Is Strategic Interaction important in Models of Entry?
Implications for Sustainability of Competitive Advantage

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Abstract

Studies of competitive entry into new businesses, technological 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. But most such empirical studies are not modeled to accommodate strategic interaction and, therefore, implicitly assume sustainability of competitive advantage upon entry. This is unfortunate since this setting also offers a fertile ground for the debate on sustainable vs. temporary competitive advantage. Firm advantages could be temporary on account of strategic interaction between entrants and incumbents as in a hypercompetitive environment. Previous research has been constrained by traditional empirical approaches which do not easily permit the analysis of such strategic interactions. In this paper we propose a new empirical methodology to analyze entry decisions that allows the analysis of strategic interactions while also taking into account resource heterogeneity among firms. Following the derivation of this empirical model, we use simulated data to illustrate our results. We contrast the use of our suggested approach with that used in previous research under different conditions of sustainable or temporary advantages. It is shown that in conditions where rivals react to outmaneuver entrants, traditional empirical approaches provide biased results. Future studies can use our empirical model to answer fundamental questions about sustainability of competitive advantage and firm entry in the strategic management literature.

Keywords: Temporary advantages, Hypercompetition, Entry Strategy, Strategic Interaction, Structural model
1 Introduction

Entry studies are common in the strategic management literature. These studies fall into two broad categories: those that do not take strategic interaction between the incumbent and the entrant into account and those that allow for strategic interactions. The former includes entry into new technological domains (e.g., Kim and Kogut, 1996; Mitchell, 1989); foreign market entry (e.g., Hennart and Park, 1994; Chang, 1995) or diversifying entry into new industries and businesses (e.g. Montgomery and Hariharan, 1991; Helfat and Lieberman, 2002) among others. Studies in this category generally build upon the resource based or related perspectives. The latter group includes studies that specifically study strategic interactive behavior between the incumbent and the entrant firms (e.g., Schmalensee, 1978; MacMillan, MacCaffery and Van Wijk, 1985). Both these perspectives present alternative lenses to study sustainability or lack of sustainability of competitive advantages, but the literature is incomplete in either category. While the entry studies that use a resource based view ignore the possibility of strategic interactions, the latter set of studies suffer from constraints in empirically modeling the strategic interactions.

The resource based view suggests that sustainable competitive advantage exists when there is heterogeneity in resources and resource immobility due to factor market imperfections (Barney, 1986; Peteraf, 1993). A typical empirical study models the likelihood of entry as a function of entrant’s resources, often with respect to the resources of the incumbent firm (e.g., Anand and Delios, 2002). Consequently, such studies implicitly assume sustainable competitive advantage upon entry. The absence of strategic interaction between the incumbent and potential entrants in these models limits the generalizability of their conclusions, at least to some settings.

Besides resource asymmetry between firms, sustainability can also arise from the strategic interactions between entrant and incumbent firms. For example, actions of incumbent firms such as, limit pricing (Bain, 1949), sunk costs (Spence, 1977), differential information (Milgrom and Roberts, 1982a), related concepts such as the reputation and/or experience (Basdeo, Smith, Grimm, Rindova and Derfus, 2006; Clark and Montgomery, 1998) and mobility barriers (Caves and Porter, 1977) can affect the entry decision by the entrant firm.
Consequently, such interactions can have a direct impact on the sustainability of competitive advantage for such firms. Strategic interactions can also lead to lack of sustainability as characterized by hypercompetitive behavior. 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). When firms and their rivals are constantly trying to outmaneuver each other, it can result in lack of sustainability in competitive advantage for all players (Grimm, Lee and Smith, 2005; D’Aveni, 1994; Makadok, 1998; Ferrier, Smith and Grimm 1999). Thus we can clearly see that strategic interaction between the incumbent and entrant presents a potentially interesting empirical tension between sustainable versus the lack of sustainable competitive advantage.

While much of the insights in the literature on strategic interaction and entry are drawn from sophisticated theoretical models extant empirical research with strategic interactions or the lack thereof has been rather limited, with virtually none considering the strategic interactions between the incumbent and entrant (Nault and Vandenbosch, 1996). Ignoring the dynamics of competing moves can prove to be theoretically inconsistent (Ferrier et. al, 1999; Ilinitch, D’Aveni and Lewin, 1996). The literature on mobility barriers suggests a role for combining heterogeneous resources with strategic interactions. But as is the case with several empirical studies that do account for strategic interaction, they suffer from serious limitations. The involvement of strategic multi player interactions implies that crisp analytical modeling requires the use of tools from game theory. However, sophisticated game theoretic analysis is not readily accommodated using traditional econometric approaches. More specifically capturing the rich information structure that a game theoretic model provides is difficult within traditional models.

We offer an empirical strategy that accommodates strategic interaction while taking into account resource heterogeneity and helps us to directly test for sustainability vs. lack of sustainability in competitive advantage. We are not aware of existing empirical models within the strategic management literature which utilizes an empirical game theoretic approach as outlined in this paper. The presence of a deterrence effect is consistent with sustainable competitive advantage, while its absence suggests lack of sustainability in advantages. We demonstrate using simulated data the value of using the suggested empirical research.
We show that in the absence of strategic interactions, current empirical research is robust. However, in the presence of strategic interactions our results demonstrate that empirical evidence 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 also show that even in settings where strategic interactions are not present or relevant, using the suggested approach still produces consistent results even though it reduces efficiency. Our approach can also take into account actions taken by the incumbent firms after controlling for other explanations of deterrence such as the presence of unique resources or the experience/reputation of the firm. In other words, our suggested approach is quite general and can be applied to a wide variety of entry contexts. We also suggest an approach to choose the correct model that fits the data, thus allowing for the data to tell us whether strategic interactions matter or not.

2 Previous Studies on Entry Decisions

2.1 Entry without Strategic Interaction: The Resource Based Perspective

A firm’s decision to enter a new market depends on several factors including among others, own resources and capabilities, corresponding resources and capabilities of potential entrants, the existing economic and industry environment and potential threats from other entrants. The decision to enter is characterized by lack of information on the potential outcome. On the one hand, entry can be disastrous for several reasons such as ex-post loss of value and mistakes in entry strategy, while on the other hand, waiting for uncertainty to resolve before entering a new market could result in potential loss of opportunity (Lieberman and Montgomery, 1988). Within the resource based perspective, we broadly classify previous entry studies into three categories. At this point we take note that the segmentation is for ease of exposition. There is some overlap and several studies can be classified into two segments.

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

\[ P(\text{Entry}) = f(A, R, C) \]

where \( A \) is the actions taken by the incumbent, \( R \) is the resources of the incumbent, and \( C \) is the capabilities of the incumbent.
The probability of entry depends primarily on $R_1, R_2, ..., R_n$ representing different resources and capabilities possessed by the incumbent and controlling for $C_1, C_2, ..., C_n$; representing 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 Hariharan, 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 spurred by access to existing resources and capabilities 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 incumbent’s absolute resource base but also the relative resource base requirement of the new market. 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 the differential resources possessed by 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 such as cultural fit or macroeconomic conditions among others. The probability of entry depends not just on the incumbent resources but also on the relative resource profiles of the new market and how well the resources they have 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 have believe that they have enough valuable resources to exploit sustainable competitive advantage.
In the third group of studies we review, the probability of entry depends not only on the absolute and relative resource profiles but also on competitive considerations such as market structure. Formally this can be expressed as:

\[
Pr(\text{Entry}) = f(R_1 - R_1', R_2 - R_2', ..., R_n - R_n'; S_1, S_2, ..., S_n; C_1, C_2, ..., C_n)
\]

The probability of entry depends not just on the differential resources possessed by the incumbent \( R_1 - R_1', R_2 - R_2', ..., R_n - R_n' \) and alternative explanations as controls \( C_1, C_2, ..., C_n \) but also on competitive considerations, such as market structure, reflected through through \( S_1, S_2, ..., S_n \) which takes into account market structure and related issues. Exploitation of sustainable competitive advantage is possible only when competitive interactions do not erode such benefits for the incumbents. Most research on entry models try to control for competitive effects through the use of industry wide measures such as concentration ratio and other measures of market power (see e.g., Mitchell 1989 Anand & Kogut, 1997). However, such industry wide characteristics might be irrelevant when dealing with situations where there is hypercompetition. For instance, firms might be dominant in an industry and hence could have erected significant entry barriers. But such entry barriers are credible only if other potential entrants perceive them to be so (D’Aveni, 1994). Further, such aggregated industry level measures do not address the presence of strategic interactions between incumbents and entrants.

2.2 Entry with Strategic Interaction

Strategic interactions and competitive rivalry forms an important part of strategic management (Bettis and Weeks, 1987; Smith, Grimm, Gannon and Chen, 1991). Entry studies have also been the focus of extensive investigation by scholars interested in understanding 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 entry barriers which would prevent the entrant from entering (e.g., Dixit, 1980). Several attempts have been made to empirically model such strategic interactions (e.g. Lieberman, 1987). Early empirical work focused on the outcomes and looked at firm performance conditional upon
observed market characteristics (see Gilbert, 1989 for a survey on this literature). The descriptive models were highly aggregated and treated market structure as exogenous.

While much of the earlier work focused on equilibrium modeling of actions, another stream of research offers an interesting spin on the notion and study of strategic interactions, based on a stimulus-response framework. This approach helps us understand competitive interactions by empirically teasing out the effect of action characteristics on the likelihood of adopting a particular reaction. Key characteristics such as competitive impact, attack intensity, implementation requirements and types of actions among others were found to be significant predictors of strategic choices (MacMillan et. al. 1985; Smith and Grimm, 1987; Chen, Smith and Grimm., 1992). This stream of research tries to address the same issues that analytical game theoretic models try to address, but places less emphasis on the information structure.

A critical assumption in the commonly used modeling frameworks is that of homogeneity of firms. Caves and Porter (1977) present a more general picture and introduce the concept of mobility barriers. They argue that firms are unlikely to be homogenous and thus the assumptions made in the prior literature on traditional entry barriers are not tenable in practice. While the empirical evidence suggests that there is no notable difference in terms of rivalry within or across groups (Smith, Grimm, Wally and Young, 1997), this stream of literature does caution us not to treat firms as homogenous in the modeling of entry decisions. Hence there is a need to use empirical approaches that don’t ignore resource heterogeneity among firms, yet also capture the advances in strategic interaction models.

2.3 Synthesis

The cumulative evidence from prior research on the likelihood of entry suggests a role for existing resources and capabilities of the incumbent and entrant as well as strategic interactions among them. The resource heterogeneity explanation suggests a role for resources but completely ignores the element of strategic interactions. On the other hand, much of the theoretical literature accommodating strategic interaction is based on analytical models which are not easily tractable into the empirical domain. Though attempts have been made to study strategic interaction, the current models do not capture the sophistication of the
available analytical models and the richness of the information structure, a key element for modeling interactive behavior. We now describe a typical analytical model of firm entry and then proceed to develop an empirical approach.

3 Challenges to Estimation of Entry Game Models

3.1 A Simple Entry Game Model

A typical entry model with strategic interaction involves two players \(^1\), the incumbent (I) and the entrant (E). The entrant is relatively new but possesses some competitive advantage and is contemplating entering the market (Milgrom and Roberts, 1982a). Expecting this, the incumbent’s problem is to decide whether to take a market action to protect their competitive advantage. If the incumbent takes an action and succeeds, it gets to keep a larger portion of the pie and hence retains sustainable competitive advantage. For instance the incumbent might decide to commit to increase capacity and this can lead to deterrence. On the other hand, an incumbent might possess valuable and rare resources but competitors might not have sufficient information on the incumbent’s resources. Thus, the incumbent might signal to the market through market actions the value of its resources. In the event of failure to deter entry, the pie is split and hence advantages are temporary. Such advantages are temporary under conditions of hyper competition. We allow for stocks of resources to determine the utilities/payoffs for each possible action. Keeping this simple sequential game in mind, we next discuss how empirical strategies not accounting for such strategic interaction creates inferential problems.

3.2 Translating Theory to Empirics

Though games with discrete action spaces are theoretically attractive, empirical modeling is challenging. We discuss two main challenges and review the current solutions. Game theoretic models possess certain unique characteristics which makes empirical estimation rather difficult (Signorino, 2003). First, simultaneous move models can suffer from multiple equilibria problems (Breshnahan and Reiss, 1990). In the presence of limited information,

\(^1\)We use a two firm model for its intuitive appeal. Generalizing it to n players is straightforward.
empirically identifying which equilibrium has been played by the actors is daunting. Several solutions have been proposed including bounding parameters and direct evaluation of the outcome equations (Tamer, 2002; Berry, Levinsohn and Pakes, 1995). These approaches are theoretically rich, robust and highly generalizable. However, they are also computationally demanding in terms of data and identification requirements for the parameters.

The second issue related to translating the theoretical model into empirics is the requirement of positive probability play for all actions (McKelvey and Palfrey, 1996, 1998). To illustrate the point, let us consider a deterministic game with a unique equilibrium. A game theoretic analysis predicts that the equilibrium outcome occurs with probability of one and the non-equilibrium outcomes occur with probability zero. On the other hand, let us look at a typical statistical model. The objective is to find a set of unknown parameters that are most likely to generate required outcomes. A typical likelihood function is as follows.

\[
L(\beta|y) \propto f(y_1, y_2, ..., y_N|x, \beta)
= f(y_1|x, \beta) f(y_2|x, \beta) ... f(y_N|x, \beta)
\]

Where \( L(\beta|y) \) defines the likelihood of observing the parameters given the data and \( f(y_i|x, \beta) \) represents the probability of occurrence for outcome \( i \) conditional on the observed data and parameters. From this function it is evident that a necessary condition for maximization is to ensure that there exists a probability distribution for each outcome. In other words, we need a positive value for each \( f(y_i|x, \beta) \). From traditional game theoretic analysis, this implies that the likelihood function will always be zero, because all outcomes, except for the equilibrium outcome are played with zero probability. This suggests that a statistical model with pure strategies can never be estimated under traditional assumptions\(^2\).

To make the problem tractable, we need a mechanism to restrict all outcomes to be played with some positive probability, thus relaxing assumptions on perfect rationality of agents.

While we discussed some of the issues related to translating game theoretic models into empirical designs, a logical question is whether traditional econometric techniques can accommodate for the same.

\(^2\)It is possible to estimate a model where mixed strategies are played over all possible outcomes using maximum likelihood procedures.
Moving from single agent to multiple agent interactions

Traditional econometric techniques used to model entry decisions apply discrete choice models (such as probit/logit), which can be derived from utility maximizing behavior of a single agent. The trouble when considering our game structure is that there is more than one agent operating and their actions interact. As an illustration, consider the game played out in the market as representing the entry game described earlier. For ease of exposition we fix the incumbents action as one where it sets up an entry barrier. The game has four outcomes as given below.

\[ Y_1 \rightarrow \text{Incumbent does not set barrier and Entrant does not enter} \]
\[ Y_2 \rightarrow \text{Incumbent does not set barrier and Entrant enters} \]
\[ Y_3 \rightarrow \text{Incumbent sets barrier and Entrant does not enter} \]
\[ Y_4 \rightarrow \text{Incumbent sets barrier and Entrant enters} \]

How do we empirically model this game using traditional modeling approaches? As a first pass we can use a discrete choice model to answer this question. This forces the researcher to apply restrictions on the decision making process simply because the econometric model only accounts for two outcomes but the theoretical entry game has four. Hence we need to come up with some procedure to simplify the game. Essentially, we need to come up with a mechanism to aggregate outcomes into two from four. Let the outcomes be represented as \( O_1 \) (associated with action "l") and \( O_2 \) (associated with action "r"). Then outcomes \( Y_1 \) and \( Y_2 \) can be pooled together as \( O_1 \) (Not Deter) and outcomes \( Y_3 \) and \( Y_4 \) can be pooled together as \( O_2 \) (Deter). Then the analysis proceeds on the choice between \( O_1 \) and \( O_2 \).

Such aggregation leads to loss of information and the strategic element in this model is suppressed. It should be noted that it is still possible to accommodate all four outcomes in a single player framework using multinomial models. But doing so does not accommodate strategic interaction as the derived choice probabilities for the multinomial logit/probit models are different when multiple players are involved\(^3\). In case real empirical data displays strategic interaction consistent with the existing conceptual models, traditional empirical

\(^3\)A comparison between the probabilities derived later in this paper and multinomial logit/probit probabilities will illustrate this point clearly.
techniques are not capable of teasing them out. This automatically induces bias and could lead to faulty inference, when such interactions are implicit and important from a theoretical perspective. Logically the next question is: Is there a solution to the problem?

3.4 A Proposed Solution - Structural Empirical Model

Having discussed the challenges with respect to empirical modeling of games, we discuss a strategy to empirically approach the topic. Our approach accommodates testing simultaneously for the presence of sustainable vs. temporary advantages. Consider the game arrangement as depicted in Figure 1. Two players (incumbent and entrant) are engaged in a game. The incumbent moves first and decides whether to erect an entry barrier or not and the entrant after observing the incumbent, decides to respond by entering the market or not.

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 interpreted as 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.

The strategy of each player is characterized as a mapping from types to actions depicted as $\sigma^i : \varepsilon_i \rightarrow A_i$ where $i = \{\text{Incumbent, Entrant}\}$. $A_i$ defines the action set for each player. The action sets are $A_{\text{Incumbent}} = \{\text{Barrier, NoBarrier}\}$ and $A_{\text{Entrant}} = \{\text{Enter, NotEnter}\}$. Econometric error is swamped with the private information component without loss of generality (Signorino, 2003) and the choice probabilities are derived recursively. The random utility structure also assumes that the fixed and stochastic parts of the players’ utility are
additively separable. 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.

Let the incumbent be represented as player A and the entrant is player B. Let (l, r) represent (Not Erect Barrier, Erect Barrier) and (L, R) represent (Not Enter, Enter) respectively. We start with player B’s decision problem. If player A plays ”r” then player B receives a payoff of \( X^{B}_{r,L} \beta^{B}_{r,L} + \varepsilon^{B}_{r,L} \) for playing L. Similarly, if B decides to play R, his expected payoff is equal to \( X^{B}_{r,R} \beta^{B}_{r,R} + \varepsilon^{B}_{r,R} \). In both payoffs, \( X \beta \) represents the systematic portion of the utility observable to the players and the researcher and represents the private information component. Player A is only assumed to know the distribution of \( \varepsilon^{B}_{r,R} - \varepsilon^{B}_{r,L} \). All players are assumed to be utility maximizers. Hence player B will choose to play R if:

\[
(1) \quad X^{B}_{r,R} \beta^{B}_{r,R} + \varepsilon^{B}_{r,R} \geq X^{B}_{r,L} \beta^{B}_{r,L} + \varepsilon^{B}_{r,L}
\]

Rewriting equation (1), in terms of differences in the private information component

\[
(2) \quad \varepsilon^{B}_{r,L} - \varepsilon^{B}_{r,R} \leq X^{B}_{r,R} \beta^{B}_{r,R} - X^{B}_{r,L} \beta^{B}_{r,L}
\]

Let \( \varepsilon^{B}_{r,R} - \varepsilon^{B}_{r,L} \) follow a probability distribution defined as \( F_{B}(.) \). In equilibrium, if player A plays r, the associated path probability that player B will play R is given by

\[
(3) \quad \Pr \left( \varepsilon^{B}_{r,L} - \varepsilon^{B}_{r,R} \leq X^{B}_{r,R} \beta^{B}_{r,R} - X^{B}_{r,L} \beta^{B}_{r,L} \right) = F_{B} \left( X^{B}_{r,R} \beta^{B}_{r,R} - X^{B}_{r,L} \beta^{B}_{r,L} \right)
\]

Consequently the path probability that player B will play L when player A plays r is given by \( 1 - F_{B} \left( X^{B}_{r,R} \beta^{B}_{r,R} - X^{B}_{r,L} \beta^{B}_{r,L} \right) \). Following the same logic, if player A plays l, then the path probability that the player B will play R is given as follows

\[
(4) \quad \Pr \left( \varepsilon^{B}_{l,L} - \varepsilon^{B}_{l,R} \leq X^{B}_{l,R} \beta^{B}_{l,R} \right) = F_{B} \left( X^{B}_{l,R} \beta^{B}_{l,R} \right)
\]

The path probability that player B will play L when player A plays l is given by \( 1 - F_{B} \left( X^{B}_{l,R} \beta^{B}_{l,R} \right) \). Player A’s path probabilities is arrived at by recursively working back. Note that player A’s payoffs are now expected payoff’s conditional on the behavior of player B. Therefore the expected payoff’s from playing l or r for player A can be written as follows
(5) Play (l) \( F_B \left( X_{i,R}^{B} \beta_{l,R}^{A} \right) \left[ X_{i,R}^{A} + \varepsilon_{l,R}^{A} \right] \)

(6) Play (r) \( F_B \left( X_{r,R}^{B} \beta_{r,R}^{B} \right) \left[ X_{r,R}^{A} \beta_{r,R}^{A} + \varepsilon_{r,R}^{A} \right] + \left[ F_B \left( X_{r,L}^{B} \beta_{r,L}^{B} \right) \left[ X_{r,L}^{A} + \varepsilon_{r,L} \right] \right] \)

Since player A is also an expected utility maximizer, he will choose to play action \( r \) if

(7) \( F_B \left( X_{r,R}^{B} \beta_{r,R}^{B} \right) \left[ X_{r,R}^{A} \beta_{r,R}^{A} + \varepsilon_{r,R}^{A} \right] + \left[ F_B \left( X_{r,L}^{B} \beta_{r,L}^{B} \right) \left[ X_{r,L}^{A} + \varepsilon_{r,L} \right] \right] \geq F_B \left( X_{i,R}^{B} \beta_{i,R}^{B} \right) \left[ X_{i,R}^{A} + \varepsilon_{i,R} \right] \)

Aggregating the unobserved private information components to the two actions and rewriting the above equation gives us

(8) \( F_B (.) \left[ \varepsilon_{l}^{A} - \varepsilon_{r}^{A} \right] \leq F_B \left( X_{r,R}^{B} \beta_{r,R}^{B} \right) \left[ X_{r,R}^{A} + \varepsilon_{r,R}^{A} \right] + \left[ F_B \left( X_{r,L}^{B} \beta_{r,L}^{B} \right) \left[ X_{r,L}^{A} + \varepsilon_{r,L} \right] \right] - F_B \left( X_{i,R}^{B} \beta_{i,R}^{B} \right) \left[ X_{i,R}^{A} + \varepsilon_{i,R} \right] \)

Assuming that \( \varepsilon_{l}^{A} - \varepsilon_{r}^{A} \) follows a distribution function \( F_A (.) \), in equilibrium, the associated path probability of player A playing action \( r \) can be written as follows

(9) \( P \text{ (eqn.}(8)) = F_A \left( F_B \left( X_{r,R}^{B} \beta_{r,R}^{B} \right) \left[ X_{r,R}^{A} + \varepsilon_{r,R}^{A} \right] + \left[ F_B \left( X_{r,L}^{B} \beta_{r,L}^{B} \right) \left[ X_{r,L}^{A} + \varepsilon_{r,L} \right] \right] - F_B \left( X_{i,R}^{B} \beta_{i,R}^{B} \right) \left[ X_{i,R}^{A} + \varepsilon_{i,R} \right] \right) \)

The path probability that player A is likely to play \( l \) can now be written as follows

(10) \( 1 - F_A \left( F_B \left( X_{r,R}^{B} \beta_{r,R}^{B} \right) \left[ X_{r,R}^{A} + \varepsilon_{r,R}^{A} \right] + \left[ F_B \left( X_{r,L}^{B} \beta_{r,L}^{B} \right) \left[ X_{r,L}^{A} + \varepsilon_{r,L} \right] \right] - F_B \left( X_{i,R}^{B} \beta_{i,R}^{B} \right) \left[ X_{i,R}^{A} + \varepsilon_{i,R} \right] \right) \)

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 variable is denoted by \( y \). The outcome of the \( i \)th game is coded as follows

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

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

(11) \( L \left( \beta_{x,y}^{h} | y \right) = \prod_{i=1}^{n} \frac{j(y_{i}=1)}{p_{1i}^{j(y_{i}=1)}} \frac{j(y_{i}=2)}{p_{2i}^{j(y_{i}=2)}} \frac{j(y_{i}=3)}{p_{3i}^{j(y_{i}=3)}} \frac{j(y_{i}=4)}{p_{4i}^{j(y_{i}=4)}} \)

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\(^4\). Note that \(p_4\) is different from \(P_4\). To be precise, \(p_4\) is the conditional probability that the entrant enters conditional on no entry barrier from the incumbent and \(P_4\) is the outcome probability that an entry barrier is observed and the entrant enters. Based on the equilibrium path probabilities, the respective outcome probabilities are as follows.

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

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

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

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

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 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\(^5\). 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

\(^4\)Note that the error structures of the two players are not correlated

\(^5\)It might be interesting to study what would be the impact when the two \(F(.\) are not the same. This brings in the interesting theoretical argument where firms can possess different expectations on the probability distribution of private information. Thus effectively we can allow for heterogeneity in the private information component to also drive choices. We leave this for further study.
a Bayesian Markov Chain Monte Carlo (MCMC) sampling approach (Rossi et al. 2005). 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 as follows.

\[
(12) \quad [\beta^A_{l,r}, \beta^B_{L,R}| all else] \propto \prod_{i=1}^n \pi (y_i | \beta^A_{l,r}, \beta^B_{L,R}, \sigma^A_{l,r}, \sigma^B_{L,R}, \sigma)
\]

Prior distributions for all parameters were specified normal with mean zero and covariance matrix equal to 100 times the identity matrix \(^6\). 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

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

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. Out of a total of 100,000 iterations, the first 30,000 readings were used as the burn in and discarded. The trimmed distribution is then used for inference purposes.

\(^6\)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.
While a structural model sounds theoretically appealing, the question remains as to whether the true data generating process depicts a hypercompetitive environment or not. For this purpose we run model selection tests to select between the two competing models. Since the models are non-nested (the structural probit 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. Hence, we use the procedure suggested by Vuong (1989) for model selection purposes.

The principal advantage of using a structural model is the ability to recover the latent process related to competitive advantage. For instance from our estimation procedure, described earlier, we derived the conditional probabilities for the actions for each of the players (for eg. probability $p_6$ in Figure 1. is the probability of the entrant choosing to enter conditional on the incumbent setting up an entry barrier). We can now directly draw inference on the deterrence effect by using the following relationship

$$\textbf{Total effect} = \Pr (\text{Enter|Barrier}) - \Pr (\text{Enter|No Barrier})$$

We interpret the total effect as follows

**When Total Effect < 0 $\implies$ Deterrence $\implies$ Sustainable advantages**

**When Total Effect > 0 $\implies$ No Deterrence $\implies$ Lack of Sustainable Advantages**

A negative value of for the total effect implies that the probability of entering is lower without a barrier as compared to with a barrier, thus suggesting that an entry barrier has been erected, thus providing evidence in favor of the deterrence effect. The deterrence effect provides the key to identifying sustainability vs. lack of sustainability in competitive advantage. The presence of a strong deterrence effect suggests that the incumbent can still keep his competitive advantage but if his actions do not change the beliefs of the rival, sustainability of competitive advantage is unlikely. A key point to note is that the empirical methodology outlined above can be easily translated into different settings in terms of actions and the deterrence effect can be arrived at for multiple actions. Further, extending the game tree for repeated play between two or more entrants is fairly straightforward. Next we present a simulation study to highlight the differences in inference when strategic interactions are allowed.
4 Testing the Proposed Model with Simulated Data

The previous section presented a technique to take into account strategic interaction between incumbents and entrants while analyzing entry behavior in various contexts such as entry into new technological domains, businesses or international markets. Taking such strategic interaction into account will help understand if competitive advantage of firms upon entry is sustainable or temporary, which in turn should affect the entry decision. Previous models, whether using a resource based formulation or a game theoretic one have not done this. We use simulated data for the purpose of illustrating how taking strategic interaction into account with the above described model with different kinds of data can substantively change our conclusions. The simulations provide enough flexibility to help us compare and contrast the nature of competition and its role on sustaining competitive advantage.

In order to illustrate the differences between previously used and our proposed methodology, we generate two kinds of stylized data based on two key assumptions. Our first data set assumes that competitive interactions are irrelevant and hence entry is clearly a function of just resources of the incumbent and entrant firms. We use this as our benchmark model, as it replicates the most common approach used in past studies. Next we generate a data set where we allow for competitive interaction between players. This is a clear departure from the traditional approach, as now we allow for ex-ante beliefs of player’s, on expected competitive reactions, to also affect their decision process. This is consistent with the view that sustainable competitive advantage can only be maintained if the incumbent can hold on to its dominance. By allowing for strategic interaction, the incumbent also has to take into account its beliefs on how entrants will react and if the reaction will lead to temporary competitive advantage.

The data generation process follows the definition in Figure (1) depicted earlier. The independent variables are simulated as random draws from a continuous probability distribution with varying support levels. From the perspective of economic interpretation, the variables represent the resources and capabilities which enter the utility function. We allow for varying support levels to simulate real data sets more closely. We allow the private information component to be private knowledge to the players. The researcher and other
players are allowed to observe only the probability distribution of private information. This completes our data and model set up.

We consider two empirical strategies to test our models on both data sets in increasing order of sophistication. The first strategy is to estimate the probability of entry just based on the resources and capability profile of the incumbent and entrant along with the necessary controls while ignoring strategic interactions. This is a replication of previous research designs. Our second strategy estimates the fully structural model developed in this paper. At this point we compare the models with and without strategic interactions directly. Next we present robustness checks by estimating two additional models, which are minor variants of our first strategy. Our robustness check strategies augment the first strategy by allowing for the entrant’s action to enter into the model as a regressor. More specifically, our first robustness strategy, which we call the ex-post strategy allows for an additional explanatory variable (apart from the resource profiles and controls.). The additional variable is coded as a binary indicator of the action taken by the entrant. The second robustness strategy, which we call the ex-ante propensity score strategy, uses a two stage model. The first stage involves estimating the probability of entry by the entrant. The predicted probabilities from this entry model are then used as a regressor in the probability of commitment model by the incumbent.

We expect that the results from our analysis will show that ignoring strategic interactions can have serious consequences for inference. However, even if strategic interaction is absent, using the structural model reduces efficiency but does not result in biased inference. The expected results can be best summarized by Table 1 below:

| Insert Table 1 here |

4.1 Generating the Data

As the first step in our simulation process we generate data, postulated as the expected behavior of firms conditional on their observable resource and capability profile. We fix the
number of observations as 1000. Larger samples should improve our analysis, but given that in strategy sample sizes can be limited, we believe that demonstrating that the strategy works for small samples is important\(^7\). Further, larger samples will strengthen results and hence evidence in smaller samples is a robust indicator. First we generate the resource and capability profiles as random numbers from a uniform distribution. We vary the level of support for the distribution and generate covariates with a tight range, for example, between (-1, 3) and a wide range, for example, between (-10, 10). Our choice of both tight and wide ranges in the same data set helps us get closer to real data sets where resources might display considerable variation. Next, we set the coefficients on each of the variables equal to 0.50. These coefficients represent the true in a traditional regression model. Hence the interpretation of the coefficients is consistent with traditional regression methods. Next we pick random draws from a continuous probability distribution to represent private information. Following our discussion earlier the normal distribution meets all the requirements for a valid probability distribution for the private information component. Hence, we take a 1000 random draws from the normal distribution representing each observation.

Decisions are made using the expected utility rule in models with and without strategic interaction. Therefore, the observed outcomes in our experiments are based on structural assumptions. We generate data sets both without and with strategic interactions. Without strategic interaction, the simulated data sets are based on the traditional probit probabilities with a linear index function determining utilities. With strategic interaction, the simulated data sets are based on the equilibrium probabilities computed earlier in the paper.

4.2 Analysis of Models without Strategic Interaction:

First, we analyze models without strategic interaction. These models are the benchmark models based on prior literature. We find that consistent with past research the traditional approaches recover the parameters and hence predicted probabilities on the likelihood of entry based on models without strategic interactions are unbiased and consistent given the

\(^7\)Studies in strategic management tend to have significant variance in terms of sample sizes. For instance Mitchell (1991) had a relatively small sample totaling 314 observations for a period spanning between 1952 and 1989. On the other hand Villalonga (2004) had a relatively large sample with a total of nearly 18,000 firm years worth of data.
absence of strategic interactions.

Table 2 represents the case where the decision to enter is made based on just A’s resources. We find that all the coefficients are statistically significant and positive. The magnitude of the coefficients suggests that they are accurate within the bounds of simulation error. Table 3, documents the case where the decision to enter is made by taking into account own resources and resources held by potential competing firms. We find that in the absence of strategic interactions, the results are statistically significant thus indicating that the traditional approach to modeling entry is efficient and consistent in the absence of multi person interactions.

The important question is whether the traditional approaches remain consistent when competitive interactions are introduced into the model. To address this issue we first estimate the data without strategic interaction using our structural model. The results from this experiment are provided in Table 4

From the results we can see that even in the case when there is no strategic interactions in our model, the structural model does not do badly. It does recover the parameters and is reasonably close to the true parameters. Therefore this suggests that if no strategic interactions are present, the structural model is still consistent but is not likely to be as robust as compared to traditional regression approaches. To further check for consistency, we test for the presence or absence of the deterrence effect as explained in our approach. From Figure (2) we can clearly see that we don’t find the deterrence effect to be statistically different from zero. Inference is drawn by using the fact that zero is contained within the
confidence intervals (thick vertical lines in the graph mark the bounds at the 5% level of confidence).

In fact a considerable mass of the distribution is centered close to zero, thus indicating that the model accurately captures the presence or absence of strategic interactions. Next, we analyze data with strategic interactions.

### 4.3 Analysis of Models with Strategic Interaction:

With strategic interactions, the action choices of the players (A&B) are based not only on observable exogenous characteristics of each other but also on their expected beliefs on how each would react to their actions. Based on these assumptions we first test the data using traditional approaches.

Table 5, presents the estimates based on data generated assuming strategic interaction. We note two important issues. First, the magnitude of the distance between the estimated and the true parameters is quite large. Hence, this is an indication that the estimation is not picking up the true effect. An even more critical point to note is that the coefficient on the third resource (AR3) is negative and statistically significant. Hence, the model is misspecified and can give misleading results (especially given the significance of the variable).

Table 6 presents the estimates also taking into account firm A’s and B’s resources. Here we find that A’s resources are statistically significant but B’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. The coefficients on all resources are considerably off the mark, from their true values. Finally, as before, the coefficient on (AR3) is negative from this model.

In sum, we can see clearly that traditional modeling approaches are misspecified when testing models in the presence of competitive effects. This suggests that testing for sustainable vs. temporary advantages based on traditional approaches might give us biased results. In this backdrop, we next estimate the fully structural approach outlined in this paper on data with strategic interactions.

Insert Table 7 here

We use both the Bayesian approach and the classical maximum likelihood approach to test the proposed methodology in this section. From the estimation results in table 7, we can clearly see that the structural model recovers the parameters within the bounds of simulation error. We can also see that the resources of both players are now statistically significant. The difference between the maximum likelihood estimate and the Bayesian estimates are miniscule, indicating that estimation methodology is not likely to create problems from an inference perspective. At this point we use the Vuong (1989) model selection test to check if the true data generating process belongs to the one with strategic interactions or not. The results from the test are presented in Table. 8

Insert Table 8 here

The results from the Vuong (1989) test indicate that the true model is the one with strategic interaction.
4.4 Deterrence Effect and the Test for Temporary Advantages

Based on our simulated data set with strategic interaction, we look at the distribution of total effect from the estimated parameters.

Insert Figure 3 here

From figure 3, we can clearly see that the total effect is negative, indicating that we are in a world where advantages are sustainable. Thus we can now “directly” test for the presence or lack of sustainable advantages. Such an analysis is not possible using traditional approaches. Next, we show that we can study how marginal changes in resource values can affect our understanding of sustainability. We vary the value of a particular resource for B, holding all other resources at their average values. For an economic interpretation, we view the value of the resource to be a good indicator of the likely action taken by the firm. We can tie this back to the literature on stimulus responses and use some of the characteristics of actions (Chen et. al. 1992) as the variable of interest and study how sustainability or lack of sustainability changes with respect to the value of the characteristic/resource.

Insert Figure 4 here

From Figure 4, we can clearly see that as resource value increases the differences initially decrease but then start increasing but still remain negative within the sample range of the resource. Therefore as the value of the specific resource for the entrant increases, the likelihood of the entrant competing first decreases but then starts increasing. However within the sample, we find that it does not reach the space in the positive orthant for there to be temporary advantages. While the graph presented here is based on a single dimension, multidimensional analysis can give us a more detailed picture resource interaction on the decision process. Next, we offer some strategies to test the robustness of our approach.
4.5 Robustness Checks with Alternative Empirical Strategies

Next we try two other empirical strategies which are potential alternatives to using the fully structural model proposed. Both alternative strategies are minor variants of the traditional approaches and hence are relatively easy to implement. We call our first alternative strategy as the “ex-post” strategy. In this framework, apart from the incumbent firm and entrant firm resources, we add another dummy variable indicating if the entrant entered or not (1=enter and 0=not enter). Hence the interpretation is to look at the likelihood of erecting entry barriers, conditional on expecting entry, thus accommodating strategic interaction, controlling for the effect of resources. The results from this experiment are presented in table 9.

| Insert Table 9 here |

Again we can clearly see that the coefficients from this model are biased and can lead to faulty inference. For instance, the coefficient on the second resource for player B is negative and statistically significant. However, by definition the true coefficient is positive and significant. Hence, we conclude that this approach does not allow us to capture strategic interaction. Moreover, the variable by construction does not capture the ex-ante effect. The observed dummy variable is basically after the fact but the true theoretical effect is estimation of the ex-ante expectations on the reaction.

Our second alternative strategy tries to offer another solution through the use of a propensity score approach to the problem. We first estimate the likelihood of reaction by the entrant (B) based on observed characteristics of B (B’s resources and capabilities). The predicted probabilities from that regression is then substituted as a regressor in the probability model for A’s decision. The result from this model is presented in table 10.

| Insert Table 10 here |

23
Again, we find that this approach fails to recover the parameters and can lead to faulty inference, especially with statistically significant coefficients and sign flips. Based on our analysis we can clearly see that both alternative strategies do not capture the multi person interactions and hence can lead to faulty inference.

We also present model selection tests using the structural model as comparisons to provide further evidence on robustness in table 11.

From the analysis we can see that the model selection test rejects both the robustness models suggested in favor of the structural model. This further provides evidence that the structural model is more efficient and consistent as compared to the alternatives proposed for modeling strategic interactions. Next we present some implications for the study of sustainable vs. the lack of sustainability in competitive advantages.

5 Implications for Temporary vs. Sustainable Advantages

How do firms obtain and retain sustainable competitive advantage? This has been a question of fundamental interest for strategic management scholars. Much of the dominant theoretical paradigms within the literature such as industry analysis and the resource based view are targeted towards answering these questions. Early work stemmed from the positioning view and focused on industry level factors and suggested that the source of competitive advantage resides primarily at the level of the industry or groups within the industry (Caves and Porter, 1977). Subsequent work focused on analytical modeling of strategic interaction
between the entrant and incumbent, but much of this work rests in the theoretical realm with little empirical validation.

On the other hand, scholars in strategic management have intensely studied firm level aspects and suggested that competitive advantage is derived from within the firm (RBV). This stream of research suggests that sustainable competitive advantage is a function of the resource profiles of the incumbent and the entrant. The inherent difference between the two approaches rests on the fact that the former paradigm focused on the external environment shaping competitive advantage, while the latter research argues that the internal environment is more relevant in sustaining competitive advantage.

The theoretical lenses have been applied to study several strategic choice problems such as market entry/exit among others. The empirical designs typically accommodate variables related to the resource based view or aggregated measures of industry attractiveness augmented with necessary control variables to test for the probability of entry. While comprehensive studies of this nature have been well developed in the literature, a critical assumption in these models is the ability to sustain competitive advantage. In other words, the objective of these studies relies on the theoretical foundation that sustainable competitive advantage is only a function of incumbent specific resources, relative resource profiles, competitive considerations and other industry/economy wide factors. What is missing is a credible story of dynamic competitive advantage. We do not know from the previous literature whether strategic interactions do take place between firms, in what settings they are likely to place, or if these interactions have a significant bearing on sustainability of firm advantages. We believe that our suggested empirical approach can help identify whether strategic interactions are an important element in entry decisions and their implications for sustainability of firm advantage.

In this paper we have asked some questions related to the role of strategic interaction as a determinant of this sustainability. What is the nature of competitive advantage? Is it sustainable or temporary? Can we empirically tease out the effects using firm actions? What
happens when there are specific market conditions such as rapid growth or hypercompetition? The motivation for our study stems from the perspective of hypercompetition, which presents an alternative picture on competitive advantage based on quick fire reactions by entrants to actions taken by the incumbent. Such actions can have a negative impact on sustainable competitive advantage leading to temporary advantages. Existing research implicitly ignores strategic actions taken by the market participants and assumes that it is irrelevant for studying competitive advantage. In this backdrop, existing empirical studies may provide an incomplete picture on the real dynamics of competitive advantage. Our approach builds on the idea that apart from resources and capabilities, incumbents and entrants may also study potential reactions from entrants before making their decisions. Hence, rather than assume sustainable competitive advantage, we allow the data to inform us of the situation prevalent in the focal context.

5.1 What happens under different industry conditions?

Different factors may assume greater or lesser importance under various industry conditions. For instance, turbulence and high potential profits are a common occurrence, especially in industries where there is rapid growth and considerable uncertainty. Such conditions can be indicative of the presence of hypercompetition D’Aveni (1994). Our approach captures this notion of different industry conditions through the information structure imposed in the model. We also show that our approach is more robust to misspecification that can arise when studying the impact of specific industry conditions using alternative techniques.

From a traditional empirical modeling perspective two approaches can be considered. One requires the exact specification on what constitutes the specific industry condition (such as turbulence) and the data collection should be focused on the precise definition of the researcher. For instance, one way is to actually use data for a given time period for a specific industry or a cross section of industries and designate parts of the time period as times when there is high turbulence or classify cross sectionally industries which are turbulent vs.
industries that are not. Hence, the inference is based on a dummy variable classifying either the time or specific industry characteristics as conditions tying them to specific industry conditions. This leads to an obvious endogeneity problem in terms of the definition of the specific industry condition (in this case turbulence). The second approach, which is along related lines, is to collect data across a given time period and then use an instrument for turbulence and look at the impact of the instrument on entry decisions. Again problems are aplenty as the quality of the instrument needs to be rigorously tested, which can be very difficult. We show through our simulations that these problems apart, these approaches do not capture the effect of strategic interactions between the players and its impact on the entry decisions.

In our suggested model, rather than assume that this information can be defined by the researcher, we allow for specific industry conditions (like turbulence or rapid growth) to manifest through the private information component in the game structure. Beliefs on specific industry conditions and sustainability during these trying times will vary with firms, their experience, reputation, stock of resources and managerial skill among other things. Hence, such specific industry conditions are factored into the decision made by the firm. Thus we let the actual outcomes observed through decisions made by firms to reveal the effect of industry conditions on the choice to enter. This approach can also be applied to the study of other industry conditions beyond turbulence.

6 Conclusions

While our approach attempts to explicitly take strategic interactions among firms into account, it does not seek to ignore firm specific theories in strategy. Rather our argument is that we can learn more about strategic choices by allowing and testing for both explanations concurrently. We allow for the existence of valuable, rare and inimitable resources (Barney, 1991). In our model formulation, we posit that the private information component of both
players refers to their inherent firm specific strengths, knowledge, experience and ability to react to different industry characteristics among others. Hence, if entrants believe that the resources held by the incumbent are indeed valuable, rare and inimitable, their expected utility should account for the same. Thus, firms might possess some resources but such resources also need to valuable, rare and inimitable from the perspective of the entrant. Because firm actions are linked to what the firms believe in terms of the value of each other’s resources, an issue of potential endogeneity follows, which we effectively deal with in our suggested approach. Therefore, the modeling approach suggested in this paper allows for either explanation to persist and accounts for the potential endogeneity concerns that arise. Our modeling approach allows us to empirically test for the tension between the two stories. We explicitly lay down a methodology which will take into account “ex-ante” expectations on the reactions from entrants as driving strategic decisions. For instance, an entry barrier is effective only as far as it can convince the entrants that it is credible and sustainable (D’Aveni, 1994). Therefore, we argue that strategic interaction coupled with the resource and capability profile of the incumbent will give us a more complete picture on the question of the nature of competitive advantage. From our analysis we can establish boundary conditions on when and how sustainability is a good assumption and vice versa. To illustrate our model we use simulation results and show that not accounting for strategic interactions, when they are actually present, can lead to faulty inference. Further, we show that non nested model selection tests can be used to answer questions on which model is better explained by the data.
References


Appendix: Non Nested Models and Model Selection

Evaluating the structural probit model with respect to existing research designs is crucial to ensure validity of this approach. Traditional approaches to testing model discrimination such as the Wald and Likelihood ratio tests will fail given the non nested nature of the model. The technical definition of non-nested models and the statistical tests for the same are based on the Kullback-Leibler Information Criteria (KLIC). Consider a regression model where an outcome $ic$ conditional on some covariates $H_\gamma = f(Y_i|X_i; \gamma)$. Vuong (1989) shows that the Kullback Leibler distance can be represented as:

$$KLIC \equiv E^0 [\ln h^0 (Y_i|X_i)] - E^0 [\ln f (Y_i|X_i, \gamma^*)]$$

Where $h^0(Y_i|X_i)$ is the true conditional density $Y_i$ given $X_i$ (the true but unknown data generating process) and $\gamma^*$ are the estimates of $\gamma$ when $f(Y_i|X_i)$ is not the true model. The best model is selected based on the minimizer of the KLIC criterion. This in turn implies that the best model is the one that is closest to the true model. Therefore intuitively, the test selects one model over the other when the average log likelihood of one is significantly greater than the average log likelihood of the other. Let $f(.)$ and $g(.)$ be the two models under consideration. The null hypothesis in the Vuong (1989) test can be stated as follows:

$$H_0 = E^0 \left[ \ln \frac{f(Y_i|X_i; \gamma^*)}{g(Y_i|Z_i; \eta^*)} \right] = 0$$

This implies that the two models being tested are equivalent. The alternative hypothesis is specified as

$$H_f = E^0 \left[ \ln \frac{f(Y_i|X_i; \gamma^*)}{g(Y_i|Z_i; \eta^*)} \right] > 0$$

$$H_g = E^0 \left[ \ln \frac{f(Y_i|X_i; \gamma^*)}{g(Y_i|Z_i; \eta^*)} \right] < 0$$
The expected value in the above hypothesis is unknown. But Vuong shows under general conditions that the expected value can be consistently estimated as \((1/n)\) times the likelihood ratio statistic. Hence, if the null hypothesis is true then, the average value of the log likelihood ratio should be equal to zero. If the true model is \(f\) then the average value of the log likelihood ratio should be significantly greater than zero and if the true model is \(g\) the average value of the log likelihood ratio should be significantly lesser than zero.
Table 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></td>
<td>Without Strategic Interaction</td>
<td>Robust</td>
</tr>
<tr>
<td>Data</td>
<td></td>
<td>Consistent but less efficient</td>
</tr>
<tr>
<td></td>
<td>With Strategic Interaction</td>
<td>Robust</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not Consistent</td>
</tr>
</tbody>
</table>

Table 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 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 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>
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<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>
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<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 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 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 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.
Table 8: **Vuong Test for Strategic Vs. Non Strategic Models**

<table>
<thead>
<tr>
<th></th>
<th>Vuong Stat</th>
<th>Std.Dev</th>
<th>Z Value</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S vs. A</td>
<td>(1286.0557)</td>
<td>0.3265</td>
<td>(3938.9645)</td>
<td>0.0000</td>
</tr>
<tr>
<td>S vs. A &amp; B</td>
<td>(1287.7875)</td>
<td>0.3282</td>
<td>(3923.9307)</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

*Note* S refers to the model with strategic interaction. A refers to the model with just A’s resources. A&B refers to the model with A & B’s resources. For interpretation consistent with Appendix A, model G is our structural model.

Table 9: **With Strategic Interaction - Ex Post Design**

| Coefficients: | TRUE | Estimate | Std. Error | Z Value | Pr(>|z|) |
|---------------|------|----------|------------|---------|---------|
| AR1           | 0.5  | (0.0611) | 0.0303     | (2.0140) | 0.0440 * |
| AR2           | 0.5  | (0.0178) | 0.0498     | (0.3570) | 0.7210  |
| AR3           | 0.5  | 0.1345   | 0.0159     | 8.4630   | 0.0000 *** |
| BR1           | 0.5  | 0.1277   | 0.0220     | 5.7970   | 0.0000 *** |
| BR2           | 0.5  | (0.1161) | 0.0103     | (11.2400)| 0.0000 *** |
| Ex Post Dummy |      | 0.0330   | 0.0497     | 0.6640   | 0.5070  |

Table 10: **With Strategic Interaction - Ex Ante Design**

| 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 . |

Table 11: **Vuong Test for Strategic Vs. Alternative Designs**

<table>
<thead>
<tr>
<th></th>
<th>Vuong Stat</th>
<th>Std.Dev</th>
<th>Z Value</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S vs. Ex post</td>
<td>(2476.6670)</td>
<td>0.6966</td>
<td>(3555.4180)</td>
<td>0.0000</td>
</tr>
<tr>
<td>S vs. Ex Ante</td>
<td>(1287.7910)</td>
<td>0.3273</td>
<td>(3934.4620)</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

*Note* Notes: S refers to the model with strategic interaction. Ex Post refers to the model with resources and ex post dummy for strategic actions. Ex ante refers to model with resources and ex ante predicted probabilities as proxies for strategic interaction. For interpretation check Appendix A, model G is our structural model.
Figure 1: Game Tree with Regressors

Player A: Incumbent Firm

\[ U_A^*(l, L) = 0 \]
\[ U_B^*(l, L) = 0 \]
\[ U_B^*(r, L) = X_{l.l}^B b_{l.l}^B \]
\[ U_B^*(r, R) = X_{l.l}^B b_{l.l}^B \]

Player B: Competing firm

\[ U_A^*(r, L) = X_{l.r}^A b_{l.r}^A \]
\[ U_A^*(r, R) = X_{l.r}^A b_{l.r}^A \]
\[ U_B^*(r, L) = X_{l.r}^B b_{l.r}^B \]
\[ U_B^*(r, R) = X_{l.r}^B b_{l.r}^B \]
Figure 2: **Posterior Distribution of Total Effects Without Strategic Interaction**
Figure 3: **Posterior Distribution of Total Effect with Strategic Interaction**
Figure 4: Marginal Change in Total Effect for Changing Value of Resources