ESSAYS ON THE ROLE OF UNOBSERVABLES IN CORPORATE STRATEGY

DISSERTATION

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The Resource Based View suggests that firms that are most successful possess certain unique resources. This logic has been applied to a wide variety of strategic choices such as market entry and mergers & acquisitions among others. An implicit assumption is that such resources or the value from such resources are perfectly observed by all concerned. However, in reality resources are imperfectly observed. Through three essays, this dissertation develops models to study the role of imperfect observability on strategic choices. Theoretically it is shown that unobservability can lead to a counter intuitive position where firms that may indeed possess valuable resources fail to capture sustainable advantages. Similarly, it is shown that firms can consider using noisy signals to reduce the unobservability problem and thereby induce an outcome favorable to them. We demonstrate this in two settings. First, where potential target firms may use signals such as open market repurchases to attract more bidders and thus gain superior valuations. Second, we also examine the case where firms use market entry as a signal of their inherent strengths and thus may deter other potential entrants. The propositions from the theoretical models are also tested empirically. The structure imposed in the theoretical models present a difficult challenge from an empirical setting. This dissertation also develops an apt empirical model which takes into account the richness of the information structure embedded in the theoretical models.
In memory of my grandparents Mrs. Sathyabhama G. Menon and Mr. K.

Gangadhara Menon
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The role of resource heterogeneity and its impact on strategic choices has been a source of inspiration within several streams of research in strategic management. Prior literature makes an implicit assumption that resources are completely observed. What if resources are imperfectly observed? Imperfect observability can arise due to their inherent tacitness or complexity. In this context, examining the impact of unobservability of resources on strategic choices becomes important. The two essays in this dissertation develop conceptual and empirical approaches to examine the impact of imperfectly observed resources on strategic choice behavior.

In Essay 1 (Chapter 2) the role of unobservability of resources is explored in depth in the context of market entry decisions. Studies of competitive entry into new businesses, technological arenas, or international domains are common in strategic management research. This research has provided important results on the implications of market structure and heterogeneous resources for entry decisions. However, such studies are not modeled to accommodate strategic interaction and, therefore, implicitly assume sustainability of competitive advantage upon entry. In this chapter, we show that imperfect observability of resources can result in strategic interactions among competing firms, which may prevent even firms with superior resources from
obtaining sustainable competitive advantages. Previous research has been constrained by traditional empirical approaches which do not easily permit the analysis of such strategic interactions. In this chapter, we also propose a new empirical methodology to analyze entry decisions that allows the analysis of strategic interactions while also taking into account resource heterogeneity. We use simulated data to illustrate our results. It is also shown that in conditions where rivals react to outmaneuver entrants, traditional empirical approaches generate biased results. This chapter opens the door for future studies in strategic management to use our empirical model to answer fundamental questions about firm entry and sustainability of competitive advantage and about the impact of unobservability of resources on strategic choices.

Essay 2 (Chapter 3) builds on the core idea of unobservable resources and we apply it in a different setting, Mergers & Acquisitions. Specifically, this chapter examines the impact of target firms conducting open market stock repurchases prior to receiving a bid on the subsequent bidding process. More specifically, we examine whether these repurchases deter or attract bids. Prior literature exclusively focuses on the role of open market repurchases as a deterrence mechanism. In this chapter we offer an alternative explanation based on unobservability of resources. Specifically we suggest that in the presence of unobservability of its resources, target firm’s have an incentive to reveal information to the market through the use of mechanisms such as stock repurchases. Thus, potential bidders decide to participate based on their expectations on the true value of resources which is a function of both the bidders’ private signal and the public signal generated by the target. We show that in the presence of complete information on the target firm resources there exists multiple equilibria and hence makes it intractable for comparative static analysis. However,
introducing unobservability into the picture allows us to generate unique equilibria which in turn allows us to use comparative static analysis. Further we show that stock repurchases as a signal might serve to attract bidders rather than deter, when the precision of the signal is beyond a threshold. This suggests that open market repurchases may also serve the role of attracting bidders.

We try to empirically resolve this tension. Specifically, we use the statistical model developed in Essay 1 to empirically model strategic interaction between the bidder and target. We also implement the estimation in a Bayesian Markov Chain Monte Carlo (MCMC) framework. We test the model using a random sample of firms that repurchase stock and received bids between 1991 and 2005 and find that on average the target’s use of open market repurchases is consistent with attraction, after controlling for agency theory explanations. It is also shown that the deterrence/attraction effect is moderated by free cash flows. Specifically our results suggest that target firm’s with high levels of free cash flow are able to credibly signal to the market that their intentions are to deter bids.

Essay 3 (Chapter 4) builds on the ideas developed in Chapter 1 of this dissertation. While Chapter 1 focused on the impact of unobservability of firm decisions, we refrain from suggesting ways to solve the problem of multiple equilibria. In this Chapter, we apply equilibrium refinement techniques similar to the technique applied in Chapter 3. We use an entry setting and model strategic interactions between potential entrants while allowing for resource heterogeneity and unobservability. We show that theoretically a focal entrant’s decision to enter may be a noisy signal reflecting its innate resources. However, we find that increasing the precision of such a signal can again be a double edged sword. When firms have good quality resources, increasing
the precision leads to an outcome where it can deter other potential entrants. However, when the quality of the resources are not relatively high, increasing the precision leads to an equilibrium where other potential entrants who were unsure about the quality of the focal entrant, now decide to enter as the entry decision resolves their uncertainty.

Thus, this results in an empirical tension. The decision to enter can either lead to deterrence or it can lead to no deterrence. Similar to chapters 2 and 3, we use our structural model and examine entry decisions in the biotech-pharmaceutical industry. The biotech-pharmaceutical industry is characterized by high levels of unobservability in resources and capabilities. Our empirical analysis finds that consistent with predictions, greater investment in emerging technologies reduces the likelihood that the two firms will compete. Thus, when the true value of the investments are unobserved, higher investment by the focal firm coupled with an early entry decision serves the purpose of deterring other potential entrants. The results from this chapter has implications not only for the literature on entry decisions under resource heterogeneity but may also make a contribution to the literature on strategic disclosures.

Collectively, essays 1, 2 and 3 contribute to our understanding of the role of unobservable resources on strategic choices. Conceptually it is shown that when resources are imperfectly observed, good resources need not necessarily lead to sustainable advantages. Empirically, this dissertation documents that the lack of observability of resources might be a blessing in disguise for firms. It is shown that target firms can use noisy signals like open market repurchases to generate a favorable outcome such as receiving more bids, which might not be the case under perfect observability. Similarly it is also shown that potential entrants can use the entry decision as a noisy
signal and make firms believe that it has superior resources even when this is not the case. From a methodological perspective, this dissertation develops new models to accommodate multi party strategic interactions which can be easily adapted to several settings of interest within the domain of strategic management.
CHAPTER 2

ESTIMATING ENTRY MODELS WHEN RESOURCES ARE IMPEERCTLY OBSERVED

2.1 Introduction

The Resource-Based View (RBV) suggests that sustainable competitive advantage may exist in the presence of resource heterogeneity and immobility due to factor market imperfections (Barney, 1986; Peteraf, 1993; Wernerfelt, 1984). The fundamental logic of the RBV has particular implications for entry studies. A typical empirical study models the likelihood of entry as a function of an entrant’s resources, often with respect to the resources of other competing firms. For example, prior literature has studied entry into new technological domains (e.g., Kim and Kogut, 1996; Mitchell, 1989); foreign market entry (e.g., Hennart and Park, 1994; Chang, 1995; Anand and Delios, 2002); or diversifying entry into new industries and businesses (e.g. Montgomery and Hariharan, 1991; Helfat and Lieberman, 2002) among others. The implicit and unstated assumption in these studies is that firms making entry decisions perfectly observe both their own resources and those of their potential competitors. In a world where resources are completely observable, a potential entrant decides to enter and generates sustainable advantage if it possesses superior resources relative
to its competitors. The preceding logic is consistent with the classic predictions of the Resource-Based View (RBV).

However, resources need not be perfectly observable due to their tacit and complex nature. Imperfect observability can lead to potential strategic interactions\(^1\) among competitors, which in turn can lead to radically different predictions in terms of sustainability of competitive advantage. The decision by a potential entrant to enter a particular domain will be conditional on its observed superiority with respect to potential competitors. A world where resources are imperfectly observed allows for several interesting scenarios. For instance, there is scope for competing firms to bluff. In that case, it is possible that firms that lack heterogeneous resources might still capture sustainable advantages. Alternatively firms with better resources but with incorrect beliefs on the superiority of their competitors’ resources may forgo entry or withdraw early. Therefore, the nature of strategic interactions becomes very important. Imperfect observability has practical implications for real decisions.

Let us consider the competition between Boeing and Airbus in the market for very large aircraft (VLA). For the 40 years since Boeing launched its flagship model, the Boeing 747, it has remained the market leader in the large aircraft segment. In the early 1990s demand for air travel was expected to witness rapid growth, thus inciting Boeing and Airbus to consider building a super jumbo jet. In the year 2000, Airbus announced plans for its A-380 model and invested $11.9 billion. Responding to this move by Airbus, Boeing subsequently announced that it was backing out from this

\(^1\)Strategic interaction is defined as the state that prevails when multiple firms take into consideration not only their own resources, but also the other firms’ potential responses when making a decision (Bettis and Weeks, 1987).
segment. These interactions between Airbus and Boeing raise interesting questions. For instance, Ghemawat and Esty (2002) note that:

“Specifically, one particular line of game-theoretic modeling offers the non-obvious insight that although the incumbent, Boeing, would earn higher operating profits if it could somehow deter the entrant, Airbus, from developing a superjumbo, entry-deterrence through new product introductions may be incredible even if the incumbent enjoys large cost advantages in new product development (e.g because of line-extension economies).”

A potential reason why Boeing did not enter the super jumbo market even though it may have possessed capabilities in terms of scale economies, was that it was uncertain about potential scope economies that Airbus could exploit upon entering this market. Thus, both Boeing and Airbus essentially faced imperfect observability of the other firm’s resources. In hindsight, one can also ponder this question: What if Boeing held erroneous beliefs about its own capabilities? This counterfactual cannot be observed since Boeing decided not to compete. However, it is certainly plausible that Boeing may have been able to capture sustainable advantages if it indeed had not withdrawn. The final outcome suggests that even in the presence of heterogeneous resources, Boeing’s inability to completely observe its own resources and that of Airbus may have potentially influenced its decision to not enter.

This example also raises an interesting question from an empirical perspective: Is it possible to empirically model such interactions and their effect on competitive advantage? Current research designs fail to help us achieve this objective. This may explain why strategic interactions, though acknowledged frequently in theoretical models, have not provided much empirical validation (Nault and Vandenbosch,
In order to uncover the potential role of strategic interaction, we need to consider the strategic interdependence among competitors. Traditional models such as logit and probit are based on single firm decision making and hence are not tuned to capture multi-firm strategic interactions. In this paper we provide a relatively simple but effective approach to solving this problem. Our approach accounts for both imperfect observability and strategic interaction among potential entrants and incumbents while being consistent with theory. We are not aware of existing empirical models within the strategic management literature that utilize the structural approach outlined in this paper.

We demonstrate the value of our approach using simulated data. We show that when resources are completely observable, strategic interactions are not critical and hence traditional empirical research designs are robust. However, when resources and capabilities are imperfectly observed and strategic interactions matter, our analysis suggests that empirical research based on traditional methods can be misleading, even to the extent of giving us statistically significant coefficients with an incorrect sign.

To illustrate robustness, we show that in settings where resources are completely observable, our approach still produces consistent results, although there is some loss in terms of efficiency. We also show that our approach is generalizable and can be applied to a wide variety of entry contexts.

2.2 Previous Studies on Entry Decisions

2.2.1 Entry without Strategic Interaction: The Resource-Based Perspective

A firm’s decision to enter a new market depends on few critical factors, such as the firm’s own resources and capabilities, the corresponding resources and capabilities
of competitors, and the external environment. We broadly classify previous studies that examine entry decisions from the RBV lens into three categories. At this point, we note that this segmentation is for ease of exposition. There is some overlap among these segments, and several studies can be classified within multiple segments.

In the first group of studies, the probability of entry is primarily modeled as a simple function of the entrant’s resources and capabilities. Formally this can be expressed as follows:

$$Pr(Entry) = f(R_1, R_2, ..., R_n; C_1, C_2, ..., C_n)$$

The probability of entry depends primarily on $R_1, R_2, ..., R_n$, representing different resources and capabilities possessed by the entrant, and controlling for $C_1, C_2, ..., C_n$, which represents variables providing alternative explanations for the likelihood of entry such as such as cultural fit, relative exchange rates between international currencies, political risk considerations, legal determinants, or other macroeconomic conditions. The resources and capabilities can include R&D, patents, brands, organizational routines, knowledge assets, and relationship management, among others. Several studies find a relationship between specific assets or combinations of assets on the likelihood of entry (e.g., Mitchell, 1988; Montgomery and Harinharan, 1991; Chatterjee and Wernerfelt, 1991; Panzar and Willig, 1981). The broad conclusion from these studies suggests that the probability of entry was primarily influenced by the competitive advantage obtained by access to existing resources which contribute significantly in the new market.

In the second group of studies, the probability of entry need not necessarily be just a function of the entrant’s absolute resource base, but also the relative resource base requirement of the new market. Formally this can be expressed as follows:
The probability of entry depends primarily on the differential resources possessed by the entrant, relative to the incumbent, represented by \( R_1 - R'_1, R_2 - R'_2, ..., R_n - R'_n \), and controlling for \( C_1, C_2, ..., C_n \), representing variables providing alternative explanations for the likelihood of entry. Thus, the probability of entry depends not only on the entrant’s resources but also on the relative resource profiles of incumbents in the new market, and how well the entrant’s resources fit the new market (Helfat and Lieberman, 2002; Helfat, 1997; Anand and Delios, 2002). In technology intensive industries, the likelihood that firms will enter a new market depends to a large extent on the resource fit between their existing technologies and the new technologies (Kim and Kogut, 1996). This suggests that firms take into account the resources needed to succeed in the new market and enter only if they believe that they have enough valuable resources to exploit sustainable competitive advantage.

In the third group of studies, the probability of entry depends not only on the absolute and relative resource profiles as in previous studies, but also on competitive considerations such as market structure. Formally this can be expressed as:

\[
Pr(Entry) = f(R_1 - R'_1, R_2 - R'_2, ..., R_n - R'_n; C_1, C_2, ..., C_n; S_1, S_2, ..., S_n)
\]

The probability of entry depends not just on the differential resources possessed by the entrant \( R_1 - R'_1, R_2 - R'_2, ..., R_n - R'_n \) and alternative explanations as controls \( C_1, C_2, ..., C_n \), but also on competitive considerations such as market structure, represented by \( S_1, S_2, ..., S_n \). Most research on entry models tries to control for competitive effects through the use of industry wide measures such as concentration ratio and other measures of market power (e.g., Mitchell 1989, Anand and Kogut, 1997).
but without explicitly modeling strategic interaction. The exploitation of sustainable competitive advantage may be possible only when strategic interactions do not erode such benefits for competing firms. However, such aggregated industry level measures, while acknowledging the presence of strategic interactions, do not effectively address it. It is interesting that even though extant empirical work on entry seems to ignore strategic interactions, it forms an important part of mainstream strategic management (Bettis and Weeks, 1987; Smith, Grimm, Gannon and Chen, 1991). Next, we review a parallel stream of literature where strategic interaction does play a critical role.

2.2.2 Entry with Strategic Interaction

Beyond the RBV-based studies reviewed above, entry studies have also been the focus of extensive investigation by scholars interested in understanding strategic interactions between competing firms. However, such studies have primarily ignored the critical role of resources and their impact on strategic interactions. Much of the work in this stream of literature relies on sophisticated analytical modeling and focuses on actions that firms could take to set up contrived deterrence mechanisms to prevent entry. For example, actions of incumbent firms including limit pricing (Bain, 1949), sunk costs (Spence, 1977), differential information (Milgrom and Roberts, 1982a), and reputation (Clark and Montgomery, 1988) among others have all been suggested as potential barriers to entry.

The insights from these models have also been a source of inspiration for empirical work (e.g. Lieberman, 1987). Early empirical work, primarily descriptive in nature,
examines the predictions generated from theoretical models using traditional econometric methods. One stream of literature, primarily grounded within the domain of economics and industrial organization, focused on investigating performance outcomes conditional upon observed market characteristics (see Gilbert, 1989 for a survey of this literature). For instance, differential protection offered to certain firms due to their association with specific strategic groups may allow those firms to consistently outperform others (Caves and Porter, 1977). A parallel stream of literature (primarily grounded within strategic management) develops a stimulus response framework to study strategic interactions (McMillan et. al. 1985; Smith and Grimm, 1987, Chen, Smith and Grimm, 1992). The primary goal of the stimulus response framework is to understand strategic interaction by empirically extracting the effect of action/reaction characteristics on the likelihood that a particular action/reaction will be adopted. A common theme running across both streams of work is the exogenous treatment of strategic interactions and does not invoke any form of ex-ante rationality. Therefore, these studies are more consistent with backward-looking behavior suggestive of an adaptive expectations framework, as against a rational expectations frame work which forms the basis for much of the analytical/theoretical models.

This issue has been long recognized by scholars focusing on empirical industrial organization (for e.g. Bresnahan, 1989). In response, the new industrial organizational scholars have proposed several alternative approaches to study market entry without losing the richness of analytical models (Bresnahan and Reiss, 1991; Berry 1992; Berry, Levinsohn and Pakes, 1994, Tamer, 2003). Much of this literature focuses on modeling very specific contexts and may require highly-specialized data (Mazzeo, 2002). Further, the modeling of dynamics involved between multiple firms can be
highly complicated, giving rise to difficulties in estimation (Doraszelski and Pakes, 2007). This literature also ignores the important role of firm resources.

2.2.3 Resource heterogeneity, observability and strategic interaction

In summary, RBV based studies suggest that the primary factor influencing entry decisions are heterogeneous resources, which in turn lead to sustainable advantages. These studies implicitly assume that the resources and capabilities are completely observable by all potential entrants. Thus, all firms know their true competitive position. On the other hand, the presence of unobservable resources could lead to a situation where strategic interactions become critical, which would generate predictions that are counter-intuitive. Though extant literature, particularly within the domain of economics and industrial organization, has examined strategic interaction in the context of entry decisions, it has largely ignored the role of firm resources. Even though these streams of research complement each other, there is still a gap in terms of an approach that integrates resources heterogeneity and strategic interactions while also presenting an empirical solution consistent with both sets of theories. In the following section, we build a simple model that attempts to fill the void between these streams of work.

2.3 Conceptual Development

We begin with the premise that there exists a domain (e.g. a product or geographic market) where there may be incumbents and potential entrants. An example of entry into a new product could be the decision faced by Boeing and Airbus to enter the very large aircraft market. Similarly, an example of international entry could be the
decision faced by General Motors and Toyota to enter the Chinese automobile market. Under the RBV, each competitor is endowed with specific resources, which may be completely observed by the other. In reality, this is highly unlikely since firms are more likely to imperfectly observe such resources, including their own. Therefore, it is important to consider the implications of imperfect observability of resources on sustainability of advantage.

According to the resource based view, resources that are rare, valuable, and inimitable generate sustainable competitive advantage (Barney, 1991; Conner, 1991; Wernerfelt, 1984). Resources with the above mentioned characteristics are also likely to be ambiguous and often not fully observable (Lippman and Rumelt, 1982). Causal ambiguity implies that the key resource leading to superior performance is inherently tacit, socially complex, and has a high degree of specificity (Reed and DeFillippi, 1990). The extreme form of causal ambiguity suggests that even the firm that possesses the resource is not completely aware of its value (Lippman and Rumelt, 1982; Mosakowski, 1997). Thus, if the firm does not fully understand its own resources, it is highly unlikely that its competitors will understand them either (Kogut and Zander, 1993). An example of such a resource could be organizational routines and processes (Nelson and Winter, 1982). For instance, it is possible that the superior performance of Toyota can be attributed to its internal processes and culture. These resources are hard for competitors to understand and replicate; therefore, Toyota continues to be a dominant player. Other possible explanations including cognitive limitations, social complexity, and hubris also provide tangible reasons for resources to be imperfectly observed.
In this backdrop, we use a simple numerical example to show how theoretical predictions regarding sustainable competitive advantage differ in the presence of imperfectly observable resources. We start by setting a benchmark model where resources are perfectly observable, and then show how predictions change when we account for imperfect observability.

### 2.3.1 Resources and Capabilities are completely observed

We start with a simple decision choice problem with one incumbent and one potential entrant. Let us suppose that the incumbent (A) moves first and decides whether to invest (I) or not invest (∼I) in a resource position that she believes will allow her to capture sustainable advantages. Upon observing A’s decision, the potential entrant B must decide whether to enter (E) or not enter (∼E). Hence, there are four possible outcomes: Status Quo (∼I, ∼E), entrant B captures payoffs (∼I, E), incumbent A captures payoffs (I, ∼E), and competition (I, E). The payoffs for the incumbent and potential entrant are determined as a function of their relevant resources and capabilities. We interpret the fourth outcome of competition as leading to temporary advantages for one of the players. Similarly, if either A or B captures the market, we interpret that outcome as sustainable advantages for the relevant firm.

Figure 2.1 shows the nature of interaction when the resources and capabilities are completely observed. The numerical payoffs are designed as follows. When the incumbent does not invest and the potential entrant does not enter, the outcome is (∼I, ∼E) and the payoff for both firms is equal to 0. Thus, both firms receive nothing when neither chooses to actively engage the market. When B enters and A has not invested, B receives a payoff of 4 and A receives a payoff of 0.25. When A invests
and B does not enter, A receives a payoff of 4 and B receives a payoff of 0. When A invests and B enters, A receives a payoff of -0.5 and B receives a payoff of 0.5. The choice of payoffs is intuitive. Note that regardless of A’s decision, B will choose to enter with this payoff structure. Implicitly, we allow firm B to have a resource advantage over firm A for illustrative purposes.

We can solve the problem through backward induction. We start with entrant B’s decision. B will choose to enter (E) if A invests (I) since 0.5 is greater than 0. Similarly, B will choose to enter (E) if A does not invest (∼I) since 4 is greater than 0. Hence, regardless of the action taken by A, potential entrant B will always choose to enter. Incumbent A has to take into account the expected reaction by potential entrant B before making her decision to invest. Thus, A’s decision is now not to invest (∼I) because she prefers a payoff of 0.25 over -0.50. Therefore, the decision in this case is for A to not invest (∼I) and potential entrant B to enter (E). It should be noted that the substantive conclusion for such an illustration does not change when the resource advantage is conferred to the other firm. Hence, in a world where the resources and capabilities of the two competitors are completely observable and such resources are valuable, rare, inimitable, and organized, we will expect that differential capabilities will provide enough information, which in turn will lead to the observed choices made by firms. This implies that the resource advantaged firm will always enter and the resource disadvantaged firm will always stay away. Hence, the outcome of temporary advantages will never arise. Based on this, we arrive at our first proposition.
Proposition 2.3.1. Heterogeneous resources generate sustainable competitive advantages when these resources are perfectly observed by the competing firms.

While the discussion with full observability of resources mirrors the theoretical predictions from the classical RBV, our interest relates to what happens when resources and capabilities are imperfectly observed.

2.3.2 Resources and capabilities are imperfectly observed

What if resources and capabilities are imperfectly observed? Figure 2.2 presents the same decision structure as we used in the case where resources are fully observable, with the notable difference that we now have imperfectly observed resources for each competitor. Imperfect observability is parameterized by adding noise terms “$\varepsilon_A$” and “$\varepsilon_B$” to the payoffs of A and B. Intuitively, the noise term implies that competing firms are unable to judge with certainty the potential advantages conferred by the resources. We will now show that when resources and capabilities are imperfectly observed, the outcomes are no longer clear cut. The two competing firms do not know the true value of the unobservable part but are aware of its associated probability distribution. Logically, a large value of the unobserved component implies that there exists a significant chunk of resources which are unobservable to both the firm and its competitor.

Building on the simple numerical example where there was complete observability, we solve the model by working up the decision tree starting with potential entrant B’s decision. B’s decision to enter (E) when A invests (I) occurs when $0.50 + \varepsilon_B > 0$. Similarly, B’s decision to enter (E) when A decides to not invest ($\sim$I) occurs when
Thus, unlike the case where we had perfect observability, now B’s decision also depends on the associated draw of the unobserved component and $\epsilon_B$.

By induction, potential entrant A’s decision to enter (E) will be a function of both the likelihood that potential entrant B enters and of the random draw of A’s own unobserved component $\epsilon_A$. Given that $\epsilon_A$ and $\epsilon_B$ are unobservable; both entrants can only guess the most likely value of the unobservable component of resources. This also suggests that both entrants can possibly conceive of strategies to capture pure information rents, for instance through bluffing. In this situation, the implications of resource heterogeneity on sustainable competitive advantage are no longer clear cut.

To illustrate this point, we use a graphical approach.

Figure 2.3 graphs the probability of observing competition between the incumbent A and potential entrant B (the outcome where the incumbent invests and the entrant enters) with respect to draws of the unobserved component. Without loss of generality, we draw $\epsilon_A$ and $\epsilon_B$ from a normal distribution. The baseline case, which is when we have complete observability of resources, is represented by the horizontal line with a value of zero. In other words, under complete observability, there is no chance that both firms will enter since they both realize which firm will have sustainable competitive advantage upon entry. In the case with less than complete observability, we can clearly see that the greater the proportion of the unobservable component, the greater is the likelihood of observing an outcome where both firms compete. The curve is increasing, but at a decreasing rate. This is fairly intuitive. First, at low levels of unobservability the most likely outcome is that firms will choose to not compete. As the ratio of unobservable resources increases, we clearly see that the likelihood of competition between the incumbent and the entrant also increases.
Where the unobservable component is very high, for instance above 80 percent of the contribution from resources, the likelihood of competition starts declining again (although it is still not zero). At such high levels of unobservability, there is very little information on which firms can act and thus rational firms may tend to stay away. But given that firms can make mistakes, such as due to errors in judgment, the likelihood of competition is still positive. Such competition implies that competitive advantages for one of the two competing firms may be temporary.

At this juncture, we should also note that, in general, any outcome under imperfect observability can lead to lack of sustainable advantages for either player. For example, consider the outcome where B decides to enter and A decides not to invest. It is quite possible that due to causal ambiguity, B misread the value of its resources and made a mistake by entering. A, being the incumbent, still competes and eventually B finds out that it was a mistake and retreats from the market. Thus, B captures only temporary advantages, if any, in this case. Alternatively, B might misread A’s resources, also leading to temporary advantages for B. An even more interesting case arises when it is possible that ex-ante, resource-endowed firms hold erroneous beliefs about their competitors’ resources and therefore withdraw from the market. For instance, B’s decision to stay out may be motivated by what it believes A’s resources to be. Thus, ex-ante, as long as B believes that A has superior resources; A can still capture sustainable advantages irrespective of the actual resource positions. Unlike the case where there is full observability, resource-advantaged firms may not necessarily capture sustainable competitive advantages. Based on this analysis, we generate the following proposition.
Proposition 2.3.2. Heterogeneous resources may not be sufficient to generate sustainable competitive advantages when these resources are imperfectly observed by the competing firms.

We have conceptually demonstrated the conditions under which competitive advantages can be sustained in the presence of both perfect and imperfect observability of resources. Further, our model has important implications for empirical analysis of entry decisions. As previously reviewed, current empirical RBV-based research assumes proposition 1. However, as we have argued in this section, such an assumption need not necessarily be true. From proposition 2 we can clearly see that in the presence of strategic interactions due to imperfect observability, fundamental predictions about the sustainability of competitive advantage can change. In the next section, we suggest a simple approach to integrate resource heterogeneity and strategic interactions in an empirical model and examine the relative effect on sustainability of competitive advantages.

2.4 Empirical Methodology

In the previous section we saw that in order to understand the determinants of sustainability, we need to consider two critical elements, namely a) heterogeneous resources and b) strategic interaction. Appropriate methods are also required to take both of these elements into account. First, we discuss why traditional methods fail to offer a solution to this problem.
2.4.1 Aggregation and loss of information

Traditional techniques such as probit/logit, which have been used extensively in prior literature on entry studies (Anand and Delios, 2002; Hennart and Park, 1994; Chang, 1995; among others), fail to capture the critical element of strategic interactions. This is because such models are fundamentally designed to capture the choice behavior of a single firm. Inherently, these models are not designed to capture multi-player interactions and therefore are not suitable to study strategic interactions among firms. We explain this point further below. A simple solution to the problem could be to aggregate all possible outcomes and estimate a reduced model with just two outcomes. To illustrate this point, consider the case of the conceptual model discussed in the previous section. There are four possible outcomes that can arise in this setting. They are expressed as follows:

\[\begin{align*}
Y1 &\Rightarrow \text{Incumbent (A) does not invest and Entrant (B) does not enter} \\
Y2 &\Rightarrow \text{Incumbent (A) does not invest and Entrant (B) enters} \\
Y3 &\Rightarrow \text{Incumbent (A) invests and Entrant (B) does not enter} \\
Y4 &\Rightarrow \text{Incumbent (A) invests and Entrant (B) enters}
\end{align*}\]

The dilemma facing the researcher is how to determine the most likely outcome. An initial attempt could be to use a simple binary choice model such as probit/logit. To do this, we need to reduce the four outcomes into two through a process of aggregating outcomes. For instance, we can classify Y1 and Y2 together into outcome O1 and Y3 and Y4 together into outcome O2 and then run a probit/logit model with O1/O2 as the dependent variable and resources as independent variables.
In the case of perfectly observable resources, this aggregation does not pose a problem since all relevant information is accounted for. But, in the case of imperfectly observed resources, all relevant information is not accounted for due to aggregation, and strategic interaction may rear its head. For instance, clubbing Y3 and Y4 substantively means that the outcomes where the incumbent captures sustainable or temporary advantages are now clubbed together. As we can see, aggregation leads to loss of critical information and the strategic element of this model is suppressed.

It should be noted that this same limitation extends to multinominal choice models also. Though outcomes need not be aggregated in multinomial models, the choice probabilities for each outcome do not take into account how the other firm is likely to act or react. Thus, these models also do not accommodate strategic interaction. We can show mathematically that the derived choice probabilities for the multinomial logit/probit models are different when multiple players are involved\(^2\). Consequently, these models are structurally misspecified. Apart from the issue with aggregation, empirical researchers face another critical roadblock. This relates to effective translation of the theoretical model into the empirical model, which we outline below.

### 2.4.2 Translating theory to empirics

Aggregation problems aside, situations which involve strategic interactions can also lead to solutions with multiple equilibria, especially when competitors act simultaneously (Bresnahan and Reiss, 1990). In a situation with multiple equilibria, it is difficult to make a prediction regarding the outcome. For instance, what happens when equilibrium predictions suggest that outcomes Y2 and Y4 are equally likely?

\(^2\)A comparison between the probabilities derived later in this paper and multinomial logit/probit probabilities will illustrate this point clearly.
Intuitively, this implies that both temporary and sustainable advantages to the incumbent are possible in equilibrium. In such a case, performing empirical analysis and drawing inference on the effect of heterogeneous resources on competitive advantage becomes very difficult. To solve this problem, a potential solution is to model sequential behavior where unique equilibria can be identified (Mazzeo, 2003; Bresnahan and Reiss, 1991). In this paper, we use this idea of sequential interaction to help identify a unique choice.

Suppose we employ a sequential choice structure; in a setting where the resources are perfectly observed, the unique equilibrium is always played with probability of one. As an example, in our conceptual model with complete observability, it is clear that the equilibrium outcome where incumbent (A) does not invest and potential entrant (B) enters, as represented by Y2, occurs with probability of one and all other outcomes occur with probability of zero. However, consider the problem that the researcher faces. The objective is to map all possible outcomes into the likelihood function and use data to estimate the most likely outcome. However, there exists no estimation problem if only one outcome is always observed! Therefore, in our example, the likelihood function itself will not exist since Y1, Y3 and Y4 occur with zero probability. Hence, a critical condition for empirically examining choices involving strategic interaction is that all outcomes should have a positive probability (even if it is very small). The case of imperfect observability of resources provides us with a perfect bridge between a conceptual model and an econometric procedure. Imperfect observability gives rise to the likelihood that every outcome may now be played with a positive probability (even if it is very small). Following this logic, we develop the mechanics of this model and provide intuition for the same.
2.4.3 Structural empirical model

Our empirical approach directly follows the development of the conceptual model discussed earlier. There are four possible outcomes in the conceptual model which can be generalized as follows: Status quo [SQ (\sim I, \sim E)]; Incumbent (A) gains advantage [ASA (I, \sim E)]; Entrant B gains advantage [BSA (\sim I, E)] and Temporary advantages to one of them [TA (I, E)]. The fundamental difference between the empirical model and the conceptual model stems from the specification of the payoffs. We replace the numerical payoffs in the conceptual model with a new value expressed as a function of the resources of the competitors. More specifically, let \( i = 1, 2, ..., n \) represent the number of entrants and incumbents in the sample. Potential entrant i’s true payoff for a given outcome is given as \( U^*_i(.) = U_i(.) + \varepsilon_i \). \( U^*_i \) represents total payoff, where \( U_i \) is the contribution from the observable part of the resources and capabilities for the competitor and \( \varepsilon_i \) represents the contribution related to the unobservable component of the resources for competitor “i”. As with any standard random utility model (McFadden, 1974) all payoffs are identified on a relative basis and hence one of the outcomes needs to be set as a base case. In this model, we establish the outcome where the incumbent does not invest and the entrant does not enter (\sim I, \sim E) as the base case and normalize the payoff to zero. It should be noted that the normalization is also consistent with the conceptual model depicted in Figure 2 (b).

The information structure follows from figure 2(b) and requires that the distribution of the unobserved components is common knowledge to the entrants and the researcher. Following McKelvey and Palfrey (1995, 1996 and 1998) and Signorino
(2003), the equilibrium probabilities can be worked out through backward induction. Thus, we start by working on B’s decision. The likelihood that B will enter given that A has invested is given by

\[ p_6 = \Pr[U_B^*(TA) > U_B^*(BSA)] = F_B[U_B(TA) - U_B(BSA)] \]

and the likelihood that B will not enter given that A has not invested is \( p_5 \), which is equal to \( 1 - p_6 \). \( F_B \) is the cumulative distribution of the contribution from the unobservable portion of the resources. Intuitively, the above equation says that B will choose to enter conditional on observing A investing when she (B) believes that her resources are indeed superior to that of A. Since A’s resources are not fully observed, B has to guess her likelihood of success before she decides to enter. Following similar logic, the likelihood that B will enter given that A has not invested is given by

\[ p_4 = F_B[U_B(BSA) - U_B(SQ)] \]

and the likelihood that B will not enter given that A has not invested is given by \( p_3 \), which is equal to \( 1 - p_4 \). Again, this suggests that if potential entrant B believes that she has resources to address this particular domain, she will still go ahead and enter.

Next we solve for A’s decision. The likelihood that incumbent A will invest given that she expects B to enter is given by

\[ p_3 \]

\(^3\text{We provide only the main results in this section and leave the details of the derivation to the Appendix.}\)
\[ p_2 = \Pr[U_A^*(I) > U_A^*(\sim I)] = F_A[p_6 U_A(TA) + p_5 U_A(ASA) - p_4 U_A(BSA) - p_3 U_A(SQ)] \]

and the likelihood that A will not invest is given by \( p_1 \), which is equal to \((1-p_2)\). \( F_A \) is the cumulative distribution function of the unobservable component for A. It should be noted that A’s decision is a function of probabilities \( p_6, p_5, p_4, \) and \( p_3 \), which represent the probabilities of expected reactions from B. Hence, the decision by A to invest depends not just on her own resources and capabilities but also on her competitor’s expected reaction and thus her competitor’s resources. What A believes about B’s resources is manifested as the expected entry probabilities \( p_6, p_5, p_4 \) and \( p_3 \). Having obtained the probabilities of the likely actions for each player, we can now set up the joint probabilities of observing each of the four possible outcomes as follows:

\[
\begin{align*}
P_{SQ} &= p_1 * p_3 \\
P_{BSA} &= p_1 * p_4 \\
P_{ASA} &= p_2 * p_5 \\
P_{TA} &= p_2 * p_6
\end{align*}
\]

Using these four probabilities, we can now construct the appropriate likelihood function and use traditional maximum likelihood methods for estimation purposes. Alternative estimation methods such as Bayesian Markov Chain Monte Carlo methods can also be used to estimate this model (Rossi, Allenby and McCulloch, 2005). Next, we develop simulations to illustrate the efficacy of this new approach and to compare its performance against the traditional designs used in prior literature.
2.5 Testing the Proposed Model with Simulated Data

The previous section presented a technique to take strategic interaction between competitors into account while analyzing entry behavior in various contexts, such as entry into technological domains, businesses, or international markets. Taking such strategic interaction into account will help clarify whether the competitive advantage of firms upon entry is sustainable or temporary, which in turn, should affect the entry decision. We use simulated data for the purpose of illustrating how taking strategic interaction into account can substantively affect our conclusions.

In order to illustrate the differences between previously-used methodologies and our proposed methodology, we generate two kinds of stylized data based on two key assumptions. Our first data set assumes away strategic interaction hence; the entry decision in this case is only a function of players’ resources. We use this as our benchmark model, as it replicates the common approach used in previous studies. Next, we generate a data set where we allow for strategic interaction. This is a clear departure from traditional designs, as now we allow for expected competitive reactions that affect the decision process.

The data generation process follows the structure depicted earlier in Figure 2(b), with the payoffs replaced by a function of resources and capabilities. We fix the number of observations at 1000. Larger samples should improve our analysis, but given that sample sizes in strategy applications can be limited, we believe that demonstrating that the method works for small samples is important. Further, larger samples will only strengthen the results; therefore, evidence in smaller samples is a robust indicator.
First, we generate three resources for incumbent A and two resources for entrant B as random numbers from a uniform distribution. We vary the distribution and generate resource values within a tight range, for example between (-1, 3), and with a wider range, for example between (-10, 10). Our choice of both tight and wide ranges accommodates heterogeneity in resources. Next, we set the true coefficients of each of the variables equal to 0.50 for both the incumbent and the entrant. These coefficients represent the positive relationship between the incumbent’s decision to invest and its resources, and the positive relationship between the entrant’s decision to enter and its resources. In essence, these coefficients represent the true in a traditional regression model.

Decisions are made using the expected utility rule in models with and without strategic interaction. Consequently, we have two kinds of data (with and without strategic interactions) as well as two kinds of estimation methods (with and without strategic interactions). Without strategic interaction, the simulated data sets are based on the traditional probit probabilities. With strategic interaction, the simulated data sets are based on the equilibrium probabilities computed earlier.

2.5.1 Empirical strategies

We consider two empirical strategies to test our models with both data sets in increasing order of sophistication. The first strategy is to estimate the probability of entry just based on the resources and capabilities of the competitors. This is a replication of previous research designs. Our second strategy estimates the fully structural model developed in this paper. We then compare and contrast between the
two designs and discuss its implications for sustainability of advantages. The results can be best summarized by Table 2.1.

2.5.2 Traditional estimation when data have no strategic interaction

First, we analyze models where we replicate previous empirical designs, which reflect the assumption that resources are completely observed. As we have shown in the conceptual model section, the presence of complete information on resources and capabilities means that advantages are sustainable; therefore, resources and capabilities can easily capture such behavior. We find that the traditional estimation approach when used with data without strategic interaction provides unbiased and consistent results.

Table 2.2 represents the case where the decision to invest by firm A is made based on just her own resources. We find that all the coefficients are statistically significant and positive. Further, the magnitudes of the coefficients are insignificantly apart from the true coefficient (0.5) and are well within bounds of simulation error. Table 2.3 documents the case where the decision to invest by A is made by taking into account her own resources and resources held by other competing firms. We find that in the presence of complete information on resources and capabilities, the results are statistically significant, as well as efficient and consistent. Again the coefficients do not deviate significantly from the true coefficient of 0.5. Further, we can use the results from the model to predict the most likely decisions. If the model predicts that the firm is likely to invest/enter, then we can infer that this firm will capture sustainable advantages.
2.5.3 Traditional estimation when data display strategic interaction

When resources are imperfectly observed, strategic interaction can become very important. The choices of the competitors are based not only on the observable exogenous characteristics of each other, but also on their expectations of the resources and capabilities of each other. Based on these assumptions, we test the data with strategic interactions using traditional approaches.

Tables 2.5 presents the estimates utilizing data generated with imperfectly observed resources and strategic interaction between players. We note two important issues. First, the absolute difference between the estimated and the true parameters (0.5) is significantly large. Hence, this is an indication that estimation without considering the effect of strategic interactions is not capturing the true relationship. However, for many studies, this might be less interesting because the sign is still positive and statistically significant. Thus, the resource still positively predicts the likelihood of entry.

The second point to note is that the coefficient on the third resource for the incumbent is both negative and significant. Thus, both the economic and statistical effects for this resource are seriously misleading. Table 2.6 presents the estimates generated when both the firm’s own resources and competitor’s resources are considered. Here we find that the firm’s own resources are statistically significant but the competitor’s resources are not. This is counter intuitive. In the presence of strategic interaction, we would expect to see that incumbents consider the resource profile of the entrants. Again, the coefficients are significantly off the mark in comparison to
Finally, as before, the coefficient on the third resource for the incumbent generated by this model is negative and significant.

In summation, we can clearly see that traditional modeling approaches can lead to serious inference problems when testing data sets that involve strategic interactions. This suggests that testing for sustainable versus temporary advantages based on traditional approaches might give us biased and inconsistent results. We next examine if the structural model performs better.

2.5.4 **Structural estimation when data display strategic interaction**

We next utilize the fully structural approach outlined in this paper to generate estimates using data with strategic interactions.

From the estimation results in table 2.7, we can clearly see that the structural model recovers the parameters close to the true parameter value of 0.5 and within the bounds of simulation error. We can also see that the resources of both competitors are now statistically significant. Thus, in the presence of strategic interactions, we need appropriate models that take into account the nature of interactions between competing firms and their respective information content to fully comprehend the relationship between resources and entry behavior.

While we have shown that the traditional model works well when the data involve full observability and the structural model performs well when there is imperfect observability *ex-ante*, we can never be certain of which type of data is available to the researcher. Next, we examine how the structural model performs when the data are based on the assumption that resources are completely observed.
2.5.5 Structural estimation when data do not display strategic interaction

To address the issue of how the structural model performs under various data generating processes, we use the structural model to generate estimates based on data without strategic interaction. The results from this experiment are provided in Table 2.4.

From these results, we can see that even in the case when there is no strategic interaction in the data, the structural model performs reasonably well. It does recover the parameters with correct signs and is insignificantly different from the true parameter value of 0.5. Therefore, this suggests that even if there is complete observability, the structural model is still consistent although not as robust as traditional regression approaches. The results are fairly intuitive. First, we should note that the model with strategic interactions is a more generalized version of the model which assumes full observability. Specifically, when the value of the unobserved component is zero, the strategic interaction model is effectively the same as two independent probit models which assume full observability. However, given that the model is still structurally related, a marginal quantity of error is attributed to strategic interactions, leading to the lower efficiency in estimates. Thus from the evidence so far, we conclude that it is always better to use the structural model regardless of the type of data.

Our evidence suggests that using the structural approach is essential in the case of data that displays strategic interactions. At the same time, it also suggests that it might be overkill for data which does not display strategic interaction. In light of this, we suggest that researchers estimate both the traditional and structural models, and then use a model selection test to indicate which model is most likely to have
generated the data. To illustrate this point, we use a Vuong (1989) model selection test to check if the true data generating process belongs to the one with strategic interactions or not. In our case given that the data were generated with strategic interactions, we unsurprisingly find the Vuong (1989) test to concur\(^4\).

In addition to the aforementioned tests with traditional and structural estimation methods, we also conducted an alternative approach using a propensity scores. This approach attempts to correct for endogeneity arising out of strategic interactions. Prior literature has suggested several approaches to control for endogeneity such as a propensity score or Heckman selection type approaches (see Hamilton and Nickerson, 2003 for an excellent review). In this paper, we provide a robustness check where we replicate a propensity score model. While a propensity score based approach is loosely similar to the more commonly used Heckman type approach, we note that the latter procedure is not intended to analyze multi-firm interaction. The result from such a model is presented in table 2.8.

Again, we find that this approach fails to recover the parameters and can lead to faulty inference, especially with statistically significant coefficients and sign inversions. Thus, the propensity score approach does not capture the multi-firm interactions and can lead to faulty inferences. This provides more evidence that the structural model is more efficient and consistent than the propensity score alternative. To conclude, our simulation results support the use of a structural estimation approach.

\(^4\)These results are available upon request.
2.6 Discussion and Conclusions

How do firms obtain and retain sustainable competitive advantage? This has been a question of fundamental interest for strategic management scholars for many years. A dominant stream of research focusing intensely on the examination of firm-level attributes suggests that competitive advantage is derived from within the firm (RBV). The crux of the argument is that sustainable competitive advantage is a function of the resources and capabilities of the firm. RBV logic has been applied in order to study several strategic choice problems such as market entry.

A critical and often unstated assumption is that resources are completely observed. When resources are completely observed, it is rational for the firm with the superior resources to enter and others to stay out; thus, sustainability is achieved for the firm that enters. A typical empirical study models the likelihood of entry as a function of the firm’s own resource level or differential resources with respect to other competitors, along with additional control variables. Again, the fundamental assumption is that sustainability is implied upon entry.

However, what if resources are not perfectly observed? In this paper we show both conceptually and empirically that the lack of observability can have serious consequences in understanding competitive advantage in the presence of heterogeneous resources. Fundamental to understanding this relationship is the concept that the lack of perfect observability introduces the issue of strategic interactions between competing firms. In the presence of imperfect observability, firms with superior resources may not obtain sustainable advantages simply because it incorrectly believes that its competitor has superior resources. More specifically, we show that even when a
firm has superior resources ex-ante, it might squander a valuable opportunity simply because it could not observe the value of its competitor’s resources.

At the same time, it is also possible that even if both firms enter, a firm with superior resources will capture sustainable advantages because upon entry, the true value of the resources is revealed ex-post. Thus, lack of perfect observability raises several issues. At the conceptual level, we show that even in the presence of superior resources, a firm may not obtain sustainable advantages. This is counter intuitive to the classical predictions from the resource based view. At the empirical level, we show that testing for sustainability versus lack of sustainability, or temporary advantages, is important precisely because of unobservability. In the presence of perfectly observable resources, sustainability of advantage is guaranteed for the firm that has superior resources.

It is interesting to note that prior literature has suggested that greater unobservability of resources arising out of causal ambiguity is usually beneficial for a firm in sustaining competitive advantage (e.g., Reed & DeFillippi, 1990), since other firms cannot imitate it, ex-post. Our research questions this fundamental point and suggests that this is not necessarily the case, ex ante. Causal ambiguity and resource unobservability are double edged swords that can sometimes deny the competitive advantages from superior but unobservable resources.

A key insight for empirical work is that in order to understand the issue of sustainability or the lack thereof, we need to model the joint likelihood of two or more competitors entering or investing instead of only the individual firm entering. Why is this so? By definition, when strategic interaction becomes important, we need to observe the impact of our theoretical constructs, such as resources and capabilities,
on the joint likelihood of both firms taking a particular action, such as the incumbent investing in a resource and the potential entrant entering. When both firms enter, it results in temporary advantages for one of the players. This insight cannot be drawn from traditional models, which implicitly assume that all firms that enter capture sustained advantages. However, within our model, entry does not imply sustainability and can still lead to temporary advantages. It is now an empirical question rather than an assumption.

2.6.1 Understanding the causal link between RBV and Hypercompetition

At this juncture, it is also important for us to think about how our work ties in with existing views on temporary advantages. RBV and hypercompetition paint different pictures of competitive advantage. While the proponents of RBV stress sustainability of competitive advantages, those of hypercompetition argue that advantages may not be sustainable. A hypercompetitive environment can be defined along several dimensions. For instance, it has been suggested that hypercompetition is “characterized by intense and rapid competitive moves, in which competitors must move quickly to build new advantages and erode the advantages of their rivals” (D’Aveni, 1994: 217 and 218). Fundamentally, scholars studying hypercompetition suggest that due to several endogenous firm-level features (such as cut throat competition) and exogenous market-level features (such as high levels of turbulence), it is impossible to generate sustainable competitive advantage. Prior research on hypercompetition has not paid much attention to how firms with heterogeneous resources deal with hypercompetition. Here, we try to bridge the gap between our work and the existing view on temporary advantages.
Observability

What happens under the condition of rapid moves and counter-moves when one of the competing firms possesses superior resources? RBV logic would suggest that even under rapid sequential actions, the firm with superior resources should be able to outmaneuver other firms and retain sustainable advantages, while the hypercompetition view would predict temporary advantages. The RBV would suggest that the prediction of temporary advantages stemming from rapid countermoves can only occur when firms do not have sufficient resources.

Our analysis shows that imperfect observability may be a critical assumption in bridging the gap between the RBV and hypercompetition predictions. If resources are perfectly observed, rapid countermoves are likely to be inconsequential since the resource-advantaged firm will simply push the disadvantaged firm out of the market. As we have shown, a lack of observability of resources can modify the RBV predictions regarding competitive advantage. When firms are forced to respond very quickly, they are less likely to process all the data satisfactorily and are more likely to act on instincts or use short cuts and heuristics rather than a comprehensive analysis. These factors are likely to effectively reduce resource observability. Therefore, rapid moves and counter-moves can accentuate the lack of resource observability, and serve to predict the lack of sustainable competitive advantages even in the presence of superior resources.

Turbulence

A second element of hypercompetition involves exogenous industry conditions such as turbulence. Domains which are attractive for entrants may sometimes be
turbulent by nature. A natural example would be the technology intensive indus-
tries, where product advantages can erode quickly due to technological obsolescence.
Understanding how to deal with such turbulence becomes an important part of the
entry decision.

Consider potential entrants contemplating entering into a domain with a high de-
mand uncertainty and turbulence. According to our approach in this paper, the key
issue is observability of resources. As an exogenous characteristic, industry turbulence
may not directly impact the resource observability, but it may indirect consequences.
In a rapidly evolving turbulent environment, it becomes much more challenging to
ascertain the relevance of a given resource. If the market or the technology require-
ments are rapidly changing, firms will find it inherently more difficult to conclude
whether their resources could generate value upon entry. Such factors can effectively
enhance the resource unobservability factor in our model, potentially causing a depar-
ture from the traditional RBV predictions regarding competitive advantage. Another
interesting outcome may arise if firms have a differential ability to address turbulent
markets, which would lead to an asymmetric effect on the firms’ ability to observe
resource levels.

2.6.2 Limitations and Future Research

We hope that our work opens the door to future research on the integration of
perspectives based on resource heterogeneity and strategic interaction, specifically
on the core issue of unobservability. However, our present conceptual and empirical
approaches are limited in several ways. For example, our model does not allow for any
ex-post learning by firms. This could be an important factor if the rate of learning is
fast enough and there is a significant time lag between the moves of competitors, or if the rate of learning was significantly different among competitors. One potential way to deal with this issue would be to model multi-period interactions.

Further, it might also be interesting to consider cases where there are only 'partial' strategic interactions. For instance firms might choose to enter partially and the incumbent’s might choose to make only a partial investment. This leads to a case where the action space is continuous and identifying unique equilibria could pose problems (Meirowitz, 2003). A pragmatic solution could be to convert the continuous measures into discrete measures and use the model suggested in this paper. However, this might not be completely appropriate as the choice of partial entry in itself is endogenous. Thus it will be interesting in the future to examine approaches which can help solve this interesting problem. In our suggested empirical approach, for the sake of simplicity we modeled all firm characteristics in a single matrix of resources. A more nuanced set up can involve a combination of firm and industry level variables in the same matrix of independent variables. Such variables may include, for instance, measures of industry turbulence, competitive intensity and growth rate.

Further, on the empirical side there is considerable scope to adapt our method to a wide variety of settings, such as mergers and acquisitions or strategic alliances, where there are strategic interactions between the target firm and potential bidder/among partners. Another interesting setting could be entry into new and emerging technology domains. Specifically, we can study the tradeoff between capabilities built in emerging technologies versus traditional technologies and its impact on competitive advantage. Also note that our model can easily be adapted to the case of two or more potential entrants rather than a set of entrants and incumbents. In summary, since
the model is set up simply as a sequential choice problem, it is not restricted to the current context.

2.6.3 Conclusions

In this paper, we address the role of strategic interaction in entry models and its consequences for competitive advantage. The RBV suggests a strong relationship between firm resources and sustainable advantages. However, we argue that this is not always the case. In the presence of imperfect observability of resources, strategic interactions play a critical role; it is possible to witness outcomes where firms who possess superior resources ex-ante might receive either no advantage or just temporary advantages. We illustrate the importance of resource unobservability and strategic interaction in the context of entry decisions. Further, we note that in the presence of resource unobservability, the existence or lack of sustainable advantages becomes an empirical question. Traditional empirical approaches do not explicitly account for strategic interactions, producing biased and inconsistent results in the presence of strategic interactions. Our approach, which is both novel and simple, accounts for resource heterogeneity as well as strategic interactions. We use simulations to show the effectiveness of our approach and find that our proposed method performs well when the data reflect strategic interactions. In the case of data without strategic interactions, the proposed method is still unbiased although there is a slight loss of efficiency.
Figure 2.1: Case with perfect observability

Figure 2.2: Case with imperfect observability
Figure 2.3: Effect of strategic interaction on equilibrium outcomes
Table 2.1: Impact of Estimation Method and the Data Generating Process

<table>
<thead>
<tr>
<th>Estimation Methods</th>
<th>Without Strategic Interaction</th>
<th>With Strategic Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Strategic Interaction</td>
<td>Robust</td>
<td>Consistent but less efficient</td>
</tr>
<tr>
<td>With Strategic Interaction</td>
<td>Not Consistent</td>
<td>Robust</td>
</tr>
</tbody>
</table>

Table 2.2: No Strategic Interaction & A’s Resources

| Coefficients: | TRUE | Estimate | Std. Error | Z Value | Pr(>|z|) |
|---------------|------|----------|------------|---------|---------|
| AR1           | 0.5  | 0.5331   | 0.0265     | 20.1300 | 0.0000  *** |
| AR2           | 0.5  | 0.5084   | 0.0321     | 15.8700 | 0.0000  *** |
| AR3           | 0.5  | 0.5323   | 0.0229     | 23.2100 | 0.0000  *** |

Table 2.3: No Strategic Interaction: A’s & B’s Resources

| Coefficients: | TRUE | Estimate | Std. Error | Z Value | Pr(>|z|) |
|---------------|------|----------|------------|---------|---------|
| AR1           | 0.5  | 0.4846   | 0.0257     | 18.8610 | 0.0000  *** |
| AR2           | 0.5  | 0.4993   | 0.0313     | 15.9630 | 0.0000  *** |
| AR3           | 0.5  | 0.4847   | 0.0215     | 22.5770 | 0.0000  *** |
| BR1           | 0.5  | 0.4824   | 0.0421     | 11.4500 | 0.0000  *** |
| BR2           | 0.5  | 0.4290   | 0.0700     | 6.1320  | 0.0000  *** |
Table 2.4: Structural Model Without Strategic Interaction

<table>
<thead>
<tr>
<th>Coefficients:</th>
<th>TRUE</th>
<th>LHPD</th>
<th>Estimate</th>
<th>HHPD</th>
<th>ML Est</th>
<th>T Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR1</td>
<td>0.5</td>
<td>0.4607</td>
<td>0.6338</td>
<td>0.8096</td>
<td>0.6332</td>
<td>19.3233 ***</td>
</tr>
<tr>
<td>AR2</td>
<td>0.5</td>
<td>0.5825</td>
<td>0.6757</td>
<td>0.8763</td>
<td>0.6738</td>
<td>16.2774 ***</td>
</tr>
<tr>
<td>AR3</td>
<td>0.5</td>
<td>0.4480</td>
<td>0.6071</td>
<td>0.7664</td>
<td>0.6061</td>
<td>23.1071 ***</td>
</tr>
<tr>
<td>BR1</td>
<td>0.5</td>
<td>0.3710</td>
<td>0.4674</td>
<td>0.5628</td>
<td>0.4684</td>
<td>9.7067 ***</td>
</tr>
<tr>
<td>BR2</td>
<td>0.5</td>
<td>0.3266</td>
<td>0.5203</td>
<td>0.7033</td>
<td>0.5223</td>
<td>5.6947 ***</td>
</tr>
</tbody>
</table>

Note: Estimate refers to the mean estimate from the Bayesian model. LHPD and HHPD refer to the lower and upper bounds of the coefficient distribution. The coefficient is statistically significant if the bounds do not contain zero.

Table 2.5: With Strategic Interaction & A’s Resources

| Coefficients: | TRUE | Estimate | Std. Error | Z Value | Pr(>|z|) |
|---------------|------|----------|------------|---------|---------|
| AR1           | 0.5  | 0.0931   | 0.0168     | 5.5380  | 0.0000 *** |
| AR2           | 0.5  | 0.0766   | 0.0251     | 3.0570  | 0.0022 **  |
| AR3           | 0.5  | (0.1235) | 0.0101     | (12.1970) | 0.0000 *** |

Table 2.6: With Strategic Interaction - A’s & B’s Resources

| Coefficients: | TRUE | Estimate | Std. Error | Z Value | Pr(>|z|) |
|---------------|------|----------|------------|---------|---------|
| AR1           | 0.5  | 0.0915   | 0.0155     | 5.9030  | 0.0000 *** |
| AR2           | 0.5  | 0.0816   | 0.0201     | 4.0550  | 0.0001 *** |
| AR3           | 0.5  | (0.1232) | 0.0101     | (12.1620) | 0.0000 *** |
| BR1           | 0.5  | 0.0275   | 0.0285     | 0.9660  | 0.3340 |
| BR2           | 0.5  | 0.0484   | 0.0507     | 0.9540  | 0.3400 |

Table 2.7: Structural Model With Strategic Interaction

<table>
<thead>
<tr>
<th>Coefficients:</th>
<th>TRUE</th>
<th>LHPD</th>
<th>Estimate</th>
<th>HHPD</th>
<th>ML Est</th>
<th>T Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR1</td>
<td>0.5</td>
<td>0.4313</td>
<td>0.5168</td>
<td>0.6004</td>
<td>0.5159</td>
<td>12.0156 ***</td>
</tr>
<tr>
<td>AR2</td>
<td>0.5</td>
<td>0.3941</td>
<td>0.5056</td>
<td>0.6147</td>
<td>0.5043</td>
<td>9.0015 ***</td>
</tr>
<tr>
<td>AR3</td>
<td>0.5</td>
<td>0.4162</td>
<td>0.4760</td>
<td>0.5361</td>
<td>0.4752</td>
<td>15.5403 ***</td>
</tr>
<tr>
<td>BR1</td>
<td>0.5</td>
<td>0.5405</td>
<td>0.6375</td>
<td>0.7359</td>
<td>0.6370</td>
<td>12.6919 ***</td>
</tr>
<tr>
<td>BR2</td>
<td>0.5</td>
<td>0.3771</td>
<td>0.5312</td>
<td>0.6841</td>
<td>0.5322</td>
<td>6.7807 ***</td>
</tr>
</tbody>
</table>

Note: Estimate refers to the mean estimate from the Bayesian model. LHPD and HHPD refer to the lower and upper bounds of the coefficient distribution. The coefficient is statistically significant if the bounds do not contain zero.
| Coefficients: | TRUE | Estimate | Std. Error | Z Value | Pr(>|z|) |
|--------------|------|----------|------------|---------|----------|
| AR1          | 0.5  | 0.1359   | 0.0168     | 8.0780  | 0.0000 ***|
| AR2          | 0.5  | 0.1243   | 0.0248     | 5.0020  | 0.0000 ***|
| AR3          | 0.5  | (0.1162) | 0.0103     | (11.2450) | 0.0000 ***|
| Ex Ante Fit 1| (0.2991) | 0.1603 | (1.8660) | 0.0621 | . |
| Ex Ante Fit 2| 0.3501 | 0.1844 | 1.8990 | 0.0576 | . |
CHAPTER 3

IMPERFECT OBSERVABILITY OF RESOURCES AND STRATEGIC INTERACTIONS BETWEEN TARGET AND BIDDER FIRMS

3.1 Introduction

In June 2007, Expedia, Home Depot and Shinsei announced combined stock repurchase plans in excess of US $28 billion. Individually, Home Depot announced one of the largest repurchase plans ever totaling $22.5 billion. Expedia Inc. announced a repurchase program totaling close to $3.5 billion, representing close to 42% of its outstanding stock. Firms repurchase shares through either a tender offer or open market repurchases. Stock repurchase refers to a firm buying back its own stock either from the open market (open market repurchase) or through a targeted repurchase (tender offers). Why do firms repurchase its own stock? While there exists several motivations for repurchasing stock (see. Dittmar, 2000 for a comprehensive review) in this chapter our primary focus rests on how stock repurchases can be used by target firms to influence outcomes in the market for corporate control.

A dominant explanation for stock repurchases suggests that firms that believe that their stock is undervalued repurchase to signal such undervaluation. This theory has

\footnote{These apart, several other instances have been documented in the literature (see. McNally, 2000; Bagwell, 1991)}
undergone extensive empirical testing and finds considerable support. For instance, Vermaelen (1981) finds that firms that announce intentions to repurchase stock record gains in market valuation. Repurchases could also be interpreted as a credible signal of unrecognized firm value (Vermaelen, 1981; Comment and Jarrell, 1991). Thus, target firms can potentially use open market repurchases as a signal of their true resources to different participants in the market including investors, stakeholders and potential bidders among others.

Prior literature documents that open market repurchases help in deterring bidders (Dittmar, 2000; Billet and Xue, 2007). The logic is straightforward. Firms use open market repurchases to return cash to shareholders. It inherently reduces agency problems as managers are no longer investing excess cash in empire building or in negative NPV projects. The reduction of agency implies that expected gains from a disciplinary takeover is absent, thus making the target less attractive. Further, repurchasing stock also reduces liquidity in the market thus raising the potential cost of acquisition for bidders. These factors suggest that open market repurchases lead to deterrence.

However, we suggest that open market repurchases can in fact also be used as a tool to attract bidders. Apart from gains from agency, potential bidders can also benefit from access to special resources which target firm’s might possess. Mergers and Acquisitions have been viewed as means to acquire resources and capabilities (Ahuja and Katila, 2001) and also to leverage on existing resources, knowledge and capabilities (Chatterjee and Wernerfelt, 1991; Jovanovic and Roussau 2002). Acquiring good quality resources implies that bidders should also have sufficient information on such resources. However, the kind of resources that can generate superior advantage
is likely tacit and complex and thus tend to be imperfectly observed. This makes the job of potential bidders more difficult and many times they may end up missing a golden opportunity or paying more for poor quality assets. For instance, a particular target firm may possess very good resources which can be leveraged substantially with one more potential bidders. Thus *ex-post* the combined value of the target firm and a potential bidder may be higher. However, the two firms may never realize this value as potential bidders refrain from bidding due to imperfect observability of the target’s resources. Thus, despite the fact that bidders and target can in theory capture abnormal rents from resources it fails to do so due to lack of observability.

In this backdrop, we suggest that target firms can use signaling mechanisms such as open market repurchases to reduce loss of rents associated with imperfectly observed resources. These signals are then used by potential bidders to update their beliefs on the target’s true value. In this chapter we first develop a formal theoretical model and generate two key propositions. First we show that increasing the value of the public signal (open market repurchases) leads to attracting potential bidders. However, credibility of the signal is equally important. We further analyze the influence of the precision of the signal on outcomes in the market for corporate control and show that when the signal is very precise open market repurchases can be a double edged sword. If the quality of the resources is high and the precision of the signal is also high, it allows for attraction as the optimal outcome. On the other hand, if the quality of the resources are poor and the provision of the signal further accentuates the bidders’s belief on the poor nature of the target’s resources, it serves to deter potential bidders.
This brings forth an interesting empirical tension. Does open market repurchases lead to deterrence or attraction? Thus our next contribution is to offer a theoretically consistent approach to solving this empirical puzzle. We empirically model the strategic interactions between the bidder and target and thus maintain consistency with the theoretical model that generated testable propositions. Empirically, the presence of strategic interaction implicitly brings in endogeneity in choice behavior. For instance, it is intuitive to think that the decision to repurchase by the bidder is influenced by his expectation on receiving the bid.

Prior literature on strategic choice has documented the nature of endogeneity and its impact on problems related to strategic management (Hamilton and Nickerson, 2003). However, the traditional models recommended for correcting such endogeneity fail to account for multi player strategic interactions. The observed outcomes from the interaction between the bidder and the target is likely to be a product of some complex strategic interaction and hence it depends on the players interacting, the sequence of decisions, their options at the respective decision points, different factors influencing their incentives for one choice vs. the other and the equilibrium effects of the interdependence of factors influencing the outcomes. Therefore our approach provides inference by keeping the richness of the information structure intact.

To implicitly accommodate the information structure we model the interaction between the target and the bidder as a sequential game with double sided asymmetric information. The target moves first and takes a costly action through executing an open market stock repurchase. The potential bidder observes the action and then decides whether to make a bid. The target’s action is based on its expected utility, which accounts for its beliefs about the bidder’s actions conditional of its (target’s)
own choice. The bidder then makes his choice having observed the targets action and having understood that the targets choice reflects its expected beliefs on its (bidders) play. Hence both players play best response strategies to each other.

To aid in statistical estimation of such games, we draw on the literature, specifically McFadden (1974) on Random Utility models and Signorino (2003) on extension of the statistical equilibrium concepts to archival data. We use the full information approach to modeling and thus recover the structural conditional probabilities of receiving a bid given either a repurchase or no repurchase. The deterrence/attraction effect can now be computed as the difference between these estimated conditional probabilities.\footnote{The direct approach would have been to evaluate the counterfactuals and compute treatment effects based on what would have been the potential outcome for a firm that did repurchase, had it chosen not to repurchase? But data on counterfactuals to conduct an inquiry through this mode is not available. Investigation along this line may be possible by using the Data Augmentation techniques applied in the literature in Bayesian Statistics.}

We find that, after controlling for agency explanations, on average open market repurchases leads to an attraction effect. Our results suggest that the target firms use of open market repurchases reduces the unobservability of resource value and thus helps potential bidders to update their information on potential benefits. Thus, the target firm successfully managed to generate heterogeneous expectations on their resources thus leading to higher likelihood of receiving a bid.

The rest of the paper is organized as follows. Next we review the literature associated with stock repurchases, resource heterogeneity and the market for corporate control followed by a formal develop of the model and key propositions. Then, we describe the data and empirical approach. Finally, we discuss the results from the analysis followed by the conclusions.
3.2 Resource heterogeneity, Stock repurchases and the Market for corporate control

Prior literature has focuses on the role of stock repurchases affecting the market for corporate control through agency mechanisms and suggests that stock repurchases tend to serve the role of deterrence. However, the important role of resource heterogeneity has been largely ignored. We offer an alternative explanation based on strategic factor market theory and the resource based view of the firm. In this setting, we argue that the information released through open market repurchases helps potential bidder's to revise the ex-ante expectations on the potential synergies from the merger. Thus the unraveling of hitherto unknown potential gains from resources leads to potential outcomes where open market repurchases serve to attract rather than deter bids.

We view the acquisition process as one where the bidder tries to acquire new resources and capabilities which when combined with their existing resources can generate inimitable cash flows and helps capture unique synergies and thus leads to superior performance. Unique synergies between the potential target and bidder lead to gains for both (Barney, 1988). Of crucial importance here is the nature of resources which can generate sustainable advantages. According to the resource based view, resources that are rare, valuable, and inimitable generate sustainable competitive advantage (Barney, 1991; Conner, 1991; Wernerfelt, 1984). Resources with the above mentioned characteristics are also likely to be causally ambiguous and often not fully observable (Lippman and Rumelt, 1982). Causal ambiguity implies that the key resource leading to superior performance is inherently tacit, socially complex, and has a high degree of specificity (Reed and DeFillippi, 1990). The extreme form of causal
ambiguity suggests that even the firm that possesses the resource is not completely aware of its value (Lippman and Rumelt, 1982; Mosakowski, 1997). Resources that are inherently intangible can also generate superior competitive advantage (Prahlad and Bettis, 1986; Coff, 1999). Empirical evidence also suggests sustainable performance in the presence of intangible assets (Villalonga, 2004). In summary, the nature of the resources prevents its quality from being completely observed by potential bidders.

If the intention behind the acquisition process is to capture potential superior competitive advantage, bidder firms are more likely to go after target firms that possess resources with the above mentioned characteristics. However, this poses a fundamental problem. Less than perfect observability implies that potential bidders may not be able to fully understand the true valuation of the target’s resources and are more likely to make mistakes. This is justified by prior empirical evidence which documents poor performance following acquisition of intangibles (Arikan, 2004). Thus, potential bidders are likely to be more wary approaching firms that possess considerable unobservable resources. Under these circumstances the question of critical interest relates to how are such valuations formed and what affects them? We turn to auction theory and explore the link between valuation and intangible assets within the purview of the acquisition process.

The acquisition process can be considered as an outcome from an auction (Bulow and Klemperer, 1996). Auctions can be of either of two types namely private or common values or a combination of both. In a private value auction, the bidder knows his valuation of the object with certainty but has no information on the valuations of his competitors. On the other hand, common value auctions represent the case where the object has the same value to every bidder, but each bidder’s private valuations on
the true value differs. Information uncertainty is crucial to the auction problem. For instance, suppose the target had perfect information about the potential gains from acquisition for each of the possible bidders, it (the target) can post a price equal to or marginally below the highest valuation among the potential bidders and close the deal. However, unobservability creates informational uncertainty.

In this backdrop, can the target firm influence the outcome in the market for corporate control? In the next section we develop a formal model to examine the impact of target actions on the outcomes in the market for corporate control.

3.3 Model

In this section we use the technique of global games to study stock repurchases by target firms influences bidding outcomes. Prior literature has applied the idea of global games in several setting such as investment decisions (Carlsson and Van Damme, 1993), currency crises (Morris and Shin, 1998; 2004), bank runs (Goldstein and Pauzner, 2000) and pricing of debt (Morris and Shin, 2003).

3.3.1 Payoffs

We consider a market for corporate control where there exists a target firm and a continuum of potential bidders index over the unit interval [0,1]. The resource value of the target firm is characterized by a state variable “θ” that can take values over the real line ℜ. A large value of θ characterizes a target firm with considerable resources and vice-versa. Target firms have an incentive to attract more bidders to ensure that it manages to capture the best possible valuation for its shareholders (Bulow and Klemperer, 1996).
Each potential bidder can choose to participate or abstain from bidding. Upon participation a successful bidder receives an expected benefit of $\Lambda$, with $\Lambda > 0^7$ and also incurs a participation cost $\psi$, with $\psi > 0$. Intuitively, $\psi$ can represent potential opportunity and transaction costs. We further assume that the costs $\psi$ are smaller relative to the payoff $\Lambda$, creating an incentive for potential bidders to play. If a potential bidder chooses to abstain, she incurs no cost and receives no benefit. Let the proportion of participating bidders equal $l$. Then the target firm’s strategy is equivalent to

$$
\xi(\theta, l) = \begin{cases} 
\text{Defend, if } l \leq \theta \\
\text{Concede, otherwise}
\end{cases}
$$

The intuition behind this set up is simple. The true value of the target firm for potential bidders is a function of $\theta$. If the value of the resources is simply exceptional ($\theta > 1$), the firm will always be a juicy target and hence will surely be taken over. In this case target firm manager’s need not worry about undertaking actions to influence bidder behavior. Similarly when the value of resources is poor ($\theta < 0$), the firm is unlikely to be a target and hence will almost surely be never taken over. However, the interesting situation is when the target resources are in the range ($0 < \theta \leq 1$) and the nature of these resources are unobservable. Specifically, success for the bidding firm occurs only when $\theta < l$. When $l < \theta$, the target firm is undervalued to its true state and hence target firm managers have incentive to deter. Hence, when the true quality of the target firm’s resources are neither too high nor too low, the outcome of a bidding process depends on the number of bidders entering the fray.

$^7$In the original Morris and Shin (1998) set up the benefits to speculators are a function of the fundamentals. However in the presence of both public and private information the model is analytically intractable. At the same time the substantive predictions are consistent even under independence
In the intermediate range \((0 < \theta \leq 1)\) potential bidders face a coordination problem. If potential bidders believe that the value of the resources of the target firm is low, it is optimal for them to abstain. Their action leads to the bad equilibrium for the target firm where it does not receive any bids. On the other hand, if potential bidders believe that the value of target resources is high, it is optimal for them to bid. This action leads to a good equilibrium where both the target and the bidder are better off. Either equilibrium is self fulfilling by nature.

### 3.3.2 Timing

The target firm and the bidders play the following game. Nature moves first and chooses the value of \(\theta\), the target’s resources. Nature’s choice of \(\theta\) is observed by the target firm but not by the speculators. The target firm then chooses to send a noisy public signal by repurchasing stock from the market, which is common knowledge to all participants. Upon observing both the public signal and their own private signal, the bidders decide either participate in the bidding process or abstain.

### 3.3.3 Information

We assume that the target firm and potential bidders have a common prior over \(\theta\) represented as an improper uniform over the real line \(\mathbb{R}\). After having observed nature’s choice of \(\theta\), the target firm provides a public signal \(y = \theta + \delta\), with \(\delta \sim N(0, \frac{1}{\alpha})\), \(\alpha > 0\) and \(E(\delta \theta) = 0\), thus implying that the noise parameter is independent of the true state of the resources. The signal is public and hence is common knowledge to all participants.

Further, each potential bidder individually receives a private signal \(x_i = \theta + \varepsilon_i\), with \(\varepsilon_i \sim N\left(0, \frac{1}{\beta}\right)\), \(\beta > 0\). The noise parameters are independent of each other, of
the fundamental value of resources and of the public signal. The information set for each potential bidder consists of two distinct parts: the common public signal and the private signal. The public signal $y$ enters the information set of all potential bidders. Thus it provides information about both the expectation on the value of resources (target firm) and also about what the other potential bidders observe.

To illustrate this note that on observing $x_i$, potential bidder $i$ believes with 95% confidence that the true value of the target firm’s resources and capabilities lie in the interval $\left( x_i - 2 \left( \frac{1}{\sqrt{\beta}} \right), x_i + 2 \left( \frac{1}{\sqrt{\beta}} \right) \right)$. Potential bidder $i$ knows that the other potential bidder(s) $j$ are also informed of the value of $\theta$ with error $\varepsilon_j$. Thus, potential bidder $i$ can now compute the number of potential bidders who observe $x_j$ below a particular value, say $\hat{\theta}$, as the area under the probability density function corresponding to $\theta < \hat{\theta}$. If she observes high $x_i$, she can be sure that only a small fraction of other potential bidders observe $x_j$ below $\hat{\theta}$. Thus in this case the fraction of bidders who might bid for the firm “$I$” is likely high, implying that the target firm upon receiving sufficient number of bidders is likely to concede and thus the potential bidder has an opportunity to capture any gains. Thus, the optimal strategy for the potential bidder is to bid. Similarly, if she observed a low $x_i$, her expected payoff from bidding will be lower as $l$ is likely to be low.

### 3.3.4 Equilibrium

The switching trigger equilibrium pair $(\theta^*, x_i^*)$ for this game is defined on the point of indifference. Thus $\theta = \theta^*$ suggests that the target firm is indifferent between defending and conceding. Similarly, potential bidders receiving a private signal $x_i^*$
are indifferent between participating and abstaining. The game has a unique equilibrium provided that the private information is precise enough compared to public information. This condition implies that each of the potential bidders collect better information privately as against the depending completely on the public information provided by the focal firm. In the context of the market for corporate control this makes sense, since it is in the best interest of each potential bidder to search for the best possible target firm in terms of valuation, its resource and integration potential.

From the perspective of the potential bidder, assuming that the target firm provides a signal $y$ and potential entrant $i$ receives a private signal $x_i$, her posterior belief on $\theta$ is given by

$$E(\theta|y, x_i) = \frac{\alpha y + \beta x_i}{\alpha + \beta}$$

(3.1)

with variance

$$Var(\theta|y, x_i) = \frac{1}{\alpha + \beta}$$

(3.2)

Thus each potential bidder, given public information $y$, updates her belief about $\theta$ using her own signal $x_i$. The posterior mean of $\theta$ is primarily influenced by the information that potential bidders have. Specifically it is a weighted average of the public and private signals with the weights being determined by the relative precisions of each signal. Thus, the precision of the private and public signals moderate the relative importance of each in influencing the expectations on $\theta$.

After receiving both signals, each potential bidder has to decide whether or not to participate in bidding. Bidding involves a cost $\psi$ and an uncertain payoff equivalent
to \( \lambda \). Alternatively, they can choose not to participate and incur no cost and receive no benefit. The point of indifference is achieved when

\[
\Lambda \cdot \text{Prob}(\text{Abstinence}|x) - \psi = 0 \quad (3.3)
\]

Since abstinence occurs whenever \( \theta < \theta^* \), and since the conditional density of \( \theta \) is given by equations (1) and (2), its probability is equal to the area under the density function for \( \theta < \theta^* \). Thus, rewriting equation(3) and normalizing to the standard normal density we get

\[
\psi = \Lambda \cdot \Phi \left( \sqrt{\alpha + \beta} \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) \right) \quad (3.4)
\]

The target firm is indifferent between defending and conceding, if the proportion of bidders participating, \( l \) given by the proportion of potential bidders receiving a private signal below \( x^* \), equals \( \theta \). Hence, \( l=\text{Prob}(x \leq x^*|\theta) \). Normalizing to the standard normal density, \( l \) is given by

\[
l = P(x \leq x^*|\theta)
\]

\[
= \Phi \left( \sqrt{\beta} (x^* - \theta) \right) \quad (3.5)
\]

Hence, the target firm is indifferent between conceding or deterring if:

\[
\theta = \Phi \left( \sqrt{\beta} (x^* - \theta) \right) \quad (3.6)
\]

Using equations (4) and (6) we can now solve for the equilibrium solution which is represented as the tuple \((\theta^*, x^*)\). Solving for \( \theta^* \) we have:

\[
\theta^* = \Phi \left( \frac{1}{\sqrt{\beta}} \left( \alpha \theta^* - \alpha y - \sqrt{\alpha + \beta} \Phi^{-1} \left( \frac{\psi}{\Lambda} \right) \right) \right) \quad (3.7)
\]
This equilibrium is unique when the private signals are sufficiently precise. Specifically, for all values of $\beta > \frac{\alpha^2}{2\pi}$ there exists a unique equilibrium consisting of a value of the resource index $\theta^*$, beyond which the target firm will always concede and a unique value for the private signal $x^*$, beyond which potential bidders will always participate. Next we show a comparative static analysis to show the effects of changing the public signal $y$ and the precision of the public signal $\alpha$ on equilibrium outcomes.

3.3.5 Comparative Statics

Comparative statics are useful as a tool only when uniqueness of equilibrium is guaranteed. Therefore our propositions are conditional on achieving uniqueness i.e. $\beta > \frac{\alpha^2}{2\pi}$. All formal proofs are relegated to the Appendix. From equation (6), which provides the equilibrium value of the fundamental index we can generate the following propositions.

**Proposition 3.3.1.** The public signal $y$ has a positive effect on the probability of participation by bidders.

The public signal $y$ in our setting is open market repurchases conducted by the target firm. Given that $E(y|\theta) = \theta$, we can clearly see that the fundamental value of resources is higher when $y$ is higher. This is consistent with prior literature which suggests that open market repurchases signal undervaluation of the stock. Since, managers may have a better understanding of their own resources, they can use repurchases to signal the value of their resources. Repurchases can serve multiple goals. First it might help reduce uncertainty on the value of target resources which could in principle lead to bidders with low valuations revising their bid and being more aggressive. Anticipating this, we expect bidders with higher valuations to not to shade their bids. Alternatively, open market repurchases might also attract hitherto
unknown potential bidders into the game. Hence, potential bidders in an attempt to thwart other potential bidders might decide to aggressively bid early and lock in the target (see Fishman, 1988; Daniel and Hirshleifer, 1998). Their incentives could be to either garner the benefits for themselves or it could be to prevent a potential rival bidder from harnessing any gains in order to protect their market share in future. Therefore, the presence of negative externalities in the form of opportunity costs can also explain the decision to aggressively bid (Blunck and Anand, 2008).

However the strength of a signal also depends on how bidders update their priors on the value of the target’s resources. Since potential bidders update their beliefs using both the public and private signal, we are also interested in determining the effect of the precision of the public signal in herding potential bidders towards participation, thus creating two countervailing effects.

Proposition 3.3.2. The precision of the public signal $\alpha$ has a negative influence on the probability of participation if $\theta^* > y + \frac{1}{(2\sqrt{\alpha+\beta} \Phi^{-1}(\frac{\psi}{\Lambda}))}$

Proposition 3.3.3. The precision of the public signal $\alpha$ has a positive influence on the probability of participation if $\theta^* < y + \frac{1}{(2\sqrt{\alpha+\beta} \Phi^{-1}(\frac{\psi}{\Lambda}))}$

The intuition here is simple. When the precision of the public information is poor, potential bidders will tend to ignore the public information in updating their beliefs. Thus they place more emphasis on their own private signals. In contrast, a more precise public signal results in potential bidders placing greater emphasis on the information provided by the target firm. Thus, more precise information on the fundamental quality of the firm’s resource $\theta$ serves to confirm the potential bidders beliefs about the quality of the target and hence facilitates coordination. This creates an attraction effect. Along similar lines, stock repurchases as a signal should also be credible. If repurchase signals are cheap, then providing the public signal
might actually confirm the beliefs of potential bidders that there exists no value in the target firm. Under these circumstances, increasing the precision of the signal is counter productive and can result in a deterrence effect.

These propositions raise interesting empirical questions. In the next section we describe the data used to test the above propositions and also outline empirical methods consistent with our theoretical framework.

3.4 Data and Methods

3.4.1 Data and Sample

The construction of the sample begins with all firms available in Compustat/CRSP between 1991 and 2005. We exclude financial institutions, public utilities and transportation companies from the final sample. Hence all firms with one digit SIC code of 4 or 6 are deleted from the sample. These firms are regulated and hence their motives for repurchasing might be different from non-regulated firms. Data on bids is taken from the Securities Data Corporation (SDC) files. A bid is recorded the day an announcement of the bid is made by a bidder.

Repurchases are computed following the method adopted by Jagannathan, Stephens and Weisbach (2000). The gross repurchases made by each sample firm in each year is taken from the Compustat database. Next we compute the redemption value of the net number of preferred shares outstanding. Since the measure of gross repurchases includes both common and preferred shares, we need to adjust for the preferred shares. Any reduction in the redemption value is treated as expenditure on

---

8Data item 115 - Purchases of common and preferred stock. Since 1984 firms have been required to report value of repurchased shares on the statement of cash flows.

9Data item 56 at time t - Data item 56 at time (t-1). This gives us the difference in redemption value.

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the purchase of preferred shares. Hence, we define the repurchase as gross repurchases less any reduction in the redemption value as computed. Further, to define utilities of both the bidder and target we use several of the measures suggested in previous studies (Billet and Xue (2007); Dittmar (2000)).

The variables used for analysis are defined as follows. The dependent variables are:

**Rep:** A dummy variable treated as 1 if the computed measure of repurchase is positive.

**Bid:** A dummy variable treated as 1 if a given firm received a bid in year t+1.

Following Billet and Xue (2007) and Palepu (1986) the following control variables were also created.

**Cdiv:** Cash dividends divided by Net income

**FCF:** Defined as operating income before depreciation minus interest expenses, the sum of preferred and common dividends, income taxes (excluding deferred taxes), all assets scaled by total assets.

**FA:** Defined as net plant, property and equipment scaled by total assets.

**IndBLIA:** Defined as the book value of debt divided by total assets, less the median ratio for firms with the same two digit SIC code.

**IndMLIA:** Defined as the book value of debt divided by the sum of the book value of debt and the market value of equity, minus the median ratio for firms with the same two digit SIC code.

**IndROIA:** Defined as operating income before depreciation divided by total assets, minus the median ratio for firms with the same two digit SIC code.
**MB**: Defined as the market value of common stock divided by the book value of common equity.

**NOPI**: Defined as non operating income scaled by total assets.

**ROE**: Defined as the net income divided by the book value of equity.

**Growth**: Defined as the natural log of the ratio of sales over the sales of the previous year.

**SizeAsset**: Defined as the natural log of total assets.

**SizeEq**: Defined as the natural log of common equity, calculated as the number of shares outstanding times the year end price.

**Options**: Defined as the common shares reserved for conversion to stock options divided by total shares outstanding.

**Tdum**: Time dummy variables D1 and D2 equal to 1 if the observation comes from the 1994-1996 and 1997-2003 period and zero otherwise.

Following Dittmar (2000) and Billet and Xue (2007) all variables except the dependent variables and the dummy variables were lagged by a year. The final sample spans the period 1991 through 2005 and contains 38,498 observations. Around 6% of the sample firms received a bid in the year following the year of repurchase. This ties in closely with the similar statistic reported in the sample used by Billet and Xue (2007), though the time period used in this analysis is different. While only 11% of the sample firms conduct repurchases in the Billet and Xue (2007) sample, close to 27% of the sample firms conduct repurchases in my sample using a threshold of 1% repurchased on current outstanding equity. Increasing the threshold to 5%, 10% and 15% respectively reduces the level to 14%, 8% and 2% respectively. Total repurchases over the years from 1991 through 2005 show an increasing trend. This observation is in line with several papers in the recent past, indicating the growth in the use of repurchases over time (see Grullon and Michaely (2003) among others).
The results presented in this paper are based on proportional sampling. Given that the proportion of firms that engaged in repurchase and received a bid is relatively very small compared to the entire population, using the full sample might be problematic (King and Zeng, 2001). Sampling was done based on proportions and Coslett (1981) shows that proportional sampling, while driving the efficiency of the estimate down is unbiased. While the results from Coslett (1981) depend on asymptotic results, our analysis does not suffer loss of efficiency on account of sample size as we use Bayesian estimation techniques (Rossi, et. al. 2005). The final sample consists of 5000 observations. The analysis is conducted using two thresholds for repurchases fixed at 1% and 5% of outstanding shares. Going higher was impractical given the small proportion of observations available to sample from. All the samples were sampled without replacement.

3.4.2 Empirical Methodology

The formal model used in this chapter as well as in extant literature share a common feature. All of them use a game theoretic approach and rely on equilibrium predictions obtained through strategic interactions between the bidder and the target. Following our theoretical development earlier, we build a statistical model based on a two sided sequential game with incomplete information. Ignoring strategic interactions, when they are present in the data can lead to biased and inconsistent inference, thus throwing our interpretation of economic effects into jeopardy (Nandialath and Anand, 2008). We follow a structural approach and keep the information structure in tact, thus estimating an empirical model which is consistent with the theoretical model generating the hypotheses.

A principal advantage offered by the setting we investigate is that the events happen in a sequence. The sequential nature of the game gives rise to a generic unique
equilibrium (Breshnahan and Reiss, 1990). Enriching the game structure by adding incomplete information eases the problem from the purview of estimation. It should be noted that the empirical approach is completely consistent with our theoretical model. In the theoretical model the target firm moves first and sends a public signal through a repurchases and bidders then decide whether to bid or not to bid. Further the signals are noisy which justifies the presence of incomplete information in the empirical model.

From a statistical estimation perspective, we can solve this problem using the random utility approach [RUM] (McFadden, 1974) to model discrete choices and the extension to equilibrium discrete choice models (Signorino, 2003). Utilities for the players can be expressed as linear combinations of factors that influence their choice of respective actions. Factors contributing to the utility could primarily be a function of the resources available and incentives of the managers making the choice. We accommodate for the information structure by accounting for the different players, their sequence of decisions, options at decision points and the equilibrium effects arising out of interdependence in outcomes.

The basic structure of the RUM allows for a deterministic and a stochastic component in the utility function. An epsilon shock added to each utility can ensure that all actions are played with a positive probability. This removes problems of observing zero likelihood’s, which would render estimation impossible. A representative agent framework is used, where if a player has to make more than one move; each move following the first is through a representative agent (whose preference distribution is unknown when the player makes his first move).

We define two players as A and B, the target firm and the bidder firm respectively. The target firm moves first and decides whether to repurchase or not and then the bidder firm after observing the target decides whether to make a bid. Each decision
maker’s utilities constitute a fixed part \((X\beta)\) and a stochastic part \((\varepsilon)\). The fixed part of the utility is observed by all players and the researcher. The stochastic part is private information. Nature draws the type for both players from a well defined probability distribution. The players and the researcher have well defined beliefs about the distribution of the private information component. It is further assumed that each type is drawn from a i.i.d cumulative distribution \(F(.)\), with a corresponding positive density \(f(.)\), with mean \(\mu\) and variance \(\sigma^2 < \infty\). The density function \(f(.)\) is assumed to be twice continuously differentiable.

Each players strategy is characterized as a mapping from types to actions depicted as \(\sigma^i : \varepsilon_i \rightarrow A_i\) where \(i = \{Target, Bidder\}\). \(A_i\) defines the action set for each player. The action sets are \(A_{Target} = \{Repurchase, NotRepurchase\}\) and \(A_{Bidder} = \{Bid, NotBid\}\). The random utility structure assumes that the fixed and stochastic parts of the players’ utility are additively separable\(^{10}\).

Since player’s play strategies that map a random variable to their action space, all actions are probabilistic. The Nash equilibrium where each player has private information as in the traditional random utility model is equivalent to the perfect Bayesian equilibrium (PBE) in a Bayesian game, where player types are private information. We can now solve for the unique equilibrium and develop an empirical estimator for the same\(^{11}\). Having constructed the path probabilities we need to define the definition of the outcomes associated with the game and the relative outcome probabilities.

\(^{10}\)Additive separability in utility functions are a computationally appealing. Non additive functions pose further difficulties in estimation

\(^{11}\)All derivations are provided in Appendix A. Derivation is similar to the technique used in Nandialath and Anand (2008)
The outcome of the $i^{th}$ game can be represented as follows

$$y_i = \begin{cases} 
1 & \text{if player A chooses l and player B chooses L} \\
2 & \text{if player A chooses l and player B chooses R} \\
3 & \text{if player A chooses r and player B chooses L} \\
4 & \text{if player A chooses r and player B chooses R} 
\end{cases}$$

The likelihood function for the model can now be written down as follows

$$L(\beta_{x,y} | y) = \prod_{i=1}^{n} I(y_i=1) P_{1i} I(y_i=2) P_{2i} I(y_i=3) P_{3i} I(y_i=4) P_{4i}$$

where $h = [A, B]$, $x = [l, r]$, $y = [L, R]$

$I(a, b)$ is an indicator function that equals 1 when $a=b$ and equals 0 otherwise and $P_1$, $P_2$, $P_3$ and $P_4$ are the associated outcome probabilities. The outcome probabilities are written as products of the associated path probabilities\textsuperscript{12}. Note that $p_4$ is different from $P_4$. To be precise, $p_4$ is the conditional probability that the bidder makes a bid conditional on not observing a repurchase and $P_4$ is the outcome probability that a repurchase is observed and a bidder makes a bid. Based on the

\textsuperscript{12}Note that the error structures of the two players are not correlated
equilibrium path probabilities, the respective outcome probabilities are as follows.

\[ P_1 = \left\{ 1 - F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right) \right\} \]

\[ \left\{ 1 - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) \right\} \]

\[ P_2 = \left\{ 1 - F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right) \right\} \]

\[ \left\{ 1 - F_B \left( X_{r,R}^B \beta_{r,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\} \]

\[ P_3 = \left\{ F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right) \right\} \]

\[ \left\{ 1 - F_B \left( X_{r,R}^B \beta_{r,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\} \]

\[ P_4 = \left\{ F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right) \right\} \]

\[ \left\{ F_B \left( X_{r,R}^B \beta_{r,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\} \]

Using an appropriate link function \( F(.) \) the joint likelihood function can be maximized. We require \( F(.) \) to be an absolutely continuous distribution function to be consistent with the Perfect Bayesian Equilibrium (PBE). Usually \( F(.) \) is assumed to be either the normal distribution (probit) or an extreme value distribution (logit). As is the case with standard discrete choice models, identification problems exist. Hence following standard practice the variance is normalized to one. Further we assume that the associated \( F(.) \) is the same for both players \(^{13}\). The likelihood function described above can be maximized using traditional maximum likelihood methods. However, the shape of the likelihood is highly irregular and most times derivative based optimization methods fail to converge. In this backdrop we estimate the model using a Bayesian MCMC sampling approach (Rossi et. al. 2005).

\(^{13}\)It might be interesting to study what would the impact when the two \( F(.) \) are not the same. We leave this for further study

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Bayesian Implementation

The non-linearities in the likelihood create significant issues in running maximization procedures. Standard derivative based optimization routines failed to maximize the likelihood function indicating that the likelihood is either flat or very irregular. We use Bayesian MCMC methods as an alternative. Bayesian implementation requires the likelihood function and a prior for all the unknown parameters. For instance in the case of the structural model outlined above, the posterior distribution $π(β|y)$ can now be obtained using Bayes theorem as follows

$$
π(β|y) ∝ L(y|β) π(β)
$$

Where $L(.)$ is the likelihood and $π(.)$ is the prior. Estimation is through a Random Walk Metropolis-Hastings algorithm (Chib and Greenberg, 1993). The likelihood of the model, using the Gaussian distribution for the private information can be written as follows.

$$
[β^A_{l,r}, β^B_{L,R}|all\ else] ∝ \prod_{i=1}^{n} π(y_i|β^A_{l,r}, β^B_{L,R}, σ^A_{l,r}, σ^B_{L,R}, p)
$$

Prior distributions for all parameters were specified normal with mean zero and covariance matrix equal to 100 times the identity matrix $^{14}$. The Metropolis Hastings algorithm works on the principle of rejection, where a candidate draw is generated from a new distribution and accepted or rejected with some probability. The candidate generating distribution $t(β^{old}, β^{cur})$ now depends on the current state $β^{cur}$ of the Markov Chain. A new candidate $β^{new}$ is accepted with some probability equal to

$^{14}$The choice of priors is diffuse but proper. We do this to ensure that our results are not driven by imposing prior information on the model. Rather, we let the likelihood to dominate our inference process.
\[ p(\beta_{\text{new}}, \beta_{\text{cur}}) \] given by

\[ p(\beta_{\text{cur}}, \beta_{\text{new}}) = \min \left\{ 1, \frac{\pi(y|\beta_{\text{new}}, \text{all else})}{\pi(y|\beta_{\text{cur}}, \text{all else})} \frac{\pi(\beta_{\text{new}})}{\pi(\beta_{\text{cur}})} \frac{\pi(\beta_{\text{old}}, \beta_{\text{cur}})}{\pi(\beta_{\text{old}}, \beta_{\text{cur}})} \right\} \]

The algorithm has to be tuned in order to ensure that the parameter space searched is wide enough and at the same time the chain converges to the stationary distribution. In this paper, the parameter was tuned to ensure acceptance rates between 35 and 50 percent. We run the estimation algorithm as outlined earlier. 300,000 runs were used and the first 100,000 readings were used as the burn in and discarded and use the trimmed distribution for inference.

While a structural model sounds theoretically appealing, the question remains as to whether the true data generating process supports such strategic interactions. For this purpose we use two additional research designs used in prior research as robustness checks. Since both the models are non nested (the structural approach is not a nested version of the traditional approach and vice versa), standard model selection tests such as the Wald or LM tests cannot be used (Greene, 2003). Hence, we use the procedure suggested by Vuong (1989) for model selection purposes\textsuperscript{15}.

### 3.4.3 Deterrence/Attraction Effect

The principal advantage of using a structural model is the ability to recover the latent process related to the deterrence/attraction effect. For instance in the case of a target firm implementing an open market repurchase, we can extract the conditional probability that a bid is received after observing the open market repurchase (\( p_6 \) from Fig. I) and the conditional probability that a bid is received with no open market repurchase (\( p_4 \) from Fig I). Thus this links back directly to our theoretical model.

\textsuperscript{15}We provide a brief description on what the Vuong (1989) test does in Appendix B.
quantity of interest is how the open market signal changes the likelihood of bidding by potential target firms. Thus, again applying Bayes rule we partial out the impact of repurchase on the bid to determine the impact of repurchases on bidding behavior. The attraction/deterrence effect can now be formulated as:

\[
\text{Total effect} = \Pr(\text{Bid|Repurchase}) - \Pr(\text{Bid|No Repurchase})
\]

Inference then proceeds as follows:

\[
\begin{align*}
\text{When Total Effect} & < 0 \implies \text{Deterrence Effect} \\
\text{When Total Effect} & > 0 \implies \text{Attraction Effect}
\end{align*}
\]

The deterrence effect provides us the key to identifying support for the propositions derived earlier. The use of the Bayesian approach to estimation also plays a beneficial role for the purpose of inference on the total affect. From the perspective of frequentist statistics, we lack information on the distributional properties of the total effect and hence traditional hypothesis testing faces numerous difficulties. From the Bayesian perspective, we generate the entire posterior distribution of the total effect. Thus hypothesis testing is now convenient as

We can easily build confidence intervals and test for significance of the effect. Another advantage of the modeling approach suggested in this paper is that we can look at the impact of changing an explanatory variable on any outcome probability and the total effect. It is important to note that in the structural model key drivers of utilities can affect the decision maker’s beliefs either directly or indirectly. Directly it can affect the targets behavior through its utilities for various outcomes and indirectly it can affect its behavior through their beliefs about the probabilities of the bidder’s actions. Separating the two out can be achieved by looking at the marginal change in beliefs by keeping all but one of the factors affecting utilities constant and by altering the last explanatory variable. Next we discuss our results.
3.5 Results

3.5.1 Interpreting Coefficients

First we look at the Bidder’s utility function. We find that the lagged size of equity is negatively correlated with two outcomes namely (Repurchase, Receive Bid) & (Repurchase, Not Receive Bid). Prior research has documented a negative relationship between measures of leverage, market to book ratio and return on assets and the probability of a takeover. When strategic interaction is accounted for, we find that leverage is statistically significant only for the case where the outcome is (Bid, No Repurchase). This result suggests again that aggregation of outcomes from four to two can lead to inferential issues on account of information loss through aggregation. Similarly with the market to book ratio, we find that it is statistically significant only in the case where the outcome is (Bid, No Repurchase). This result is interesting in itself. The market to book ratio has been used as a proxy for signaling undervaluation and this result suggests that bidders possibly consider the target’s action to repurchase as an important signal. However, in line with our structural approach, we reserve our substantial inference on the signaling or deterrence hypothesis to the deterrence/attraction effect.

The results are tabulated in table 3.1. The coefficient on the industry adjusted return on assets is positive and significant in the case where we see (No Repurchase, Bid) and negative and significant in the case where we see (Repurchase, Bid). The opposite signs for the two outcomes offer an interesting explanation. An increase in industry adjusted ROA suggests that the firm is doing well and since that information is likely to be observed by the market, bidders might think that an action such as open market repurchases might be more in line with a deterrence objective and hence we see that the likelihood of a bid being made reduces. On the other hand, an improvement
in the industry adjusted ROA with no repurchases seem to attract bidders as the firm seems to be a better pick than others from the perspective of prior performance. We also note that the changes in statistical significance for several variables could be on account of the loss of information due to aggregation and also on account of not taking into account the elements of strategic interaction between the bidder and the target. We also find that the number of bidders has a positive impact on the outcome being target repurchases and the bidder makes a bid. This seems consistent with our hypothesis that bidders may practice jump bidding and hence the more the number of bidders, the higher the likelihood of receiving a bid.

Next we turn our attention to the Target firm. The coefficient on cash dividend is positive but not statistically significant. Considerable attention has been paid into the question of whether repurchases act as complements or substitutes with dividends. The empirical evidence has been mixed (Dittmar (2007)). The insignificance of the coefficient on cash dividends seems to suggest that cash dividends are neither substitutes nor complements. In the target’s utility function, the coefficients on free cash flow and return on equity is positive but again not statistically significant. The coefficient on non operating income is positive and statistically significant. Size of assets is negative and statistically significant. The coefficient on size has attracted considerable attention in the literature. Dittmar (2000) indicates that the positive association between size and repurchases is rather puzzling. Since size is used as a proxy for information asymmetry, the bigger the firm, the less likely it is to be mis-valued. Contrary to past research we find that size of assets is significantly negative when we account for strategic interaction.
3.5.2 Deterrence/Attraction Effect

Our modeling approach is different for several reasons. First we base our inference on structural parameters drawn from the game structure presented. Hence direct inference on the coefficients is incorrect as we are effectively not testing comparative static predictions. Further, as is the case with standard discrete choice models, it is difficult to draw conclusions based on the estimates of the coefficients. Taking these factors into account, we propose to use the difference in estimated latent conditional probabilities to inform us about the deterrence/attraction effect. From Figure (3.1) we can clearly see that the total effect is positive and statistically significant at the 5% level of significance.

Zero is not included within the confidence intervals constructed (bounds as indicated by the thick vertical lines). Hence given that the total effect is positive, we find evidence in favor of the attraction effect. Thus we find support for both Proposition 3.1 and Proposition 3.2. Essentially our analysis indicates that the firm’s use of open market repurchases does not really deter takeovers on average but rather helps to attract other bidders. We find this result after controlling for agency problems. Such attraction can come from either new bidders entering the fray post action from the target or existing prospective bidders, jump bidding in order to prevent access to the target firm to other potential bidders. Our analysis also lends support to the strategic factor market theory by showing that by creating heterogeneous expectations, potential target firms are more successful at attracting bids.

3.6 Conclusions

This paper examines the influence of target firm actions, such as implementing open market repurchases, on outcomes in the market for corporate control. Prior
research suggests that open market repurchases primarily deter takeovers through removal of agency rents. In this paper we present an alternative picture. We suggest that gains to potential bidders might also arise from acquisition of good resources. From the resource based perspective, acquisitions can be viewed as actions taken by the firm to obtain valuable, rare and inimitable resources. Resources (target firms) with these characteristics are likely to be tacit, complex and difficult to perfectly observe by nature.

Unobservable resources are hard to value and hence there is a high likelihood that bidders may either overpay or not consider purchasing at all. This suggests that in the absence of further information, firms may hold homogeneous expectations on the value of the target’s resources and hence the price of the asset will be bid up till all rents have dissipated. Thus, in effect bidders tend to overpay for the target, when the value of the asset is uncertain. Barney (1988) suggests that bidder firms can benefit only when there are inimitable cash flows generated out of unique synergies between the bidder and the target, known only to the focal bidder and unknown to the target and all other bidders. This assertion suggests that there is an important role for the private value element for each bidder. However, without more information, bounded rationality on the part of the bidders can lead to overpayment. This brings us to an important question. Can the target execute a market action which alters the expectations and thus the equilibrium in the bidding process.

Specifically we focus on the role of open market repurchases by the target firm prior to receipt of a bid. It has been documented that firms with high level of intangibles use stock repurchases to update their true valuation in the market (Barth and Kasznik, 1999). The target firm is likely to have a better grasp on the valuation of their resources and capabilities. By releasing such information to the potential targets, they allow the targets to update their priors. We use a game theoretic approach
to show that providing information through open market repurchases increases the likelihood of receiving a bid and thus open market repurchases can serve to attract more bidders. However, we also show that the attraction effect depends critically on the precision of the signal. Thus, when the fundamental quality of the resources are poor, providing more information can lead to deterrence as the outcome when potential bidders believe that the signal justifies their initial belief that the target firm has weak resources.

This brings forth an interesting empirical tension and relies primarily on the strategic interactions between the bidder and target. Do open market repurchases lead to attraction or deterrence? We empirically model the game between the bidder and the target as a sequential game with two sided incomplete information. Our technique allows for us to capture the richness of information structure within the game for analysis. Using a random sample of firms during the time frame 1991-2005, we find that on average the use of repurchases by target firm’s leads to an attraction effect. Our results provide insights to practicing managers. Open market repurchases in general are considered to be good mechanisms since they represent returning cash to the shareholders. Our analysis suggests that the average target firm need not worry much about repurchases preventing potential value generating deals. On the contrary, releasing information on the target firm can lead to generating greater value.

Future research can consider extending our work and use a richer game structure, allowing for multiple moves. At present the model presented in this paper does not allow players to learn from their previous actions. Since in reality multiple moves by each player are more than likely, extending the model in that direction might be a fruitful exercise. Another interesting extension would be to use behavioral decision rules rather than expected utility maximization. Further, much work also needs to go into studying identification issues, especially on the attraction and deterrence...
effect. Our paper focuses on only one part of the puzzle namely the attraction vs. the deterrence effect. Future work can also consider performance issues associated with the release of information by the target. For instance, the release of private information adds to the total surplus and updates the private value component for the bidders, thus allowing for the bidder to capture some of the informational rents. This suggests that bidders should do better when they buy target firm’s that conducted an open market repurchase vs. one that did (with similar characteristics).
Figure 3.1: Posterior Distribution of the Deterrence/Attraction Effect
<table>
<thead>
<tr>
<th></th>
<th>UB (4)</th>
<th>UB (2)</th>
<th>UT (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>(0.517)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ind Adj ROA</td>
<td>(0.857)</td>
<td>0.714</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[1.90),(0.39]</td>
<td>[0.11,1.29]</td>
<td></td>
</tr>
<tr>
<td>Size of equity</td>
<td>(0.328)</td>
<td>(0.310)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.36),(0.29]</td>
<td>[0.33),(0.28]</td>
<td></td>
</tr>
<tr>
<td>Ind BV of Leverage</td>
<td>0.023</td>
<td></td>
<td>(0.591)</td>
</tr>
<tr>
<td></td>
<td>[0.26), 0.40</td>
<td>[1.09),(0.27]</td>
<td></td>
</tr>
<tr>
<td>Market to Book</td>
<td>0.043</td>
<td></td>
<td>(0.955)</td>
</tr>
<tr>
<td></td>
<td>[(0.12), 0.33</td>
<td>[1.28),(0.66]</td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td>0.292</td>
<td>0.032</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.06, 0.65]</td>
<td>[0.13),0.24]</td>
<td></td>
</tr>
<tr>
<td>Fixed Assets</td>
<td>1.392</td>
<td>1.409</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[(0.42),2.24</td>
<td>[0.90,2.60]</td>
<td></td>
</tr>
<tr>
<td>Number of Bidders</td>
<td>0.807</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.21,1.97]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Dummy</td>
<td>0.141</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.027,0.30]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cash Dividends</td>
<td></td>
<td>1.792</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1.31),2.74]</td>
<td></td>
</tr>
<tr>
<td>Free Cash Flow</td>
<td></td>
<td>1.383</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.63),2.26]</td>
<td></td>
</tr>
<tr>
<td>Return on Equity</td>
<td></td>
<td>0.165</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.23),1.35]</td>
<td></td>
</tr>
<tr>
<td>Size of Assets</td>
<td></td>
<td>(1.524)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[(2.00),(1.02)]</td>
<td></td>
</tr>
<tr>
<td>Ind MV of Leverage</td>
<td></td>
<td>1.656</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.67,2.41]</td>
<td></td>
</tr>
<tr>
<td>Non Operating Income</td>
<td></td>
<td></td>
<td>(3.205)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[(3.89),(1.87)]</td>
</tr>
<tr>
<td>Stock Options</td>
<td></td>
<td></td>
<td>(1.633)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[(2.44),0.90)]</td>
</tr>
</tbody>
</table>

Note: Parameter estimates are accompanied by the the bottom 2.5% and top 97.5% cutoff points in High Posterior Density region. The presence of zero within the interval implies that the coefficient is not statistically different from zero.
CHAPTER 4

IMPERFECT OBSERVABILITY OF RESOURCES AND STRATEGIC INTERACTIONS BETWEEN POTENTIAL ENTRANTS

4.1 Introduction

In this chapter we look at the effect of discontinuous technological change and competition in resource markets. Discontinuity arising out of technological changes has been a topic of considerable interest to strategy scholars (Tushman and Anderson, 1986; Henderson and Clark, 1990; Hill and Rothaermel, 2003). This literature primarily draws on the ideas of Schumpeterian competition (1950). For instance, it has been shown that technological change can hasten the destruction of firms that may have been industry leaders in the past (Schmalensee, 2000). How can firms compete in the face of such discontinuity? At the very least, a necessary condition would be that they require the technological capabilities to compete. For sufficiency, firms should also have the ability of dynamically developing capabilities to stay ahead in the race (Teece, Pisano and Schuen, 1997). However, firms may be characterized by factors such as organizational inertia and path dependence which may impede its ability to keep up with the rapid pace of advancing technologies (Helfat, 1994; Cohen and Levinthal, 1990). Similarly, there is considerable variance in the ability of firms to develop appropriate capabilities (Dierickx and Cool, 1989; Helfat and Lieberman, 2002).
The heterogeneity among firms in developing capabilities gives rise to interesting scenarios particularly from the perspective of competitive interactions. In the presence of a technological discontinuity the value of developing new capabilities is not completely known. The focus of this chapter is precisely to investigate the relationship between capabilities and competitive interactions in the presence of technological discontinuity. The importance of understanding competitive interactions under discontinuous technological change is an area of growing interest especially in the case of new technologies. Prior literature has considered competitive interactions mainly from the purview of multi-market competition (Gimeno, 1999; Karnani and Wernerfelt, 1985) and with very few focusing on technology competition (e.g. Anand, Mesquita and Vassolo, 2009). The focus of these studies are on how rivalries across markets can temper competition in individual markets. However, they do not examine the role of capabilities in tempering or worsening competition. Our primary research question revolves around how different types of capabilities affect competitive interactions between firms.

The focus of much of the prior literature on technological discontinuity has been competition between old firms and new firms (Tushman and Anderson, 1986; Henderson and Clark, 1990). However an interesting situation is what happens to competition between old firms? The schumpeterian hypothesis suggests that new firms with better technologies may drive out the old firms. We choose the pharmaceutical-biotechnology industry as our example as the nature of the industry is prone to technological discontinuity (especially the biotechnology industry). Technological advancement through areas such as molecular biology and genetic engineering, which can be broadly classified under biotechnology, forces firms to be at the cutting edge of scientific discovery in order to retain a competitive edge. This implies that firms are constantly adapting its capabilities to stay ahead of the crowd.

Consider the case of two pharmaceutical firms with different types of capabilities. Each has a strong position in traditional technologies (organic chemistry based compounds). Further suppose that both these pharmaceutical firms invest in building their strengths in emerging technologies and are considering entering a new segment. Several scenarios can
be played out. One such scenario suggests that since firms know that each has differential abilities to build emerging technologies, though there might be an outward signal that both the firms are developing such technologies only one might be eventually successful in the domain yet to be entered. The problem becomes more interesting as discontinuity in technologies implies that there is very little information on which to judge the capabilities of individual firms.

*Ex-Ante*, success for a firm is conditional on two important pieces of information. First, firms need to evaluate whether its capabilities can be translated into value in the new domain. Second, firms also need to evaluate their resource position relative to other competing entrants and its impact on potential outcomes in the new domain. In the case of traditional technologies this problem seems trivial and firms can observe each others performance over the years. However, the problem is not so trivial in the case of emerging technologies which are a result of the discontinuity and there is lack of prior history on the effectiveness of these capabilities. Thus firms can no longer be absolutely certain that a particular strategy will work. For instance consider the case where firms are trying to enter a new domain. What might have been a worthwhile decision to enter *ex-ante* may turn out to be a missed opportunity *ex-post* simply because the potential entrant held erroneous beliefs about its own capabilities or that of its competitors and decided not to enter. Thus both capability development and competitive interactions plays a crucial role in determining the outcome.

We start by building a simple model that captures strategic interactions between potential entrants. We identify a firm as a focal entrant and the other firms considering entry as potential entrants. All firms initially invest in building their pre existing resources. The focal entrant moves first and decides to enter. To other potential entrants, the decision to enter provides a noisy public signal on the quality of the focal entrant’s resources. Thus, other potential entrants decide on entry or no entry after updating their beliefs using both the public signal and their own private signals. Our results show that the the key factor in provision of information relates to the precision of the public signal. If the the signal is precise enough to indicate that the focal firm indeed possesses superior resources, it will
deter entry. However, the precision of the signal can be a double edged sword. If the signal is precise enough to indicate that the focal firm does not possess superior resources, it will enhance the likelihood of entry by potential competitors.

Resolving this theoretical puzzle is an empirical exercise. The key empirical question is what is the role of investing in new technologies on competitive interactions regarding entry decisions into new domains? Similarly another empirical question is related to the role of strength in traditional technologies on competitive interactions regarding entry decisions. In this chapter we test the propositions of the model using data from the US and European pharmaceutical-biotechnology industry. It is well received in the literature that biotechnology represents a technological discontinuity (Shan, Walker and Kogut, 1994; Powell, Koput, and Smith-Doerr, 1996). The capabilities of pharmaceutical firms’ in biotechnologies represent considerable heterogeneity. For instance, much of the technological revolution in biotechnology is centered in North America and particularly the United States. On the contrary, development in the traditional organic chemistry based businesses is more evenly spread across both Europe and North America.

Further we use a novel approach to empirically model competitive interactions between the focal entrant and other potential entrants and thus maintain consistency with the theoretical model that generated testable propositions. The presence of strategic interaction implicitly brings in endogeneity in choice behavior. For instance, it is intuitive to think that the decision to enter by the focal entrant is influenced by her expectation on other potential entrants also entering. Prior literature on strategic choice has documented the nature of endogeneity and its impact on problems related to strategic management (Hamilton and Nickerson, 2003). However, the traditional models recommended for correcting such endogeneity fail to account for multi player strategic interactions. The observed outcomes from the interaction between the focal entrant and other potential entrants is likely to be a product of some complex strategic interaction and hence it depends on the players interacting, the sequence of decisions, their options at the respective decision points, different factors influencing their incentives for one choice vs. the other and the equilibrium effects of
the interdependence of factors influencing the outcomes. Therefore our approach provides inference by keeping the richness of the information structure intact.

To implicitly accommodate the information structure we model the interaction between the focal entrant and other potential entrants as a sequential game with double sided asymmetric information. The focal entrant moves first and decides to enter the new domain. Potential entrants observe this action and decide to react by entering or not entering after updating their beliefs. The focal entrant’s action is based on its expected utility, which accounts for its beliefs about the potential entrants actions conditional of its (focal entrant’s) own choice. Other potential entrants then make their choice having observed the focal entrants action. Hence both players play best response strategies to each other. To aid in statistical estimation of such games, we draw on the literature, specifically McFadden (1974) on Random Utility models and Signorino (2003) on extension of the statistical equilibrium concepts to archival data.

Our study has several implications. First, we find that in the case of the focal entrant and potential entrants increasing investment in emerging technologies has a negative impact on competition. Thus, it might be the case that the a potential entrant is less likely to enter upon observing entry by the focal entrant and a high index on new technologies. Not surprisingly, we find the opposite result in favor of traditional technologies. Greater the traditional technologies, it is more likely to enhance competition. These results are in line with our intuition. The lack of observability is greater for new technologies and thus significant investment in such technologies coupled with entry signals that the entering firm is indeed quite strong or serious about the the new business. On the other hand, traditional technologies are observable since they have been around for a longer period of time and firms would have invested in studying each others technologies considerably. Further the results also suggest that in the context of the pharmaceutical-biotechnology sector, providing a noisy signal through early entry could be profitable for firms as it deters competition.
The rest of the paper is organized as follows. Next we discuss our model and develop testable propositions followed by the description of the data and variables used for empirical analysis. Next we discuss the results followed by our conclusions.

4.2 Model

In this section we use the technique of global games to examine strategic interaction between potential entrants in the presence of resource heterogeneity. Prior literature has applied the idea of global games in several setting such as investment decisions (Carlsson and Van Damme, 1993), currency crises (Morris and Shin, 1998; 2004), bank runs (Goldstein and Pauzner, 2005) and pricing of debt (Morris and Shin, 2003). To the best of our knowledge this approach has not been used to study entry decisions under resource heterogeneity.

4.2.1 Payoffs

We consider a market where there are \( n \) potential entrants contemplating entering a new market. Success upon entry depends on the number of competitors and the relative resource positions of each competitor. For ease of exposition, the \( n^{th} \) potential entrant is considered as the focal entrant. The remaining \( n - 1 \) potential entrants are indexed over the unit interval \([0,1]\). Each potential entrant possesses some level of resources and capabilities in new technologies. However, such resources are imperfectly observed. Thus assume that the true resources of the focal entrant is characterized by a state variable “\( \theta \)” that can take values over the real line \( \mathbb{R} \). A large value of \( \theta \) characterizes a focal entrant with very good quality resources and \textit{vice-versa}.

Payoffs for potential entrants are monotonically decreasing with the number of entrants. Upon successful entry an entrant can earn a benefit of \( B, B > 0 \) and also incurs a cost \( c, c>0 \). We create an implicit incentive for firms to enter by allowing the benefits \( B \) to be greater relative to the costs \( c \). If a potential entrant chooses not to enter, she does not incur...
a cost and receives no benefits. Let the proportion of participating entrants equal \( l \). Then the focal entrant’s strategy is equivalent to

\[
\xi(\theta, l) = \begin{cases} 
\text{Enter, if } l \leq \theta \\
\text{Not Enter, otherwise}
\end{cases}
\]

The intuition behind this set up is simple. The true value of the focal entrant’s resources for other potential entrants is a function of \( \theta \). If the resources are extremely good (\( \theta > 1 \)), other potential entrants have strong incentives to not enter, since they realize that the focal entrant will eventually drive them out of the market. Similarly, if the resources are extremely poor (\( \theta < 0 \)), other potential entrants have a very strong incentive to enter, since they realize that the focal firm is unlikely to succeed. Both these outcomes are consistent with the predictions of the resource based view (RBV). However, an interesting situation is when the focal entrant’s resources are in the range \((0 < \theta \leq 1)\). When \( \theta \) is closer to one it indicates that the resources of the focal firm are closer to being superior. On the other hand, when \( \theta \) is closer to zero it indicates that the resources are closer to being inferior.

Thus the focal entrant succeeds only when other potential entrants believes that she (focal entrant) has superior resources. This occurs when \( l \leq \theta \). When \( l > \theta \), the focal entrant is better off by staying out as it knows that other entrants believe that she (focal entrant) has weaker resources. Hence, when the true quality of the focal entrant’s resources are neither too high nor too low, the outcome of a entry game depends on the beliefs and actions of other potential entrants. However, the lack of observability in the intermediate range \((0 < \theta \leq 1)\) creates coordination problems for potential entrants. If potential entrants believe that the value of the resources of the focal entrant is low relative to their resources, it is optimal for them to enter. On the other hand, if potential entrants believe that the value of focal firm’s resources is high, it is optimal for them to not enter. Either equilibrium is self fulfilling by nature.
4.2.2 Timing

The timing of the game is as follows. At time $t = 0$ all potential entrants build their relative strengths through investments in resources. Such investments are heterogeneous and certain firms may have access to resources of superior quality. However, the quality of the resources remains unobserved. At time $t = 1$ nature draws a value of $\theta$. Nature’s draw is observed only by the focal entrant. Upon observing this draw by nature the focal entrant sends a noisy signal on the quality of its resources to other potential entrants by deciding to enter or stay out. The signal is public and observed by all other potential entrants. In the next period at time $t = 3$ potential entrants upon observing this public signal and also accounting for their own private signals, decide whether to enter the market or stay out. The time line can be represented as follows:

4.2.3 Information

The game between the focal firm and the potential entrants is then structured as follows. Nature chooses the value of the resources and capabilities index $\theta$ according to a uniform distribution. Intuitively, we can see that this case reflects one where all potential entrants have very diffuse prior information about the distribution of the focal entrant’s resources. After having observed $\theta$, the focal firm provides a public signal $y = \theta + \delta$, with $\delta \sim N \left(0, \frac{1}{\alpha}\right)$,
\( \alpha > 0 \) and \( E(\delta \theta) = 0 \), thus implying that the noise parameter is independent of the true state of the resources and capabilities. The signal is public and hence is common knowledge to entrants.

Further, each potential entrant individually receives a private signal \( x_i = \theta + \varepsilon_i \), with \( \varepsilon_i \sim N\left(0, \frac{1}{\beta}\right), \beta > 0 \). The noise parameters are independent of each other, of the fundamental value of the resources and of the public signal. The information set for each of the potential entrants consists of two distinct parts: the common public signal and a private signal. The public signal \( y \) enters the information set of all potential entrants. Thus it provides information about both the expectation on the value of resources held by the focal entrant and also on what the other potential entrants observe. It is important to note that in this model \( \theta \) is not common knowledge\(^ {16} \).

To illustrate, note that on observing \( x_i \), potential entrant \( i \) believes with 95% confidence that the true value of the focal entrant’s resources and capabilities lie in the interval \( \left(x_i - 2\left(\frac{1}{\sqrt{\beta}}\right), x_i + 2\left(\frac{1}{\sqrt{\beta}}\right)\right) \). Potential entrant \( i \) knows that the other potential entrant(s) \( j \) are also informed of the value of \( \theta \) with error \( \varepsilon_j \). Thus, potential entrant \( i \) can now compute the number of potential entrants who observe \( x_j \) below a particular some value, say \( \hat{\theta} \), as the area under the probability density function corresponding to \( \theta < \hat{\theta} \). If she observes high \( x_i \), she can be sure that only a small fraction of the potential entrants observe \( x_j \) below \( \hat{\theta} \). Thus in this case the fraction of potential entrants who might choose to enter “\( l \)” is likely low, implying that the focal entrant has better resources and hence is more likely to capture the market. Thus, the optimal strategy for potential entrants is also to not enter. Similarly, if she observed a low \( x_i \), her expected payoff from entering will be higher as \( l \) is likely to be higher.

\(^{16}\)If \( \theta \) is common knowledge, the game is transformed into one with complete information and can suffer from multiple equilibria (Obstfeld, 1996).
4.3 Equilibrium

The switching trigger equilibrium pair \((\theta^*, x_i^*)\) for this game is defined on the points of indifference for the focal entrant and the potential entrants. Specifically, for \(x_i = x_i^*\), potential entrants are indifferent between entering and not entering and for \(\theta = \theta^*\) the focal entrant is indifferent between entering and not entering. The game has a unique equilibrium provided that the private information is precise enough compared to public information. This condition implies that each of the potential entrants collect better information privately as against the depending completely on the public information provided by the focal entrant. Given the unobservable nature of resources, the focal entrant has an incentive to misrepresent the true value of resources. Thus, it is in the best interest of other potential entrants to collect private information on the value of the focal entrant’s resources. From the perspective of the potential entrant, assuming that the focal entrant provides a signal \(y\) and potential entrant \(i\) receives a private signal \(x_i\), her posterior belief on \(\theta\) is given by

\[
E(\theta|y, x_i) = \frac{\alpha y + \beta x_i}{\alpha + \beta} \tag{4.1}
\]

with variance

\[
Var(\theta|y, x_i) = \frac{1}{\alpha + \beta} \tag{4.2}
\]

Given public information \(y\), each potential entrant, updates her belief about \(\theta\) using her own signal \(x_i\). The posterior mean of \(\theta\) is primarily influenced by the information that potential entrants have. Thus the precision of the private and public signals moderate the relative importance of each in influencing the expectations on \(\theta\). After receiving both signals, each potential entrant has to decide whether or not to enter. The point of indifference is achieved when
\[ B. \text{Prob}(\text{Successful Entry}|x) - c = 0 \quad (4.3) \]

Since the focal entrant will not enter when the value of its resources are smaller than or equal to \( \theta^* \), the probability that each potential entrant will succeed is equal to the probability that \( \theta \) is less than or equal to \( \theta^* \), given \( x \). Thus, rewriting equation (3) and normalizing to the standard normal density we get

\[ c = B \Phi \left( \sqrt{\alpha + \beta} \left( \frac{\theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x}{\alpha + \beta} \right) \right) \quad (4.4) \]

The focal entrant is indifferent between entering and not entering, if the proportion of potential entrants entering, \( l \) given by the proportion of potential entrants receiving a private signal below \( x^* \), equals \( \theta \). Hence, \( l = \text{Prob}(x \leq x^*|\theta) \). Normalizing to the standard normal density, \( l \) is given by

\[
\begin{align*}
l &= P(x \leq x^*|\theta) \\
&= \Phi(\sqrt{\beta}(x^* - \theta)) \\
&= \Phi \left( \sqrt{\frac{\beta}{\alpha + \beta}} (x^* - \theta) \right) \quad (4.5)
\end{align*}
\]

Thus, the focal entrant is indifferent between entering and not entering if:

\[ \theta = \Phi \left( \sqrt{\frac{\beta}{\alpha + \beta}} (x^* - \theta) \right) \quad (4.6) \]

Using equations (4) and (6) we can now solve for the equilibrium solution which is represented as the tuple \((\theta^*, x^*)\). Solving for \( \theta^* \) we have:

\[
\theta^* = \Phi \left( \frac{1}{\sqrt{\beta}} \left( \frac{\alpha \theta^* - \alpha y - \sqrt{\alpha + \beta} \Phi^{-1} \left( \frac{c}{B} \right)}{\alpha + \beta} \right) \right) \quad (4.7)
\]

This equilibrium is unique when the private signals are sufficiently precise. Specifically, for all values of \( \beta > \frac{\alpha^2}{2\pi} \) there exists a unique equilibrium consisting of a value of the resource index \( \theta^* \), beyond which the focal entrant will always enter and a unique value for the private signal \( x^* \), below which potential entrants will always enter. All formal proofs are relegated
to the Appendix. Next we show a comparative static analysis to show the effects of changing the public signal $y$ and the precision of the public signal $\alpha$ on equilibrium outcomes.

**4.3.1 Comparative Statics**

Comparative statics are useful as a tool only when uniqueness of equilibrium is guaranteed. Therefore our propositions are conditional on achieving uniqueness i.e. $\beta > \frac{\alpha^2}{2\pi}$. For ease of exposition we define the key outcome of interest as competition. Specifically, competition arises when both the focal entrant and other potential entrants enter the market and compete. From equation (6), which provides the equilibrium value of the fundamental value of resources we can generate the following propositions with respect to the effect of the public signal on the likelihood of competition.

**Proposition 4.3.1.** The public signal $y$ has a negative effect on the likelihood of competition.

The public signal $y$ in our setting is the build up of specific resources which are only noisily observable which help the focal entrant in capturing the market. Given that $E(y|\theta) = \theta$, we can clearly see that the fundamental value of resources is higher when $y$ is higher. Thus the greater the investment in specific resources that are fundamentally unobservable, costly to copy and hard to imitate, the more likely other potential entrants will stay out. This proposition provides the focal entrant with strategic motivations to disclose information regarding its capabilities on new technologies.

While the earlier argument favors disclosure of information, it might be counter productive due to unobservability of resources on both sides. Specifically, the focal entrant may not fully observe the resources of other potential entrants and thus *ex-ante* may not be in a position to understand their relative strength. Similarly, despite the disclosure by the focal entrant, private information collected by other potential entrant’s might suggest that the public signal generated by the focal entrant is weak and thus not a very reliable signal of
her true capabilities. Thus a more critical element which influences the eventual outcome is the precision of the public signal provided by the focal entrant.

**Proposition 4.3.2.** The precision of the public signal \( \alpha \) has a positive influence on the likelihood of competition if there exists a \( y_\alpha \) such that, \( \forall y > y_\alpha, \theta^* < y + \frac{1}{(2\sqrt{\alpha + \beta} \Phi^{-1}(\frac{z}{\pi}))} \)

**Proposition 4.3.3.** The precision of the public signal \( \alpha \) has a negative influence on the likelihood of competition if if there exists a \( y_\alpha \) such that, \( \forall y < y_\alpha, \theta^* > y + \frac{1}{(2\sqrt{\alpha + \beta} \Phi^{-1}(\frac{z}{\pi}))} \)

The intuition is simple. When the precision of the public information is poor, potential entrants tend to place less weight on the public signal. In contrast, a more precise public signal results in potential entrants placing a greater emphasis on the information provided by the focal entrant. However, the critical feature to note is that greater precision can be a double edged sword. First, when the true value of the focal entrant’s resources is indeed high, reducing information problems through the signal is beneficial for the focal entrant, if and only if the true value of its resources are indeed high. In this case, other potential entrants clearly see that the focal entrant has stronger resources and thus are incentivized to stay out. However, what if the focal entrant does not possess superior resources relative to at least one other potential entrant? In this situation, increasing the precision of the public signal leads to a greater likelihood of competition.

These propositions raise interesting empirical questions. In the next section we describe the data used to test the above propositions and also outline empirical methods consistent with our theoretical framework.

### 4.4 Data and Methods

#### 4.4.1 Data

We use the US and European biotech-pharmaceutical industry as our context. Specifically we study biotech entry decisions made by 19 large US and European pharmaceutical companies over a period of 10 years from (1989 to 1999). We argue that this context is
apt to study the effects of competition under unobservability. Biotechnology is a technique which arises from scientific advance. More specifically it has led to the growth and development of the field of molecular genetics and recombinant DNA. These technologies have witnessed rapid growth over the last few years mainly in biology and agricultural sciences. Success in biotechnology depends heavily on innovations that may be foreign to established firms.

Established pharmaceutical firms have strong capabilities in traditional organic chemistry but may not have sufficient strengths in fields such as molecular biology and biochemistry which form the core development in bio-technology. Further there is considerable heterogeneity between pharmaceutical firms in terms of their biotech related capabilities. Thus, given this context it is more than likely that competing firms are more likely to imperfectly observe capabilities and have to make decisions based on such imperfect information. The biotech industry has been used to study the effects of technological competence (Henderson and Clark, 1990; Penner-Hahn, 1998 and McGrath and Nerkar, 2004; Anand, Oriani and Vassolo, 2009) and also competition (Anand et. al. 2008).

We test the propositions from our theoretical model using data on pharmaceutical firms’ decisions to enter a particular domain. Biotechnology research involves many kind of domains. Our data set consists of 143 such domains. We also have information on firms’ decision to invest in biotech related capabilities. Our data set includes all biotech entry decisions made by 19 of the world’s largest pharmaceutical companies between 1989 and 1999. Our main source of information on biotechnology investments comes from BioScan. The starting point of this period relates to the first year of complete information provided by BioScan while the ending period relates to the appearance of the first commercial products derived from biotech. Therefore, at the end of this period the level of uncertainty regarding these investments started to substantially decrease. These 19 firms come from several different countries, including USA, England, France, Germany, and Switzerland.
Firms can invest in the biotechnology industry through a wide variety of mechanisms such as in-house investments, alliances and acquisitions. BioScan captures R&D investments information by technological domain, six times a year. Technological domains can include but are not restricted to areas such as AIDS therapeutics, Bones Therapeutics and Vaccines. Domain classification is achieved through two different sources. First the information is collected through surveys from the relevant firms. Second, BioScan classifies domains based on hand collected information available from press releases and company websites. The information regarding equity agreements and acquisitions were gathered from different databases, including Recombinant Capital, North Carolina Biotechnology Industry databases, Ernst & Young Biotechnology Industry Reports, Predicast F&S Index of Corporate Change, Lexis/Nexus, Dow Jones News Service, SEC Schedule 13D filings, and pharmaceutical firms annual reports.

The final sample includes 876 total entries, of which 393 in-house and 483 entries through alliances. We excluded acquisitions from our sample because we had just 2 entries through outright acquisitions. In fact, the acquisitions normally followed alliances once a firm had already entered in the technological field.

4.4.2 Empirical Methodology

The formal model used in this chapter as well as in extant literature share a common feature. All of them use a game theoretic approach and rely on equilibrium predictions obtained through strategic interactions between the bidder and the target. Following our theoretical development earlier, we build a statistical model based on a two sided sequential game with incomplete information. Ignoring strategic interactions, when they are present in the data can lead to biased and inconsistent inference, thus throwing our interpretation of economic effects into jeopardy (Chapter 2). We follow a structural approach and keep the information structure in tact, thus estimating an empirical model which is consistent with the theoretical model generating the hypotheses.
A principal advantage offered by the setting we investigate is that the events happen in a sequence. The sequential nature of the game gives rise to a generic unique equilibrium (Breshnahan and Reiss, 1990). Enriching the game structure by adding incomplete information eases the problem from the purview of estimation. It should be noted that the empirical approach is completely consistent with our theoretical model. In the theoretical model the target firm moves first and sends a public signal through a repurchases and bidders then decide whether to bid or not to bid. Further the signals are noisy which justifies the presence of incomplete information in the empirical model.

From a statistical estimation perspective, we can solve this problem using the random utility approach [RUM] (McFadden, 1974) to model discrete choices and the extension to equilibrium discrete choice models (Signorino, 2003). Utilities for the players can be expressed as linear combinations of factors that influence their choice of respective actions. Factors contributing to the utility could primarily be a function of the resources available and incentives of the managers making the choice. We accommodate for the information structure by accounting for the different players, their sequence of decisions, options at decision points and the equilibrium effects arising out of interdependence in outcomes.

The basic structure of the RUM allows for a deterministic and a stochastic component in the utility function. An epsilon shock added to each utility can ensure that all actions are played with a positive probability. This removes problems of observing zero likelihood’s, which would render estimation impossible. A representative agent framework is used, where if a player has to make more than one move; each move following the first is through a representative agent (whose preference distribution is unknown when the player makes his first move).

Consider the game structure depicted in figure 4.1. We define two players as A and B, the focal entrant and a potential competing entrant respectively. The focal entrant moves first and decides to enter or not enter. Upon observing this the other potential entrant decides to enter or not enter. Each decision maker’s utilities constitute a fixed part \((X\beta)\) and a stochastic part \((\varepsilon)\). The fixed part of the utility is observed by all players and the researcher.
The stochastic part is private information. Nature draws the type for both players from a well defined probability distribution. The players and the researcher have well defined beliefs about the distribution of the private information component. It is further assumed that each type is drawn from a i.i.d cumulative distribution $F(.)$, with a corresponding positive density $f(.)$, with mean $\mu$ and variance $\sigma^2 < \infty$. The density function $f(.)$ is assumed to be twice continuously differentiable.

Each players strategy is characterized as a mapping from types to actions depicted as $\lambda^i : \varepsilon_i \rightarrow A_i$ where $i = \{FocalEntrant, PotentialEntrant\}$. $A_i$ defines the action set for each player. The action sets are $A_{FocalEntrant} = \{Enter, NotEnter\}$ and $A_{PotentialEntrant} = \{Enter, NotEnter\}$. The random utility structure assumes that the fixed and stochastic parts of the players’ utility are additively separable\(^{17}\).

Since player’s play strategies that map a random variable to their action space, all actions are probabilistic. The Nash equilibrium where each player has private information as in the traditional random utility model is equivalent to the perfect Bayesian equilibrium (PBE) in a Bayesian game, where player types are private information. We can now solve for the unique equilibrium and develop an empirical estimator for the same\(^{18}\). Having constructed the path probabilities we need to define the definition of the outcomes associated with the game and the relative outcome probabilities.

The outcome of the $i^{th}$ game can be represented as follows

$$y_i = \begin{cases} 
1 & \text{if player A chooses } l \text{ and player B chooses } L \\
2 & \text{if player A chooses } l \text{ and player B chooses } R \\
3 & \text{if player A chooses } r \text{ and player B chooses } L \\
4 & \text{if player A chooses } r \text{ and player B chooses } R 
\end{cases}$$

The likelihood function for the model can now be written down as follows

\(^{17}\)Additive separability in utility functions are a computationally appealing. Non additive functions pose further difficulties in estimation

\(^{18}\)All derivations are provided in Appendix A. Derivation is similar to the technique used in Chapter 2 of this dissertation
\[
L \left( \beta_{x,y}^h | y \right) = \prod_{i=1}^{n} p_{1i} I(y_i=1) p_{2i} I(y_i=2) p_{3i} I(y_i=3) p_{4i} I(y_i=4)
\]

where \( h = [A, B], x = [l, r], y = [L, R] \)

\( I(a, b) \) is an indicator function that equals 1 when \( a=b \) and equals 0 otherwise and \( P_1, P_2, P_3 \) and \( P_4 \) are the associated outcome probabilities. The outcome probabilities are written as products of the associated path probabilities\(^{19}\). Note that \( p_4 \) is different from \( P_4 \). To be precise, \( p_4 \) is the conditional probability that the a potential entrant will enter conditional on observing that the focal entrant did not enter and \( P_4 \) is the outcome probability that both the focal entrant and the potential entrant entered. In other words, \( P_4 \) represents our key variable of interest as it reflects the outcome where competition ensues.

Based on the equilibrium path probabilities, the respective outcome probabilities are as follows.

\[
P_1 = \left\{ 1 - F_A \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right\}
\]

\[
\left\{ 1 - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) \right\}
\]

\[
P_2 = \left\{ 1 - F_A \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right\}
\]

\[
P_3 = \left\{ F_A \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right\}
\]

\[
\left\{ 1 - F_B \left( X_{r,R}^B \beta_{r,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\}
\]

\[
P_4 = \left\{ F_A \left( X_{r,R}^B \beta_{r,R}^B \right) X_{r,R}^A \beta_{r,R}^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_{r,L}^A \beta_{r,L}^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_{l,R}^A \beta_{l,R}^A \right\}
\]

\[
\left\{ F_B \left( X_{r,R}^B \beta_{r,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\}
\]

Using an appropriate link function \( F(.) \) the joint likelihood function can be maximized. We require \( F(.) \) to be an absolutely continuous distribution function to

\(^{19}\)Note that the error structures of the two players are not correlated.
be consistent with the Perfect Bayesian Equilibrium (PBE). Usually \( F(.) \) is assumed to be either the normal distribution (probit) or an extreme value distribution (logit). As is the case with standard discrete choice models, identification problems exist. Hence following standard practice the variance is normalized to one. Further we assume that the associated \( F(.) \) is the same for both players \(^{20}\). The likelihood function described above can be maximized using traditional maximum likelihood methods. However, the shape of the likelihood is highly irregular and most times derivative based optimization methods fail to converge. In this backdrop we estimate the model using a Bayesian MCMC sampling approach (Rossi et. al. 2005).

**Bayesian Implementation**

The non-linearities in the likelihood create significant issues in running maximization procedures. Standard derivative based optimization routines failed to maximize the likelihood function indicating that the likelihood is either flat or very irregular. We use Bayesian MCMC methods as an alternative. Bayesian implementation requires the likelihood function and a prior for all the unknown parameters. For instance in the case of the structural model outlined above, the posterior distribution \( \pi(\beta|y) \) can now be obtained using Bayes theorem as follows

\[
\pi(\beta|y) \propto L(y|\beta) \pi(\beta)
\]

Where \( L(.) \) is the likelihood and \( \pi(.) \) is the prior. Estimation is through a Random Walk Metropolis-Hastings algorithm (Chib and Greenberg, 1993). The likelihood of the model, using the Gaussian distribution for the private information can be written

\(^{20}\)It might be interesting to study what would the impact when the two \( F(.) \) are not the same. We leave this for further study
as follows.
\[
\left[ \beta^A_{l,r}, \beta^B_{L,R}, \text{all else} \right] \propto \prod_{i=1}^{n} \pi \left( y_i | \beta^A_{l,r}, \beta^B_{L,R}, \sigma^A_{l,r}, \sigma^B_{L,R}, p \right)
\]

Prior distributions for all parameters were specified normal with mean zero and covariance matrix equal to 100 times the identity matrix. The Metropolis Hastings algorithm works on the principle of rejection, where a candidate draw is generated from a new distribution and accepted or rejected with some probability. The candidate generating distribution \( t(\beta^{old}, \beta^{cur}) \) now depends on the current state \( \beta^{cur} \) of the Markov Chain. A new candidate \( \beta^{new} \) is accepted with some probability equal to \( p(\beta^{new}, \beta^{cur}) \) given by

\[
p(\beta^{cur}, \beta^{new}) = \min \left[ 1, \frac{\pi(y | \beta^{new}, \text{all else}) \pi(\beta^{new}) t(\beta^{old}, \beta^{cur})}{\pi(y | \beta^{cur}, \text{all else}) \pi(\beta^{cur}) t(\beta^{old}, \beta^{cur})} \right]
\]

The algorithm has to be tuned in order to ensure that the parameter space searched is wide enough and at the same time the chain converges to the stationary distribution. In this paper, the parameter was tuned to ensure acceptance rates between 35 and 50 percent. We run the estimation algorithm as outlined earlier. 300,000 runs were used and the first 100,000 readings were used as the burn in and discarded and use the trimmed distribution for inference.

4.4.3 Dependent Variable

Our key dependent variable is the decision to enter or not enter by both the focal entrant and potential entrants. Thus within our sample of 19 pharmaceutical firms we evaluate strategic interaction between all firms. Thus, the dependent variable is defined as a tuple \((y_1, y_2)\) where \(y_1\) refers to the focal entrant’s decision to enter or

\(^{21}\)The choice of priors is diffuse but proper. We do this to ensure that our results are not driven by imposing prior information on the model. Rather, we let the likelihood to dominate our inference process.
not enter and \( y_2 \) refers to the potential entrant’s decision to enter or not enter. The dependent variable for each firm \((y_1 and y_2)\) is set to 1 if firm \( i \) entered the emerging technological field \( j \) between 1989 and 1999 through either an alliance or internal development and 0 otherwise. Firm \( i \) is categorized as entering domain \( j \) through *internal development* when, based on the data from BioScan the firm was not present in the technological field \( j \) in year \( t-1 \) and was present in the technological domain \( j \) in year \( t \). Similarly, we classify firm \( i \) as entering the emerging technology domain \( j \) through an *alliance* if BioScan reports an alliance of firm \( i \) in the emerging technological domain \( j \) in year \( t-1 \) before internal development occurs.

### 4.4.4 Independent Variables

To test our propositions we also need measures of firm resources. We build measures using patent data (Patel and Pavitt, 1997). In pharmaceuticals and biotechnology, patents play a crucial role in deterring potential imitators thus allowing the patent holder to appropriate all the returns from innovation (Gittelman and Kogut, 2003).

Patent information is gathered from the NBER database, which reports all the patents granted by the United States Patent & Trademark Office (USPTO) from 1963 to 1999 (see Hall, Jaffe and Trajtenberg, 2002 for a detailed description). The Patent Classification System (USPC) is a system for organizing all U.S. patent documents into relatively small collections based on common subject matter patent classes. Patent classes have been considered a reasonable proxy for technological areas (e.g., Anand et.al. 2009). Following Penner-Hahn (1998), we assign the patent classes defined by the USPTO to the three distinct sets of capabilities (technological resources in the traditional technology, technological resources in the emerging technology, and complementary capabilities). For each firm in the sample we calculated three different
patent stocks in 1988. The stocks represent different patent classes that approach different type of capabilities.

The patent stocks were calculated through the perpetual inventory method (Anand et. al. 2009). For each firm, all the patents in given patent class were added up from 1963 to 1988 and depreciated at a yearly rate of 15. We chose the application year instead of the grant year of the patents for the calculation because the former should be more informative of the availability of a given capability within the firm.

In the case of the pharmaceutical industry, the traditional drug search process and the emerging biotechnological techniques relied on two distinct sets of core technological capabilities (Penner-Hahn, 1998). The traditional process required the synthesis and the test of several hundreds of organic compounds, which involved strong capabilities in organic chemistry. In biotechnological search, therapeutic proteins are synthesized through the manipulation of genetic structure of cells, building on a distinct set of capabilities in molecular biology and biochemistry.

Based on this distinction and on the USPTO patent classes, the measure of Capabilities in the traditional technology was calculated as the stock of the patents in the insurance and Boyes, Hofman and Low (1989) for an application to the analysis of credit default. 22 USPTO classes from 532 to 570 entitled “Organic compounds”. The patents in these classes signal strength of the firm in the organic chemistry. The measure of Capabilities in the emerging technology was calculated as the stock of the patents in the USPTO class 435 entitled “Chemistry: Molecular Biology and Microbiology”\textsuperscript{22}.

\textsuperscript{22}The fact that patents in class 435 are at the core of a distinct drug search process is confirmed by the fact that many subclasses of class 435 are clearly related to genetic manipulation. For example, subclass 4 “Measuring or testing process involving enzymes or micro-organism; composition or test strip therefore; process of forming such composition or test strip” or subclass 41 “Microorganism, tissue cell culture or enzyme using process to synthesize a desired chemical compound or composition”.

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In order to further validate our measures, we interviewed an expert from the biopharmaceutical industry. Specifically, our goal was to confirm that in our context, the use of different patent classes as core and complementary capabilities was appropriate. The answer we received was that the capabilities of organic chemistry lie at the core of the traditional drug research process, requiring the search and screening of new chemical compounds, whereas biochemistry and, above all, molecular biology represent the basis for genetic manipulation in the biotechnological drug search process\textsuperscript{23}. This confirms and reinforces our idea that patents in class 532-570 and 435 measure core technological capabilities underlying two alternative drug research processes.

As regards Complementary capabilities, it should be noted that the process to discover and develop new drugs is inherently difficult and it requires the integration of several distinct specialized technological capabilities. Consistent with the definition of complementary capabilities assumed in this paper, the measure of complementary capabilities should reflect the ability of the firm to combine its core capabilities in organic chemistry or biology and biochemistry into a new potentially marketable product. Accordingly, we measure this variable as the stock of patents in the USPTO class 424 entitled “Drug, bio-affecting and body treating compositions”. This class mainly contains patents on new products (drugs, bio-affecting compositions capable of preventing, alleviating, treating or curing abnormal and pathological conditions and antibiotics) and processes for their use or preparation (see the USPTO Manual of

\textsuperscript{23}This claim is supported also by the technical literature on drug development. For example, Ohlstein, Ruffolo and Elliot (2000), comparing different drug development methods, say about medical chemistry (p. 182): “Organic synthesis is, and is likely to be for some time, the cornerstone upon which medicinal chemistry is built”. As regards biotechnology, instead, they add (p. 187): “The development of proteins as drugs has been the principal focus of the biotechnology industry as well as a component of the drug pipeline of several larger pharmaceutical companies for some time” (i.e., the development of proteins falls under patent class 435 within the USPTO classification system).
Classification), signaling the ability of the firm to develop new products and processes from its existing core technological capabilities.

4.4.5 Control Variables

This study uses a measure of organization size to control for the financial resource position: the natural logarithm of total pharmaceutical annual sales (US$ millions) in 1988, the year just before the start of the study period. Organizational size is a previously used predictor of alliance formation (Gulati, 1995), since larger firms may be more able to establish larger in-house exploration and more equity agreements. The values for these variables were taken from Compustat, Lexis-Nexis, Global Access, and the annual reports of the firms. For most of the cases, the information was available under US accounting standards, ensuring the compatibility of the measure across countries. Different sources were used for early observations. In particular, substantial work was needed to get early observations for non-US companies. In some cases, English versions of the Annual Reports were not available, so that it was necessary to consult the originals in French and German.

We control for organizational innovation using the number of therapeutic classes in which the pharmaceutical firm was investigating in 1988, since broader research scope seems to indicate a higher commitment to innovation. The source of this information

24Penner-Hahn (1998) uses the same classes to calculate different variables. This difference is mostly due to the different research design of her study. Penner-Hahn analyzes the internationalization of R&D activities of Japanese pharmaceutical firms. She considers patents in classes 424 and 514 (later integrated in class 424) as domestic research competence, while patents in class 435 (Molecular Biology and Biochemistry) are seen as a platform (complementary capability) to access foreign R&D activities. Our research design, instead, aims to analyze whether the possession of competencies in the traditional technology (class 532-570) and the emerging technology (class 435), at the core of two alternative drug search processes, affects the likelihood and the mode of entry into new therapeutic classes. In this perspective, the ability of a firm to obtain patents on new drugs (class 424) should signal its ability to combine its core technologies to enter new therapeutic classes, independently of the nature of the core technological capabilities mobilized in the drug search progress.

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was BioScan. We also control for the US origin of the companies since the main innovations in biotechnology were achieved in the US. Firms operating in the US were then closer to the locus of the emerging technology, which could have made their entry into the new technological fields easier. Finally, in the equation predicting the entry mode, we use a set of dummy variables to control for the entry year. In this way we control for the fact that the entry timing can affect firms decisions on the entry mode.

4.5 Results

Table 4.1 and 4.2 present the results of our analysis. Since the model is non-linear in parameters we cannot interpret the magnitude of coefficients. However, the test of our propositions only require consistency with the signs and hence we ignore computing the marginal effects.

Our first model includes all variables including the controls on firm size and the total number of patents. The results from table 4.1 suggests that there is consistent evidence that greater investment in emerging technologies is likely to lead to reduced competition. Specifically we find that with respect to the focal entrant’s utility function for competition, the coefficient on the potential entrant’s emerging technology is negative and statistically significant. Similarly, with respect to the potential entrant’s utility function for competition, we find that the focal entrant’s emerging technology is negative and statistically significant. Both results confirm that signaling strong investments in emerging technologies leads to reduction in the likelihood of competition. Thus in the face of greater unobservability the signal is strong and precise enough that it prevents entry by potential competitors. Thus, from a strategic policy perspective, firms that build up strengths in new technologies may be better off by moving first and accessing the market early rather than waiting.
On the other hand we find that with respect to traditional technology, the likelihood of competition increases. Therefore, greater the investment in traditional technology more likely that firms are likely to compete in the new technology domain. This result fairly intuitive and is also consistent with prior research which suggests that firms with significant strengths in traditional technologies may find it hard to compete in new technologies. Thus, firms that focus more on traditional technologies may suffer from organizational inertia or may simply lack the capabilities to build new technologies successfully. Further, given that existing technologies do not suffer from the problem of unobservability (or it is likely to be quite low), competitors may be well aware of the real strengths and capabilities of the focal firm. Our results further vindicates this point and when competing firms observe greater investments in traditional technologies they perceive a lower likelihood of the that firm doing well in the emerging field. Thus, the likelihood of competition increases.

We also find that the focal entrant’s emerging technology investment positively affects its decision to enter the market when potential entrant’s do not react. This is consistent with the traditional predictions of the resource based view. On the other hand a rather puzzling result is that the effect is not symmetric across potential entrants. When the focal entrant does not enter and the potential entrant enters, we find that the coefficient on the emerging technologies for the potential entrant is negative and significant. This suggests that greater investments in new technologies leads to a lower likelihood that potential entrants will enter given that the focal entrant stays out. Why is this so? One potential explanation could be that in the face of great uncertainty firms are trying to reduce their risk of costly strategic mistakes through herding behavior. Thus, when they do not observe a first mover into the market, other entrants are also unsure if they are making a mistake and this uncertainty looms over their decision. This explanation is consistent with a real
options perspective of the problem. Investments in new technologies are fraught with a high level of uncertainty. Thus, when firm’s do not observe competing firms entering, they may be waiting for uncertainty to resolve before making a move that could prove to be costly ex-post. Table 4.2 examines the same variables with the exception that we now add a squared emerging technologies term to the utility functions of both the potential entrant and the focal entrant when the expected outcome is competition. We find that the results are largely consistent and the results are qualitatively similar.

4.5.1 Is market entry a good signal to deter potential entrants?

While our earlier result suggest that market entry coupled with strong resources can be a good signal to deter potential entrants, we fail to capture the true treatment effect from the analysis of coefficients. When is the signal effective? A signal is effective only when it prevents entry that would have otherwise occurred. More specifically, potential entrants may enter under two possible scenarios, either after the focal entrant has entered or if the focal entrant decides not to enter. Thus to capture the effect of the focal entrants signal we compute the difference in probabilities between $Pr(\text{Potential Entrant Enters} \mid \text{Focal Firm signals}) - Pr(\text{Potential Entrant Enters} \mid \text{Focal Firm does not signal})$. Thus if the probability of the potential firm entering is lower when she receives a signal than when she does not receive a signal, we suggest that the signal is effective in deterring potential entrants.

Figure 4.1 represents the histogram of computed differences in these probabilities. The thick horizontal lines at the tails of the histogram mark the 95% confidence intervals. The graph suggests that the difference is negative. This indicates that the $Pr(\text{Potential Entrant Enters} \mid \text{Focal Firm Signals}) < Pr(\text{Potential Entrant Enters} \mid \text{Focal Firm Does not Signal})$, thus suggesting that the signal is quite effective.
Overall we find considerable support for the theoretical argument in favor of reducing the unobservability problems through noisy public signals. We find that when firms invest more in emerging technologies and such investments become public knowledge through their decision to enter, it leads to deterring potential entrants from entering.

4.6 Discussion and Conclusions

This chapter investigated how development of capabilities and competitive considerations affect firms facing discontinuous technological changes. In doing so it is the first study to jointly examine the impact of types of capabilities and how they temper or enhance competitive considerations. We accomplish this in two stages. We make contributions across both theory and empirical work. At the broader level we show that in the face of technological discontinuity there is considerable information problems associated with strengths in emerging capabilities. Understanding the effects of this lack of information is critical to understand the impact of competitive considerations on key strategic decisions such as entering a new domain. We illustrate this point using a formal model which helps differentiate the effects of different types of capabilities.

More specifically, we use a model to show that in the case of new technologies, signaling through an entry decision can potentially be a double edged sword. Competitive reactions will depend to a large extent on the quality (precision) of the signal. Further we also use a new empirical model which helps accommodate competitive interactions more effectively. We use a structural approach to estimating competitive interactions. The presence of competitive interactions makes empirical modeling of phenomena difficult using traditional approaches such as probit and logit. In this paper, we use a novel methodology which specifically accounts for the information
structure and endogeneously models the action-reaction framework. We show that implementation with real data from the pharmaceutical industry requires the use of Markov Chain Monte Carlo (MCMC) methods in a Bayesian framework.

Our results provide several implications for the literature on technological change and on dynamic capabilities. Prior literature notes that firms that have an advantage in emerging technologies are more likely to enter that domain (Christensen, 1997; Hill and Rothaermel, 2003; Anand, Oriani and Vassolo, 2009). While this literature provides us with interesting insights into the role of capabilities on entry decisions, little is known about how capabilities influence competitive reactions. This chapter attempts to fill this gap using a novel and simple approach to empirically model competitive reactions. We find that when we account for competition between potential entrants, strengths in new technologies reduce the likelihood of two or more firms competing against each other. Thus, our result tempers the results from the prior literature and suggests that greater strengths in new technologies need not always lead to entry into the new domain. It depends on the strengths of immediate competitors.

Our work also has implications for further understanding the role of dynamic capabilities in entry decisions. Traditional logic would suggest that when firms have the ability to rapidly adjust their capabilities to meet the requirements of the new market, they should inherently be successful and should be able to create value (Eisenhardt and Martin, 2000; Helfat et al., 2007). In the presence of a competitive environment, we argue that imperfect observability of the quality of the dynamic capabilities can lead to less than desirable outcomes for firms. This is more so in the case of a technological discontinuity where imperfect observability is part of the phenomenon. If the capabilities are perfectly observed then the firm with superior capabilities will always be able to succeed as other firms with inferior capabilities are likely to stay out. Our empirical results are consistent with this and suggests that in the face of
uncertainty, it might be more sensible for managers who are reasonably sure about their capabilities to enter the field rather than wait.

We have also to acknowledge some of the limitations of the study. An important limitation of our approach is that it does not accommodate for *ex-post* learning by firms. This could be an important factor because the rate of learning can have important consequences on how quickly firms react and this might in turn lead to different outcomes. One potential solution is to model multi-period interactions which we leave for future research. Another important limitation is we restrict our capabilities set to either emerging or traditional technologies. An important capability that is ignored refers to complementary capabilities. Complementary technologies can be critical because the bigger pharmaceutical firms might possess complementary capabilities which are required for the smaller bio-technology firms to actually succeed. Therefore, even if pharmaceutical firms do not possess the emerging technology they can leverage on their complementary capabilities and still be successful. Complementary capabilities are also more prone to issues such as unobservability, thus making it an interesting area for future research.

To conclude, this study has theoretically and empirically demonstrated that firms should consider not only capability development but also the nature of competitive interactions when coping with discontinuous technological change. Different types of capabilities impact competition differently. While capabilities in emerging technologies tends to temper competitive interactions, capabilities in traditional technologies enhances them. Our study thus offers insights into how firm outcomes are determined not just by capabilities but also through competitive effects, in the presence of technological discontinuity.
Figure 4.2: Posterior Distribution of the Deterrence Effect
Table 4.1: **Bayesian Structural Probit Regression Model I**

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Lower Bound</th>
<th>Coefficient</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome: Competition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Focal Entrants: Utility Function</strong></td>
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<td></td>
</tr>
<tr>
<td>FE Log Sales</td>
<td>(0.0089)</td>
<td>0.0013</td>
<td>0.0145</td>
</tr>
<tr>
<td>FE Total Patents</td>
<td>(0.0426)</td>
<td>(0.0211)</td>
<td>(0.0054)**</td>
</tr>
<tr>
<td>FE Traditional Technology</td>
<td>0.0127</td>
<td>0.0312</td>
<td>0.0377**</td>
</tr>
<tr>
<td>FE Emerging Technology</td>
<td>(0.0101)</td>
<td>0.0016</td>
<td>0.0161</td>
</tr>
<tr>
<td>PE Emerging Technology</td>
<td>(0.0479)</td>
<td>(0.0263)</td>
<td>(0.0026)**</td>
</tr>
<tr>
<td>PE Emerging Technology $\hat{2}$</td>
<td>(0.0003)</td>
<td>0.0003</td>
<td>0.0007</td>
</tr>
<tr>
<td><strong>Potential Entrants utility function</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE Log Sales</td>
<td>(0.0093)</td>
<td>(0.0021)</td>
<td>0.0086</td>
</tr>
<tr>
<td>PE Total Patents</td>
<td>0.0002</td>
<td>0.0261</td>
<td>0.0371**</td>
</tr>
<tr>
<td>PE Traditional Technology</td>
<td>0.0051</td>
<td>0.0181</td>
<td>0.0247**</td>
</tr>
<tr>
<td>PE Emerging Technology</td>
<td>(0.0125)</td>
<td>(0.0051)</td>
<td>0.0079</td>
</tr>
<tr>
<td>FE Emerging Technology</td>
<td>(0.0501)</td>
<td>(0.0207)</td>
<td>(0.0024)**</td>
</tr>
<tr>
<td>FE Emerging Technology $\hat{2}$</td>
<td>(0.0037)</td>
<td>(0.0021)</td>
<td>(0.0004)**</td>
</tr>
<tr>
<td><strong>Outcome: Only PE enters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE Log Sales</td>
<td>(0.0117)</td>
<td>(0.0017)</td>
<td>0.0092</td>
</tr>
<tr>
<td>PE Total Patents</td>
<td>(0.0351)</td>
<td>(0.0255)</td>
<td>(0.0187)**</td>
</tr>
<tr>
<td>PE Emerging Technology</td>
<td>(0.0419)</td>
<td>(0.0229)</td>
<td>(0.0089)**</td>
</tr>
<tr>
<td><strong>Outcome: Only FE enters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE Log Sales</td>
<td>(0.0150)</td>
<td>(0.0053)</td>
<td>0.0107</td>
</tr>
<tr>
<td>FE Total Patents</td>
<td>(0.0299)</td>
<td>(0.0151)</td>
<td>(0.0051)**</td>
</tr>
<tr>
<td>FE Emerging Technology</td>
<td>(0.0220)</td>
<td>(0.0112)</td>
<td>0.0038</td>
</tr>
</tbody>
</table>

Note: Parameter estimates are accompanied by the bottom 2.5% and top 97.5% cutoff points in HPD region. The presence of zero within the interval implies that the coefficient is not statistically different from zero. PE refers to Potential Entrant and FE refers to focal entrant.
Table 4.2: Bayesian Structural Probit Regression Model II

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Lower Bound</th>
<th>Median</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome: Competition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Focal Entrants: Utility Function</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE Log Sales</td>
<td>0.4860</td>
<td>0.2938</td>
<td>0.0477 **</td>
</tr>
<tr>
<td>FE Total Patents</td>
<td>0.1109</td>
<td>0.0027</td>
<td>0.0920</td>
</tr>
<tr>
<td>FE Traditional Technology</td>
<td>0.0833</td>
<td>0.1462</td>
<td>0.2238 **</td>
</tr>
<tr>
<td>FE Emerging Technology</td>
<td>0.4386</td>
<td>0.2564</td>
<td>0.1397 **</td>
</tr>
<tr>
<td>PE Emerging Technology</td>
<td>0.0368</td>
<td>0.0238</td>
<td>0.0042 **</td>
</tr>
</tbody>
</table>

**Potential Entrants utility function**

| PE Log Sales          | 0.1225      | 0.0483 | 0.1919      |
| PE Total Patents      | 0.1337      | 0.2479 | 0.4261 **   |
| PE Traditional Technology | 0.0000  | 0.0137 | 0.0297 **   |
| PE Emerging Technology| 0.0656      | 0.0343 | 0.0058 **   |
| FE Emerging Technology| 0.2472      | 0.1534 | 0.0439 **   |

**Outcome: Only PE enters**

| PE Log Sales          | 0.7098      | 0.4843 | 0.2189 **   |
| PE Total Patents      | 0.2373      | 0.4515 | 0.6597 **   |
| PE Emerging Technology| 0.1078      | 0.0739 | 0.0399 **   |

**Outcome: Only FE enters**

| FE Log Sales          | 0.0719      | 0.1032 | 0.2089      |
| FE Total Patents      | 0.3693      | 0.2495 | 0.1483 **   |
| FE Emerging Technology| 0.0314      | 0.1281 | 0.1907 **   |

Note: Parameter estimates are accompanied by the bottom 2.5% and top 97.5% cutoff points in HPD region. The presence of zero within the interval implies that the coefficient is not statistically different from zero. PE refers to Potential Entrant and FE refers to focal entrant.
A.1 Derivations and Proofs for Chapters 3 and 4

In this section we characterize the proofs for the results obtained in Chapters 3 and 4. The models used in both chapters are similar and therefore the proofs apply to both chapters.

A.1.1 Derivation of the equilibrium solution

We start with the two basic indifference conditions which characterize the equilibrium. In the case of chapter 3, our concern is with the conditions that indicate repurchase vs. no repurchase by the target firm and the conditions that indicate bid vs. no bid by the potential bidders. In the case of the entry game in chapter 4, the two basic conditions leading to equilibrium is indicated by entry or no entry by the focal entrant and the potential entrant. For the purpose of demonstrating the proof we stick one of the two settings for consistency but note that it can be directly translated to the other setting.

For this proof we use the game between potential entrant as our context. Thus the potential entrant’s decision can be characterized by
\[ c = B \Phi \left( \sqrt{\alpha + \beta} \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) \right) \]  

(A.1)

The focal entrant’s decision is given by

\[ \theta = \Phi \left( \sqrt{\beta} (x^* - \theta) \right) \]

(A.2)

Equation (1) can be rewritten as follows

\[ \frac{c}{B} = \Phi \left[ \sqrt{\alpha + \beta} \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) \right] \]

\[ \Rightarrow \Phi^{-1} \left( \frac{c}{B} \right) = \sqrt{\alpha + \beta} \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) \]

\[ \Rightarrow \frac{\beta}{\sqrt{\alpha + \beta}} x = \sqrt{\alpha + \beta} \theta^* - \frac{\alpha}{\sqrt{\alpha + \beta}} y - \Phi^{-1} \left( \frac{c}{B} \right) \]

Multiplying throughout by \( \frac{\sqrt{\alpha + \beta}}{\beta} \)

\[ x^* = \frac{\alpha + \beta}{\beta} \theta^* - \frac{\alpha}{\beta} y - \sqrt{\alpha + \beta} \Phi^{-1} \left( \frac{c}{B} \right) \]  

(A.3)

Next we turn our attention to equation (2) which can be rewritten as follows

\[ \Phi^{-1} (\theta) = \sqrt{\beta} (x^* - \theta) \]

Dividing throughout by \( \sqrt{\beta} \) and rearranging terms we get

\[ x^* = \frac{1}{\sqrt{\beta}} \Phi^{-1} (\theta) + \theta \]  

(A.4)

Next we can solve for \( \theta^* \) using equations (3) and (4). Rewriting (3) and (4) as

\[ \frac{1}{\sqrt{\beta}} \Phi^{-1} (\theta) + \theta = \frac{\alpha + \beta}{\beta} \theta - \frac{\alpha}{\beta} y - \sqrt{\alpha + \beta} \Phi^{-1} \left( \frac{c}{B} \right) \]
\[ \Rightarrow \frac{1}{\sqrt{\beta}} \Phi^{-1}(\theta) = \frac{\alpha}{\beta} \theta - \frac{\alpha}{\beta} y - \frac{\sqrt{\alpha + \beta}}{\beta} \Phi^{-1}\left(\frac{c}{B}\right) \]

Multiplying throughout by \( \sqrt{\beta} \) and rearranging terms we get

\[ \Phi^{-1}(\theta) = \frac{\alpha}{\sqrt{\beta}} \theta - \frac{\alpha}{\sqrt{\beta}} y - \frac{\sqrt{\alpha + \beta}}{\sqrt{\beta}} \Phi^{-1}\left(\frac{c}{B}\right) \]

Rearranging and solving for \( \theta^* \) gives us the equilibrium solution

\[ \theta^* = \Phi \left[ \frac{\alpha}{\sqrt{\beta}} \theta^* - \frac{\alpha}{\sqrt{\beta}} y - \frac{\sqrt{\alpha + \beta}}{\sqrt{\beta}} \Phi^{-1}\left(\frac{c}{B}\right) \right] \quad (A.5) \]

Equation (5) above is equivalent to the equation (4.7) in the main text. Next we determine the uniqueness of this solution.

### A.1.2 Proof of Uniqueness

The uniqueness result for this model can be arrived at by looking at equation 1. To show uniqueness we need to show that there is only value of the resource index \( \theta \) and one value of the private signal \( x^* \) which makes all entrants indifferent between entering and not entering. We can ensure this requiring that the derivative of equation (1) with respect to \( x \) is greater than zero. Specifically:

\[ \phi \left[ \sqrt{\alpha + \beta} \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) \right] \cdot B \sqrt{\alpha + \beta} \left( \frac{d\theta^*}{dx} - \frac{\beta}{\alpha + \beta} \right) < 0 \]

The above inequality holds when

\[ \frac{d\theta^*}{dx} - \frac{\beta}{\alpha + \beta} < 0 \quad (A.6) \]

Implicit differentiation of equation 2 give us
\[
\frac{d\theta^*}{dx} = \frac{\sqrt{\beta} \phi \left[ \sqrt{\alpha + \beta \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) } \right]}{1 + \sqrt{\beta} \phi \left[ \sqrt{\alpha + \beta \left( \theta^* - \frac{\alpha}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) } \right]}
\]

Substituting back into equation (6) we get

\[
\frac{\alpha + \beta}{\beta} < \frac{\phi \left[ \sqrt{\alpha + \beta \left( \theta^* - \frac{1}{\alpha + \beta} y - \frac{\beta}{\alpha + \beta} x \right) } \right] + \sqrt{\beta}}{\sqrt{\beta}}
\]  
(A.7)

For this equation to hold it is sufficient to show that

\[
\frac{\alpha + \beta}{\beta} < \frac{\left[ \max_x \phi(x) \right] + \sqrt{\beta}}{\sqrt{\beta}}
\]  
(A.8)

The minimum of the maximum value of \( \phi(x) \) is given by the reciprocal of the \( \frac{1}{2\pi} \).

Substituting this back and rearranging terms we get

\[
\frac{\alpha}{\beta} < \frac{\sqrt{2\pi}}{\sqrt{\beta}}
\]

Squaring both sides and canceling terms we arrive at the condition for uniqueness namely:

\[
\beta > \frac{\alpha^2}{2\pi}
\]

Hence, for a given precision of public information given by \( \alpha \), the equilibrium is unique as long as the precision of the private signal \( \beta \) is high enough. Further, if \( \theta^* \) is unique then \( x^* \) must be unique as well.
A.1.3 Comparative Static Analysis

In this section we evaluate how the sensitivity of unique equilibrium tuple \((\theta^*, x^*)\) on the specific parameters such as the public signal \(y\) and the precision of the public signal \(\alpha\).

To study the impact of changing the public signal \(y\) on the equilibrium outcome we partially differentiate the equilibrium condition equation (5) with respect to \(y\).

\[
\frac{\partial \theta^*}{\partial y} = \phi(.) \left[ \alpha \frac{\partial \theta^*}{\partial y} - \frac{\alpha}{\sqrt{\beta}} \right]
\]

Rewriting and collecting terms together we can rewrite the above equation as follows

\[
\frac{\partial \theta^*}{\partial y} \left( 1 - \phi(.) \frac{\alpha}{\sqrt{\beta}} \right) = -\phi(.) \frac{\alpha}{\sqrt{\beta}}
\]

Thus,

\[
\frac{\partial \theta^*}{\partial y} = -\phi(.) \frac{\alpha}{\sqrt{\beta}} \left( 1 - \phi(.) \frac{\alpha}{\sqrt{\beta}} \right)
\]

Thus we can see that \(\frac{\partial \theta^*}{\partial y} < 0\), which implies that higher the value of the public signal \(y\) lower the value of \(\theta^*\). In the case of stock repurchases, since potential bidders are likely to be attracted to the firm when \(\theta > \theta^*\), this implies that greater the \(y\) greater the likelihood that attraction is the most likely outcome. In the case of
potential entrants, a lower signal of $\theta^*$ implies that the space within which entry is successful is contracted further. Thus, the signal is likely to have a negative impact on the likelihood of entry.

Next we study how changes in the precision of the public signal $y$ represented by $\alpha$ affects equilibrium outcomes. Specifically, we derive the partial derivative of $\theta^*$ with respect to $\alpha$.

$$\frac{\partial \theta^*}{\partial \alpha} = \frac{1}{\sqrt{\beta}} \phi(.) \left[ \theta^* + \alpha \frac{\partial \theta^*}{\partial \alpha} - y + \frac{1}{2\sqrt{\alpha + \beta}} \Phi^{-1} \left( \frac{c}{B} \right) \right]$$

Rearranging terms

$$\frac{\partial \theta^*}{\partial \alpha} = \frac{\phi(.) \left[ \theta^* - y + \frac{1}{2\sqrt{\alpha + \beta}} \Phi^{-1} \left( \frac{c}{B} \right) \right]}{\sqrt{\beta} - \alpha \phi(.)}$$

The partial derivative, $\frac{\partial \theta^*}{\partial \alpha}$ is positive iff $\theta^* > y + \frac{1}{2\sqrt{\alpha + \beta}} \Phi^{-1} \left( \frac{c}{B} \right)$ and is negative iff $\theta^* < y + \frac{1}{2\sqrt{\alpha + \beta}} \Phi^{-1} \left( \frac{c}{B} \right)$. The function which facilitates the switching point is represented by the term $y + \frac{1}{2\sqrt{\alpha + \beta}} \Phi^{-1} \left( \frac{c}{B} \right)$. We denote this function by $f(y)$, which is increasing in $y$. Further, the partial derivative $\frac{\partial \theta^*}{\partial y} < 0$ and hence $\theta^*(y)$ is decreasing in $y$. Thus, given uniqueness and the single crossing property, there must be a unique $y$ represented by $y_\alpha$ such that $\theta^*(y_\alpha) = f(y_\alpha)$. Hence, if $y > y_\alpha$, then $\theta^*(y) < f(y)$ implying that $\frac{\partial \theta^*}{\partial y} < 0$. Thus if the true $\theta^*$ is high enough to exceed the threshold value $y + \frac{1}{2\sqrt{\alpha + \beta}} \Phi^{-1} \left( \frac{c}{B} \right)$, then increasing the precision of the signal should facilitate attraction in the case of the target-bidder game and should facilitate deterrence in the case of the potential entrants game and vice versa.
APPENDIX B

ESTIMATION ALGORITHMS

B.1 Estimation algorithms for chapter 2, 3 and 4

Consider the game arrangement as depicted in Figure 2(b) (the same structure as our conceptual model with the exception that the payoffs are now written as functions of a regressor). Two players, namely incumbent (A) and entrant (B) are competing with each other. Incumbent (A) decides to move first and either invests (I) or does not invest (~I) in the domain. Entrant (B), observes the action by Incumbent (A) and then decides whether to enter (E) or not enter (~E). The estimation algorithm is very similar for the applications in Chapters three and four. The only difference would be in labeling the players. For the application in chapter 3, the two players are the target firm and the bidder firm and similarly for the application in chapter four the two players are the focal entrant and the potential entrant. Thus, the technique described below can be directly translated to the settings described in this dissertation.

B.1.1 Informational assumptions

Each competitor’s utility consists of a fixed part and a stochastic part (ε) interpreted as the contribution to the payoff from uncertainty. The fixed part of the utility is represented by $X\beta$. $X$ represents the observed matrix of capabilities and resources.
that is common knowledge to all potential entrants and the analyst. In addition, the matrix \( X \) can include industry variables such as proxies for turbulence, demand uncertainty and competitive conditions, as well as other firm or industry controls. We can rewrite \( X \) with the relevant subscript and superscript as follows: \( X_{E,E}^A \). Here, \( X \) represents the relevant resources, superscript \( A \) represents the incumbent’s identity, and the subscript \((I, E)\) represents the outcome where the incumbent invests and the entrant enters. \( \beta \) represents the sensitivity of the resources and capabilities with respect to the observed outcome and represents the unobserved component. It should also be noted that, following the earlier description of \( X, \beta \) and \( \varepsilon \), other outcomes also have the relevant superscripts and subscripts.

For the stochastic part, only the distribution is known. The stochastic part \( (\varepsilon) \) is picked from a continuous probability distribution. The competitors and the researcher have well-defined beliefs about the distribution of the unobserved component. We assume that each type is drawn from an i.i.d cumulative distribution \( F(.) \), with a corresponding positive density \( f(.) \), with mean \( \mu = 0 \) and \( \sigma^2 < \infty \). The density function \( f(.) \) is assumed to be twice continuously differentiable. The strategy for each player is characterized as a mapping from types to actions depicted as \( \lambda^i : \varepsilon_i \rightarrow \Psi_i \) where \( i = \{Incumbent(A), Entrant(B)\} \). \( \Psi_i \) defines the action set for each player. The action sets are \( \Psi_A = \{Invest, Not \ Invest\} \) and \( \Psi_B = \{Enter, Not \ Enter\} \). The choice probabilities are derived recursively. We also assume from the random utility structure that the fixed and stochastic parts of the players’ utilities are additively separable.

**B.1.2 Equilibrium**

To solve for the equilibrium, we start with the entrant’s decision problem. If player A plays “I”, player B receives a payoff of \( X_{I,\not E}^B \beta_{I,\not E}^B + \varepsilon_{I,\not E}^B \) for not entering.
Similarly, if B decides to enter, the payoff for B is equal to $X^B_{I,E} \beta^B_{I,E} + \varepsilon^B_{I,E}$. In both payoffs, $X \beta$ represents the systematic portion of the utility observable to the players and the researcher and represents the uncertainty component. All players are assumed to be utility maximizers. Hence, B will choose to enter if her utility from entering is greater than her utility from not entering. Formally this is expressed as

$$X^B_{I,E} \beta^B_{I,E} + \varepsilon^B_{I,E} \geq X^B_{I,\sim E} \beta^B_{I,\sim E} + \varepsilon^B_{I,\sim E}$$

(B.1)

Rewriting (1), in terms of differences in the unobserved component

$$\varepsilon^B_{I,\sim E} - \varepsilon^B_{I,E} \leq X^B_{I,E} \beta^B_{I,E} - X^B_{I,\sim E} \beta^B_{I,\sim E}$$

(B.2)

Let $\varepsilon^B_{I,\sim E} - \varepsilon^B_{I,E}$ follow a probability distribution defined as $F(.).$ In equilibrium, if A decides to invest, the associated path probability (i.e. probability of the individual taking a particular action) that entrant B will also enter is given by

$$\Pr (\varepsilon^B_{I,\sim E} - \varepsilon^B_{I,E} \leq X^B_{I,E} \beta^B_{I,E} - X^B_{I,\sim E} \beta^B_{I,\sim E}) = F_B \left( X^B_{I,E} \beta^B_{I,E} \right)$$

(B.3)

Since B’s utility from not entering when A invests is zero, the term $X^B_{I,\sim E} \beta^B_{I,\sim E}$ equals zero. Consequently, the path probability that B will not enter when A invests is given by $1 - F_B (X^B_{I,E} \beta^B_{I,E})$. Following the same logic, if A does not invest, then the path probability that the B will enter is given as

$$\Pr (\varepsilon^B_{\sim I,\sim E} - \varepsilon^B_{\sim I,E} \leq X^B_{\sim I,E} \beta^B_{\sim I,E}) = F_B \left( X^B_{\sim I,E} \beta^B_{\sim I,E} \right)$$

(B.4)

Consequently, the path probability that B will not enter when A does not invest is given by $1 - F_B (X^B_{\sim I,E} \beta^B_{\sim I,E})$. Given, B’s expected actions, A’s decision can be
arrived at through the process of induction. Note that A’s payoffs are now conditional on the behavior of B. If A invests, then her expected payoff can be written as

\[
\text{Play}(I) \quad [F_B (X^B_{I,E} \beta^B_{I,E}) [X^A_{I,E} \beta^A_{I,E} + \varepsilon^A_{I,E}]] + [F_B (X^B_{I,\sim E} \beta^B_{I,\sim E}) [X^A_{I,\sim E} \beta^A_{I,\sim E} + \varepsilon^A_{I,\sim E}]]
\]

(B.5)

\[
\text{Play}(\sim I) \quad F_B (X^B_{\sim I,E} \beta^B_{\sim I,E}) [X^A_{\sim I,E} \beta^A_{\sim I,E} + \varepsilon^A_{\sim I,E}]
\]

(B.6)

Since A is an expected utility maximizer, she will choose to invest if

\[
[F_B (X^B_{I,E} \beta^B_{I,E}) [X^A_{I,E} \beta^A_{I,E} + \varepsilon^A_{I,E}]] + [F_B (X^B_{I,\sim E} \beta^B_{I,\sim E}) [X^A_{I,\sim E} \beta^A_{I,\sim E} + \varepsilon^A_{I,\sim E}]] \\
\geq F_B (X^B_{\sim I,E} \beta^B_{\sim I,E}) [X^A_{\sim I,E} \beta^A_{\sim I,E} + \varepsilon^A_{\sim I,E}]
\]

(B.7)

Aggregating the uncertainty components to the two actions and rewriting the above equation gives us

\[
F_B (\cdot) [\varepsilon^A_{I,E} - \varepsilon^A_{I,\sim E} - \varepsilon^A_{\sim I,E} - \varepsilon^A_{\sim I,\sim E}] \\
\leq F_B (X^A_{I,E} \beta^A_{I,E}) X^A_{I,E} \beta^A_{I,E} \\
+F_B (X^B_{I,\sim E} \beta^B_{I,\sim E}) X^A_{I,\sim E} \beta^A_{I,\sim E} - F_B (X^B_{\sim I,E} \beta^B_{\sim I,E}) [X^A_{\sim I,E} \beta^A_{\sim I,E}]
\]

(B.8)

Let \( \varepsilon^A_{I,E} - \varepsilon^A_{\sim E} \) follow a distribution function \( F(\cdot)_A \). In equilibrium, the associated path probability of A investing can be written as

\[
P(\Omega) = F_A (F_B (X^B_{I,E} \beta^B_{I,E}) X^A_{I,E} \beta^A_{I,E} + F_B (X^B_{I,\sim E} \beta^B_{I,\sim E}) X^A_{I,\sim E} \beta^A_{I,\sim E}) \\
-F_B (X^B_{\sim I,E} \beta^B_{\sim I,E}) [X^A_{\sim I,E} \beta^A_{\sim I,E}]
\]

(B.9)
Where

\[
\Omega = F_B(.) \left[ \varepsilon_E^A - \varepsilon_E^B \right] \leq F_B \left( X_{I,E} I \beta_{I,E}^B \right) X_{I,E}^A \beta_{I,E}^A + F_B \left( X_{I,\sim E} I \beta_{I,\sim E}^B \right) X_{I,\sim E}^A \beta_{I,\sim E}^A \\
- F_B \left( X_{\sim I,E} I \beta_{\sim I,E}^B \right) \left[ X_{\sim I,E}^A \beta_{\sim I,E}^A \right]
\]

The path probability that A will not invest can now be written as

\[
1 - \left( F_A \left( F_B \left( X_{I,E} I \beta_{I,E}^B \right) X_{I,E}^A \beta_{I,E}^A + F_B \left( X_{I,\sim E} I \beta_{I,\sim E}^B \right) X_{I,\sim E}^A \beta_{I,\sim E}^A \right) \\
- F_B \left( X_{\sim I,E} I \beta_{\sim I,E}^B \right) \left[ X_{\sim I,E}^A \beta_{\sim I,E}^A \right] \right)
\]

(B.10)

Having constructed the necessary path probabilities, we need to define the outcomes associated with the game and then derive the joint “outcome” probabilities (i.e. probability of the joint outcome of two actions, such as both firms entering). The outcome variable is denoted by \(y\). The outcome of the \(i\)th game is coded as follows:

\[
y_i = \begin{cases} 
1 & \text{if A chooses } \sim I \text{ and B chooses } \sim E \\
2 & \text{if A chooses } \sim I \text{ and B chooses } E \\
3 & \text{if A chooses } I \text{ and B chooses } \sim E \\
4 & \text{if A chooses } I \text{ and B chooses } E 
\end{cases}
\]

The likelihood function for the model can now be written down as

\[
L \left( \beta_{x,v}, y \right) = \prod_{i=1}^{n} p_{1i}^{I(y_i=1)} p_{2i}^{I(y_i=2)} p_{3i}^{I(y_i=3)} p_{4i}^{I(y_i=4)}
\]

where \(h = [A, B], x = [\sim I, I], v = [\sim E, E], n = \text{observations} \)

(B.11)

\(I\) (a, b) is an indicator function that equals 1 when a=b and equals 0 otherwise and \(P_{SQ}, P_{BSA}, P_{ASA}\) and \(P_{TA}\) are the associated outcome probabilities\(^{25}\). The outcome probabilities are consistently defined with respect to the description of the empirical model in the main text.

\(^{25}\)The outcome probabilities are consistently defined with respect to the description of the empirical model in the main text.
probabilities are written as products of the associated path probabilities. Further let 

\((l,r)\) denote the action where the incumbent \((\sim \text{Invests, Invests})\) and \((L,R)\) denotes the action where potential entrants choose to \((\sim \text{Enter, Enter})\). The equilibrium probabilities can then be computed as follows

\[
P_1 = \left\{ 1 - F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_r^A \beta_r^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_r^A \beta_r^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_l^A \beta_l^A \right) \right\} \\
\left\{ 1 - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) \right\}
\]

\[
P_2 = \left\{ 1 - F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_r^A \beta_r^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_r^A \beta_r^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_l^A \beta_l^A \right) \right\}
\]

\[
P_3 = \left\{ F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_r^A \beta_r^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_r^A \beta_r^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_l^A \beta_l^A \right) \right\} \\
\left\{ 1 - F_B \left( X_{l,R}^B \beta_{l,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\}
\]

\[
P_4 = \left\{ F_A \left( F_B \left( X_{r,R}^B \beta_{r,R}^B \right) X_r^A \beta_r^A + F_B \left( X_{r,L}^B \beta_{r,L}^B \right) X_r^A \beta_r^A - F_B \left( X_{l,R}^B \beta_{l,R}^B \right) X_l^A \beta_l^A \right) \right\} \\
\left\{ F_B \left( X_{r,R}^B \beta_{r,R}^B - X_{r,L}^B \beta_{r,L}^B \right) \right\}
\]

\[26\) Note that the multiplication of probabilities is possible here because the private information component is not correlated across players.\]
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