6 presents the propensity scores (pscore) for target and peer firms before and after matching. After matching, the distribution of pscore in target and peer samples becomes more similar, and the sample size becomes the same, both with 103 firms.

Table 4.6

Pscores of targets and peers before and after matching

This table presents the distribution of propensity scores (pscores) for targets and peers before and after matching. The estimation of the propensity scores is estimated from a probit regression with control variables for CAPX/Assets, FCF/Assets, and Long-term debt/Assets, plus HHI and the institutional holdings.

Panel A: pscores before matching					
	N	Mean	Std. Dev.	Min	Max
Targets	106	0.114	0.045	0.038	0.265
Peers	998	0.094	0.042	0.000	0.287
Panel B: pscores after matching					
	N	Mean	Std. Dev.	Min	Max
Targets	103	0.111	0.039	0.038	0.215
Peers	103	0.111	0.039	0.038	0.216

Table 4.7 reports new regression results in pooled sample after matching. More interaction terms are introduced to separate the impact for target and peer firms. Panel A shows new estimates for investment and capital structure policies. The interaction term

between the institutional holdings and the After dummy has a positive coefficient of 1.70 for capital expending, and a negative coefficient of -12.71 for FCF/Assets. It indicates that monitoring from institutional investors can motivate target firms to spend more on capital investment and to reduce more on undistributed capital after failed takeovers. If a firm increases its institutional holdings by one standard deviation, its CAPX/Assets will increase by 1.70%*0.188=0.320%, and its free cash flow/Assets will decrease by 12.71*0.188=2.389%. Different from previous findings, the interaction term between the HHI and the After dummy loses the significance on its coefficient for regression on CAPX/Assets. Furthermore, the interaction term between the institutional holdings (the HHI), the After dummy, and the Peer dummy does not have any significant coefficient in Panel A, which means that corporate governance does not make any difference in peer firms' responses to failed takeovers in their investment and capital structure policies.

Panel B of Table 4.7 reports new estimates for stock performance. Different from the finding in section 4.2, the HHI does not have a significant coefficient for CARs any more, neither does the stand-alone HHI nor the interaction term between the HHI and the Peer dummy. This suggests that the positive correlation between the HHI and CARs in section 4.2 can be attributed to the link between the product market competition and the probability of becoming a target. Since the peer firms in more concentrated markets are more likely to become the next target,[36] they experience higher abnormal returns after failed takeovers. Once controlled for the probability of being acquired, the impact of the product competition on CARs disappears. Moreover, the monitoring from institutional investors stays trivial in determining firms' stock performance. Neither the stand-alone

[36] In fact, in the probit regression that estimates propensity score, the HHI has a positive coefficient of 0.822 with a p-value of 0.016.

institutional holdings nor their interaction term with the Peer dummy has a significant coefficient. This indicates that the difference in the institutional investors' presence in a firm's ownership does not form different expectations of future profitability among investors and professional analysts after a failed takeover. Though Panel A of Table 4.7 suggests that the monitoring from institutional investors changes target firms' decisions on capital spending and free cash flow, it appears too weak to affect stock performance. These results can be summarized in Result 3:

Result 3: When an improved estimation is made, taking into account the influence of the two corporate governance variables on the probability of a peer firm to be acquired, only institutional holding is found to be a complement to takeover threat in cutting down free cash flows (both target and peers). Competition in the production market does not improve the firm's response to takeover threats. Neither institutional holding nor competition in the production market has a significant impact on the post-failed-takeover stock performance of the firm. These findings provide support for Hypothesis 1, but not for Hypotheses 2–5.

Table 4.7

Corporate governance and performance in failed takeovers after matching

This table presents the impact of corporate governance on firms' financial decisions and stock performance in failed takeovers, where the target and peer samples are matched by pscore. Panel A reports the regression outcomes on the operational performance, and panel B reports the regression outcomes on the stock performance. The variables CAPX/Asset, FCF/Asset, and Long-term Debt/Asset are capital expenditure, free cash flow, and long-term debt per firm, respectively, scaled by total assets. The variable CAR(-1,1) is the 3-day cumulative abnormal return around the announcement day, based on market model parameters. The variable CAR(-42,end) is the market-adjusted cumulative abnormal return from 42 trading days before the announcement of the first bid to the end date, which is defined as the earliest between 126 trading days after the withdrawn date and the delist date. Δ EPS forecast is calculated as the difference between the first average earning forecast in the six-month period after the takeover attempt is withdrawn (normalized by the stock price at the 42nd trading day after the withdrawn date) and the last average forecast in the six-month period before the takeover announcement (normalized by the stock price at the 42nd day before the announcement date). All these performance measures are recorded in percentage. Peer is a dummy indicating whether a firm belongs to the peer sample or not. After is a dummy variable that assumes a value of 1 in the years after the withdrawal of the takeover and 0 otherwise. Institutional holdings denote the percentage of shares held by institutional investors. They are computed from Thomson Reuters based on the shares held by institutional investors. HHI refers to Herfindahl–Hirschman index. It is computed as the sum of squared market shares of all firms in a given three-digit SIC industry. Market shares are computed from firms' sales, which comes from Compustat. Control variables are described in the Appendix. Regressions on stock performance are done by OLS, whereas regressions on operational performance are based on fixed-effect panel regression. Standard errors are in brackets and are clustered at the firm level. Coefficients denoted with ***, **, or * are significant at the 1%, 5%, or 10% level, respectively.

Panel A: investment and capital structure policies

	CAPX/Assets	FCF/Assets	Long-term debt / Assets
After	-1.12	0.82	-0.42
	(0.93)	(4.29)	(2.41)
Peer*After	-1.13	0.64	4.96
	(1.85)	(5.04)	(3.02)
Institutional holdings * After	1.70*	-12.71**	1.31
	(0.90)	(5.33)	(4.73)
HHI * After	-1.35	5.88	6.80
	(2.08)	(10.70)	(7.12)
Institutional holdings* After*Peer	-1.57	12.14	-3.71
	(1.58)	(7.51)	(4.03)
HHI*After*Peer	4.89	-9.74	-12.10
	(3.75)	(13.00)	(7.61)
Institutional holdings	0.02	-0.31	2.61***
	(0.10)	(0.35)	(0.30)
HHI	7.19**	26.70*	-8.98
	(3.57)	(15.80)	(7.30)
Institutional holdings*Peer	-0.02	-0.09	-0.22
	(0.14)	(0.48)	(0.28)
HHI*Peer	-8.85**	-9.83	4.82
	(4.14)	(22.10)	(7.55)
Control variables	Yes	Yes	Yes
Coefficient estimate	FE panel	FE panel	FE panel
N	1324	1349	1306
R-squared	0.000	0.029	0.239

Table 4.7 (continued)

Panel B: stock performance

	CAR(-1,1)	CAR(-42,126)	Δ EPS forecast
Peer	-17.73***	-31.14	-0.68
	(4.51)	(28.58)	(3.80)
Institutional holdings * Peer	-3.47	3.69	0.87
	(6.65)	(32.73)	(6.14)
HHI * Peer	4.85	5.09	-3.05
	(11.20)	(61.00)	(11.50)
Institutional holdings	-5.61	21.17	-6.56
	(5.48)	(21.34)	(5.01)
HHI	0.32	-8.75	-7.40
	(8.83)	(47.20)	(11.40)
Control variables	Yes	Yes	Yes
Coefficient estimate	OLS	OLS	OLS
N	205	206	108
R-squared	0.593	0.318	0.539

4.5. Conclusion

This article studies whether different corporate governance mechanisms are complements or substitutes in improving firms' decisions and stock market performance. More specifically, I study how monitoring by institutional investors and competition from the product market affect firms' responses in failed takeovers. In the context of failed takeovers, I investigate the impact of monitoring by institutional investors and competition in the product market on the firms' performance in terms of operational performance and market recognition, which has not been studied earlier.

The result provides weak evidence on the complement argument for corporate governance mechanisms, in particular in terms of firms' financial decisions. Institutional holdings have a mixed impact on reducing overinvestment in target firms and have no impact on peer firms' operational decisions. For the target firms, it decreases free cash flow on the one hand, but increases capital spending on the other hand. Furthermore, it has no impact on the stock performance—for either target firms or peer firms—around the takeovers, which indicates no difference in investors' view on firms' performance with different institutional holdings. Competition in the product market also shows no influence on firms' responses. Although it affects peer firms' stock returns around takeovers, this influence is attributed to the positive correlation between industry concentration and the strength of takeover threat.

The result has important policy implications. Since governance mechanisms are not good complements, they suggest little spill-over effect by improving corporate governance in alternative forms in the presence of a well-functioning governance force. Thus, more effort should be directed to places where one form of corporate governance is weak. For example, it can be more beneficial to improve governance quality in non-competitive industries than in competitive industries.

This study focuses on three aspects of corporate governance. Future work can be extended to how other corporate governance mechanisms, such as monitoring by large non-institutional holders or the board, influence a target firm’s response to takeover threats, or the interaction between internal governance mechanisms when the firm is not faced with a takeover initiative.

Appendix 4.A

Control variables

This table gives a summary of control variables used in this article. The control variables used for accounting measures (CAPX/Assets, Long-term Debt/Assets, and FCF/Assets) are similar to those in Servaes and Tamayo (2013), and the control variables used for stock performances (CARs and delta EPS forecast) are similar to those in Dai, Gryglewicz, and Smit (2013).

Dependent variable	Control variables
CAPX/Assets	lagged Tobin's q, measured as (book value of assets - book value of equity + deferred taxes + market value of equity) / book value of assets;
Long term debt / Assets	i. EBIT / assets; ii. net property, plant and equipment / assets; iii. log assets; iv. R&D / assets; v. selling, general and administrative expenses / assets.
FCF / Assets	log assets.
CAR(-1,1), CAR(-42, end), and Δ EPS forecast	i. size of toeholds; ii. number of analysts making one-year-ahead earnings forecasts in the announcement year; iii. Log of market value at the 42nd trading day before the announcement date normalized at the price level of 1987; v. the average of the daily turnovers over the window [-166, -42] ; iv. a dummy equal to 1 if the stock price is less than one dollar at the 42nd trading day before the announcement date; vi. a dummy equal to 1 if the stock is listed on NYSE or AMEX; vii. a dummy equal to 1 if it is a tender offer. viii. a dummy equal to 1 if the takeover is paid by 100% cash; ix. a dummy equal to 1 if the deal attitude is hostile; x. a dummy equal to 1 if there are multiple bidders; xi. a dummy equal to 1 if the firm is incorporated in an antitakeover state; xii. year dummies; xiii. industry dummies (using 48 Fama-French industries).

Summary

This dissertation investigates three key questions about efficiency in corporate takeovers. They are 1) What are the optimal decisions in takeover contests? 2) How to measure the efficiency of a takeover strategy? and 3) How to improve firms' performance in takeovers? Three chapters, in this dissertation, are written to provide our thoughts on these questions.

Chapter 2 proposes that the level of similarity in bidders' valuations is an important factor that determines bidders' entry and bidding decisions. When bidders in a corporate takeover have related resources and post-acquisition strategies, their valuations of a target are likely to be interdependent. This chapter analyzes sequential-entry takeover contests in which similar bidders have correlated private valuations. The level of similarity affects information content of bids and bidding competition. Our model predicts that expected acquisition prices and the probability of multiple-bidder contests are the highest for intermediately similar bidders. We test these predictions in laboratory experiments in which we control the similarity between bidders. The experimental data confirm the non-monotonic effects of similarity on prices and on the frequency of multiple-bidder contests.

Chapter 3 introduces a dynamic perspective in evaluating the takeover strategy with toeholds[37]. Despite their decreasing popularity, toehold strategies to acquire targets do, in fact, perform better overtime. We propose a new explanation for the improved execution of

[37] Toeholds refer to the minority ownership of the target's shares owned by the acquirer before a takeover.

the toehold strategy: Qualified acquirers learn to use the strategy effectively, while unqualified acquirers have learned to walk away, because of the pitfalls involved in bidding with toeholds. Evidence, using self-selection models, supports this notion. Corporate governance, such as institutional holdings, also appear successful in improving outcomes in a toehold acquisition strategy, suggesting that firms with better monitoring are the more qualified toeholds acquirers.

In the context of failed takeovers, chapter 4 investigates whether internal (i.e. monitoring from institutional investors) and external governance mechanisms (i.e. competition form product markets) can improve firms' response to takeover threats and their stock performance. I collect data for two groups of firms (1) *targets* that are faced with strong threats and (2) *peers* that are faced with weak threats. The results indicate that governance mechanisms are at most weak complements to takeover threats in terms of promoting firms' performance. The internal and external governance mechanisms can improve targets' restructuring decisions (i.e. on free cash flow) to some extent, but cannot enhance peer firms' response. Furthermore, both governance mechanisms fail to bring higher stock performance for firms.

Samenvatting (Summary in Dutch)

Dit proefschrift onderzoekt drie belangrijke vragen over efficiency bij bedrijfsovernames. Deze zijn: 1) Wat zijn optimale beslissingen bij bedrijfsovernames? 2) Hoe kan de efficiency van een overnamestrategie worden gemeten? 3) Hoe kan de prestatie van bedrijven bij een overname verbeterd worden? Deze vragen worden in drie opeenvolgende hoofdstukken van dit proefschrift nader uitgewerkt.

Hoofdstuk 2 stelt dat de mate waarin de waardebepaling van verschillende bieders overeenstemt een belangrijke factor is, die zowel de beslissing van een bieder om mee te dingen als de hoogte van het uitgebrachte bod bepaalt. Wanneer de bieders vergelijkbare middelen en post-acquisitiestrategieën hebben, dan is het waarschijnlijk dat er een interdependentie is van hun waardebepaling van het overnamedoelwit. Dit hoofdstuk analyseert overnames waarbij de beslissing om mee te bieden sequentieel (opeenvolgend) is en waarbij er een correlatie is tussen de individuele waardebepalingen van op elkaar lijkende bieders. De mate van gelijkenis beïnvloedt het informatiegehalte van de biedingen en de biedstrijd. Ons model voorspelt dat de verwachte acquisitieprijs en de kans dat er een biedingenstrijd tussen meerdere bieders ontstaat hoger is wanneer er sprake is van een beperkte mate van gelijkenis tussen de bieders. We testen deze voorspelling met laboratoriumexperimenten waarbij we de mate waarin bieders op elkaar lijken laten variëren. De resultaten van het experiment bevestigen het bestaan van niet-monotone effecten die dermate van gelijkenis heeft op zowel de acquisitieprijs, als op de kans dat een overnamestrijd ontstaat.

Hoofdstuk 3 introduceert een dynamisch perspectief waarbij een 'toehold' strategie gehanteerd wordt. Dit betekent dat de bieder voorafgaand aan een overnamestrijd al een minderheidsbelang heeft in het overnamedoelwit. In weerwil van hun afnemende populariteit blijkt dat 'toeholds' uiteindelijk een beter resultaat opleveren. Wij vinden een nieuwe verklaring voor de betere resultaten van een toehold strategie: kopers met goede kwalificaties leren hoe ze de strategie optimaal kunnen inzetten, terwijl kopers met slechte kwalificaties leren om de overnamestrijd niet aan te gaan, vanwege de valkuilen die gepaard gaan met toehold biedingen. Resultaten van zelf-selectiemodellen ondersteunen deze hypothese. Governance maatregelen, zoals institutioneel aandeelhouderschap, lijken ook te leiden tot betere resultaten van een toehold strategie, wat suggereert dat bedrijven met een betere monitoring ook beter gekwalificeerde kopers zijn.

In het kader van gefaalde overnames onderzoekt hoofdstuk 4 of interne governance mechanismen (zoals institutioneel aandeelhouderschap) en externe governance mechanismen (zoals concurrentie op de productmarkt) een positief effect hebben op de reactie van een bedrijf op een overnamedreiging en op de aandelenkoers. We verzamelen informatie voor twee groepen bedrijven: 1) "overnamedoelwitten" die een sterke overnamedreiging voelen en 2) een controlegroep met vergelijkbare bedrijven die een zwakke overnamedreiging voelen. Uit de resultaten blijkt dat governance mechanismen hooguit een zwak complement voor een overnamedreiging vormen bij het verbeteren van de aandelenkoers van het bedrijf. Interne en externe governance mechanismen kunnen de herstructureringsbeslissing van een overnamedoelwit (bijvoorbeeld vrije cash flows) enigszins verbeteren, maar verbetert niet de respons van de controlegroep op een overnamedreiging. Tenslotte resulteren geen van beide governance mechanismen in een hogere aandelenkoers.

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