Anticipated Entry and Entry Deterrence: Evidence from the American Casino Industry

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Abstract

Using a novel data set on entry plans into the American casino industry, I find that incumbent firms respond to the threat of entry by expanding capacity, and that these strategic investments are effective in deterring actual entry. Specifically, a standard deviation increase in incumbent casino capacity leads to 47 percent more failed plans for entry, *ceteris paribus*. Apart from providing credible evidence on entry deterrence and its form, this paper provides new empirical evidence on how the capital structure of firms relates to economic activity. In particular, incumbents that are highly leveraged tend to expand capacity less in response to an entry plan by a potential entrant, which suggests that highly leveraged firms engage in less aggressive strategic behavior. To quantify the benefit of entry deterrence using a stock market event study, I estimate that a failure of an entry plan increases the equity value of incumbent firms by 10.4 to 13.3 percentage points. Additionally, I find that incumbents that increase capacity during a rival's planning stage retain a larger share of loyal customers. This finding suggests a mechanism by which incumbents can deter entry; strategic investments by incumbents increase patron loyalty to the incumbent firm, which decreases the potential entrant's profits conditional on entry.

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A large body of theoretical work beginning with Spence (1977) outlines conditions under which incumbent firms can deter the entry of a rival by making preemptive strategic investments (see Dixit 1979, 1980; Aghion and Bolton 1987; Klemperer 1987; Milgrom and Roberts 1982; Maskin 1999).[1] Within this literature, several authors (Bolton and Scharfstein, 1990; Chevalier and Scharfstein, 1996) have argued that financial distress can constrain firm preemption strategies. More generally, the relationship between firm financing and product market decisions is an important locus of questions in corporate finance that has generated considerable theoretical and empirical attention (Myers, 1977; Maksimovic, 1988; Brander and Lewis, 1986; Phillips, 1995; Chevalier, 1995; Khanna and Tice, 2000). Nevertheless, there is not much direct empirical evidence on the effect of leverage on strategically-motivated investment.

As a contribution to this literature, I empirically investigate preemptive strategic investments by incumbent firms and their relationship to incumbent firm leverage. My analysis uses a newly-constructed data set of on entry plans into the American casino industry (from March 2003 to August 2012) to study the nature of preemptive investments made by incumbents, and the extent to which these investments depend on the leverage of incumbent firms. Given that these entry plans occur well before actual entry, I can directly observe the incumbent response to anticipated entry – i.e., strategic investments around the time that a new casino is announced – as well as evaluate the effectiveness of incumbent actions to deter entry.[2] Relative to existing empirical work on strategic entry deterrence, the fact that I directly observe entry plans (in the planning stage, prior to construction) allows me to distinguish incumbent investments in response to threatened entry from those made in response to actual entry.[3]

I find that geographically-proximate incumbents respond to the threat of entry by expanding capacity during the planning period prior to actual entry, and the response is more dramatic among incumbent casinos that successfully thwart the entry plan. For the median failed entry plan, the average incumbent expands its casino size by approximately 8300 square feet (14.9%) during a two-year period surrounding first planning. For the median successful entry, the average incumbent expands its casino size by only 2000 square feet (4.2%).

Incumbent casino firms with high leverage respond less aggressively to the threat of entry than do low-leverage incumbents. Specifically, I find that incumbents with greater than median leverage do not significantly expand capacity during the planning stage of a rival casino. In contrast, incumbents with leverage below the median make meaningful investments during the planning stage of rival casinos. In a difference-in-difference specification where incumbents between 100 and 200 miles of the entry plan are the control

[1] Despite considerable theoretical attention to this issue, the empirical assessment of strategic entry deterrence is sparse apart from a few recent empirical studies (Ellison and Ellison 2011; Goolsbee and Syverson 2008; Snider 2009).

[2] The mixed fortunes of entry plans in my data set allow me to evaluate the effectiveness of entry deterrence. Among the 134 entry plans, 60 casino projects were stalled. In the data set, I classify a planned entry to be stalled if the casino (i) was never observed as an open casino during the 113 months of data, and (ii) has at least three years of data.

[3] This problem is well recognized in the empirical literature on preemption. In less rich data environments, researchers rely on particularly clever identification strategies to distinguish responses to the threat of entry from actual entry. For example, in the context of the entry of low cost carriers into the airline industry, related work by Goolsbee and Syverson (2008) must infer threatened entry from what the structure of Southwest's airline network implies about likely entries in the future.

group, I find that low-leverage incumbents within 100 miles of a planned casino expand their casino floor space by nearly 15,000 square feet during the planning period of a rival casino.[4]

Not only do incumbents respond preemptively to entry plans, but expanding capacity can be an effective deterrent to entry. Using a Cox proportional-hazards model, I estimate that large initial incumbent casino size and greater expansion of the casino size at the start of the planning stage are strongly associated with low hazard rates out of the planning stage. The estimates from the hazard model imply that 47 percent more entry plans meet failure if the incumbent casino is one standard deviation (60,000 square feet) above the mean relative to the average incumbent casino size. For a standard deviation increase in capacity adjustment (for the two-year window around first planning), I find similarly significant effects.

I supplement the evidence on incumbent response to anticipated entry with a stock market event study that helps quantify the benefit of entry deterrence. Three years after first planning, the cumulative average abnormal return for incumbents near a successful entry plan is 10.4 percentage points lower than for incumbents near a failed entry plan. After controlling for heterogeneity in a regression of cumulative abnormal returns, I estimate the benefit of entry deterrence to be 13.3 percent of the equity value of incumbent firms,[5] an estimate that is statistically significant at the ten percent level.[6] To the extent that uncontrolled demand shocks contribute to the success of entry plans, this difference represents a lower bound on the effect of entry deterrence on incumbent firm value.[7]

To distinguish entry deterrence from entry accommodation, I examine how incumbent attributes and preemptive capacity investments determine the *ex post* performance of successful entrants. I find that preemptive capacity investments by incumbents do not significantly predict the market share of entrants upon successful entry.[8] This suggests the capacity response by incumbents reflects an entry deterrence motive, rather than an early entry accommodation motive. Nevertheless, I find that entrants into markets where incumbents have low leverage are able to acquire significantly less market share after successful entry. This finding suggests that incumbents are able to successfully mitigate the effect of anticipated entry, but that the success of incumbents depends on their financial position.[9]

[4] In addition, the strength of the entrant is important for how the incumbent casino firms respond to the plans of a new rival. In fact, incumbents expand capacity more dramatically in the presence of weak entrants – those that are not publicly traded, and those with additional regulatory hurdles – which is additional evidence for an entry deterrence motive for the capacity investment. As I describe in the empirical section, these results on capacity adjustment are robust to alternative explanations and are statistically significant.

[5] Using the median debt-to-asset ratio of incumbent firms from the data set (0.659), we can rescale this estimate to reflect the impact on the total value of the firm (debt + equity). After rescaling, the estimate implies that the effect of entry deterrence is 4.54 percent of the value of incumbent firm assets. Given that the typical incumbent has 15 to 20 properties and that the stock market evidence would net out costs of entry deterrence, this estimate is reasonable in magnitude.

[6] The heterogeneity exhibits some sensible patterns as well. Incumbents with low leverage (one standard deviation below the mean) experience more than twice as large of an effect of entry relative to the average incumbent, 29.8 versus 12.8 percentage points. This finding is consistent with costly investments in mitigating entry. Taken together, these estimates imply incumbents that succeed in deterring entry are best off, incumbents that try and fail are worst off, and incumbents that do not respond to the entry plan experience an effect of entry that is somewhere in between.

[7] My estimate is a lower bound because of two types of demand shocks. First, if actual entry occurs in high demand states, but stalled entry plans occur in low demand states, the incumbent should have greater firm value in the actual entry case. Second, if actual entry of a close rival expands the market, actual entry should increase firm value through expanding the market.

[8] In this part of the empirical exercise, I use a proprietary ATM withdrawal data set to construct approximate market shares.

[9] In an unreported exercise using the casino visitation data, I constructed measures of casino demand that are adjusted for patron heterogeneity (distance to casino, market segment, gender, and age group). In an event window, I find that this measure of incumbent casino demand increases sharply after first planning of a geographic rival. This finding suggests that incumbent casinos

Finally, to investigate the mechanism through which capacity installations affect strategic entry decisions, Section 6 uses proprietary casino visitation data to investigate the link between capacity investments and patron loyalty. I find evidence that capacity installations are related to greater casino loyalty. This relationship to casino patron loyalty provides a credible reason to preemptively invest in capacity (as in Klemperer (1987)), and suggests that casino brand switching costs are important to casino patron demand.

My findings contribute to the literature in financial economics that seeks to understand the nature of the relationship between firm financing and the product market (Brander and Lewis, 1986; Chevalier, 1995; Chevalier and Scharfstein, 1996; Hendel, 1996; Povel and Raith, 2004). In this respect, my findings are complementary to recent work on the indirect cost of financial distress by Hortacsu et al. (2013) who find empirical evidence that financial distress can reduce demand for a firm's product in the context of automobile manufacturing. My results illuminate a strategic channel through which financial distress exerts costs on the real side of the firm. Specifically, in finding that casino firms with greater leverage respond less to entry plans, this paper suggests that debt constrains the range of strategies incumbent firms can take in response to entry.

Within the industrial organization literature, my use of data on entry plans complements the growing empirical literature that seeks to understand strategic entry deterrence and its effectiveness (Ellison and Ellison 2011; Goolsbee and Syverson 2008; Snider 2009). My empirical results on the conditions under which entry deterrence can be successful are a novel contribution to this literature. Previous studies have focused on detecting whether incumbents invest for the sake of entry deterrence rather than documenting heterogeneity in entry deterrence strategies. The richness of my data set allows me to also empirically document heterogeneous responses to the threat of entry.

Among studies of entry, the event study approach is novel because most studies of entry and exit use a structural approach that relies on product market information (prices and quantities) and detailed information about the pattern of entry and exit decisions.[10] A related study by Whinston and Collins (1992) uses a stock market event study to quantify the effect of entry in regional airline markets.[11] As in Whinston and Collins (1992), the findings in this paper demonstrate that exploiting stock market information can be fruitful.

My use of rival links and performance of rivals is related to a broader literature in financial economics that uses real links between firms to understand the determinants of firm performance (Hoberg and Phillips, 2010, 2011; Bernile and Lyandres, 2010). Within this literature, my approach of exploiting geographic links between rivals within a single industry complements other approaches that use cross-industry links (Bernile and Lyandres, 2010) and those that use text analysis of product descriptions (Hoberg and Phillips, 2010, 2011). Relative to this work, my findings imply that geographic rival linkages can be useful, especially for local industries.[12]

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stoke demand (e.g., through loyalty programs and promotions) in response to the threat of new entry.

[10]Empirical analyses of entry usually rely on structural estimation of firm value (Berry and Waldfogel, 1999; Seim, 2006; Seim and Waldfogel, 2010). The standard practice to estimate parameters of the firm value function is to first estimate demand (Berry et al., 1995) then use the first order conditions of the firm's problem to recover marginal costs. With prices and market share information, the researcher can estimate the firm's value function for counterfactuals.

[11]Whinston and Collins (1992) use stock market movements about a series of 24 entry announcements by People Express airlines to understand the effect of entry on incumbent firms.

[12]Specific to previous work on casino gambling, my estimates quantify the effect of competition more precisely than previous studies that are based on tax receipts from related industries and price regressions (Anders, 1999; Anders et al., 1998; Thalheimer

The remainder of this paper proceeds as follows. Section 1 describes the history of casino gambling in the United States and the regulatory environment that applies to the casino gambling market. Section 2 outlines a model of strategic entry deterrence that is adapted to casino market competition, and describes its testable implications for the empirical exercise. Section 2.2 summarizes the data and motivates the empirical study of entry deterrence. Section 4 presents the main evidence on strategic entry deterrence by incumbent firms. Section 5 presents event study evidence that quantifies incumbent benefits to engaging in entry deterrence. Section 6 presents evidence on accommodation and patron loyalty using casino visitation data. The last section concludes and offers directions for future research.

1 Casino Gambling in the United States

The casino gambling era was ushered in by a crackdown on gambling in most legal jurisdictions in the United States at the same time as the broad legalization of gambling in Nevada in 1931.[13] Largely driven away from their operation of illegal gambling enterprises, organized crime syndicates moved into operating legally-authorized casino establishments in Nevada. During the 1950s, the United States Senate investigated the casino industry for undue mafia influence and the resulting investigation led to a cleansing of the casino industry, transferring casino ownership interests to reputable companies without connections to organized crime.

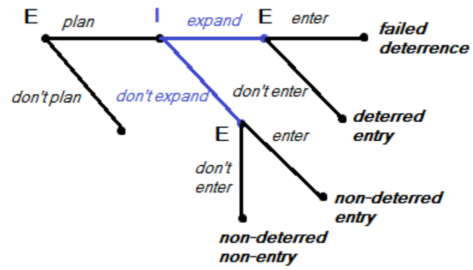
By the 1950s, casino gambling in the United States was legal exclusively in Nevada, but during the next 50 years, various other United States jurisdictions outside of Nevada authorized casino gambling. In 1976, New Jersey was the first state outside of Nevada to allow high-stakes casino gambling, leading to the Atlantic City casinos. American Indian tribes were the next major source of casino gambling in the United States, cropping up throughout the 1980s, but booming after Congress passed the Indian Gaming Regulatory Act (IGRA) of 1988.[14] After IGRA, several states authorized casino gambling off of American Indian reservations. Between 1989 and 1993, South Dakota and Colorado authorized limited stakes gambling while Iowa, Illinois, Mississippi, Louisiana, Missouri and Indiana authorized riverboat gaming establishments to operate in their states (Bourie, 2011).

and Ali, 2003). Finally, related to casino gambling, this paper contributes to a growing body of research on the origins and consequences of the growth of casino gambling over the past two decades (Evans and Topoleski, 2002; Grinols and Mustard, 2001, 2006; Evans and Kim, 2008; Cookson, 2010). In this respect, this paper links the specific literature on casino gambling to broader questions related to firm financing decisions and the strategic nature of entry.

[13] Gambling has had a turbulent history in the United States. Rose (1991) describes three waves of gambling in the United States. The first wave (1600 - 1850) was comprised mostly of colony- and state-run lotteries, but also included some riverboat gambling. Under pressure from those in the temperance movement at the time, most states banned state lotteries, a move that largely pushed organized gambling underground (Dunstan, 1997). The second wave of gambling cropped up in California around the Gold Rush (1849 - 1855) largely because illegal gambling met lax enforcement until the early 1900s when enforcement of gambling laws became more stringent. The third wave of gambling is the casino gambling era, which provides the setting for this paper

[14] The Seminole tribe won a legal battle in 1981 to continue operating their high-stakes bingo enterprise despite the state of Florida's attempt to regulate it (*Seminole Tribe v. Butterworth* 658 F.2d. 310, 314–315 (5^{th} Cir. 1981)). Two other landmark cases, *Barona v. Duffy* (694 F.2d 1185, 9^{th} Cir. 1982) and *California v. Cabazon* (480 U.S. 202, 1987), clarified that states's authority over Indian gaming was "regulatory but not prohibitory," wording that essentially authorized any Indian casino in existence at the time. Shortly after *Cabazon* in 1988, Congress passed the Indian Gaming Regulatory Act (IGRA), which required good faith bargaining between states and tribes to authorize Indian gaming. Ultimately, this regulatory structure legitimized Indian gaming and led to a clear process for its approval. The result was a boom in casino activity on American Indian reservations.

Figure 1: Strategic Entry Model: Timing and Terminology



Over the course of the next two decades, the extent of casino gambling continued to expand. There are currently casinos in urban centers such as Detroit and St. Louis as well as plans for a new casino in downtown Chicago. At present, there are 41 states in the United States with some form of casino gambling (Bourie, 2011). Although there is persistent moral opposition to new authorizations of casino gambling, the general tendency continues to be toward more widespread legalization.

2 Theoretical Predictions Regarding Strategic Entry

2.1 Strategic Entry Model

The model, provided in more detail in Appendix A, formalizes the interaction between a potential entrant and an incumbent in a strategic entry deterrence game. Entrants pay a small fixed cost to enter the planning stage. If a potential entrant begins the planning stage, it takes a draw from the marginal cost distribution $c_e \sim G(c)$ that determines its cost of production. This marginal cost draw is known to the entrant and incumbent. The incumbent responds to entry plans by expanding capacity (a credible commitment to additional output) or by taking no action. The ability of the incumbent to finance additional capacity is unknown to the entrant, but in a separating equilibrium,[15] the incumbent's action is a signal of its type. Upon observing the incumbent's action, the entrant either enters or discontinues its entry plan.

Figure 1 portrays the timing of actions and classification of outcomes in the strategic entry deterrence model. In equilibrium, an unconstrained incumbent will always expand capacity because expanding capacity is useful for entry deterrence and entry accommodation. If the cost of financing capacity expansion is sufficiently high, a financially-constrained incumbent will not expand output in response to an entry plan. Appendix A develops this result in detail as an adaptation of the simple version of the entry deterrence model

[15] For a separating equilibrium to exist, financially-constrained incumbents cannot benefit from imitating financially-unconstrained incumbents. On an intuitive level, the financing cost for additional capacity for constrained incumbents must guarantee that it is more costly to expand capacity and successfully deter entry than it is to not respond and allow entry.

put forward by Dixit (1980),[16] and as extended to demand with switching costs by Klemperer (1987).[17]

If an incumbent expands capacity and the entrant has sufficiently high cost (either marginal cost of production or fixed cost of entry), entry will be deterred. Based on cutoffs in entrant marginal cost (see Appendix A.3), some relatively high-cost entrant types will be deterred by an expanding incumbent (in equilibrium, financially unconstrained), but will not be deterred by a non-expanding incumbent (in equilibrium, financially constrained).

Beyond the capacity-investment model of entry deterrence, the incumbent's choice to expand capacity can signal the incumbent's strength in competition, which may otherwise be unobserved to the entrant.[18] For example, an incumbent that invests significantly in new capacity at the announcement of a new entry plan signals the ability to finance other activities relevant to competition.

2.2 Testable Implications

Aside from the implication that incumbents expand capacity in response to a new entry plan, the model of strategic entry has two additional testable implications:

1. Incumbent capacity adjustment will be most effective in deterring relatively weak potential entrants – those with high fixed cost of entry and high marginal cost. For this reason, incumbents near *ex ante* weak potential entrants will expand capacity more than incumbents near *ex ante* strong potential entrants.

2. Given that financially-constrained incumbents will find entry deterrence investment (capacity and associated loyalty/promotional investments) to be more expensive, incumbent firms that are more leveraged will respond less to potential entry.

This second prediction is related to a rich theoretical literature on how the capital structure of firms relates to product market competition (Brander and Lewis, 1986; Maksimovic, 1988; Bolton and Scharfstein, 1990; Chevalier and Scharfstein, 1996; Povel and Raith, 2004). More generally, the theoretical literature has shown the effect of debt on strategic aggressiveness is ambiguous, and hence, an empirical question.[19] I

[16] These models are inherently static while the actual process of entry deterrence takes place in an uncertain dynamic environment. In a framework that models strategic investments as real options, Huisman and Kort (2013) characterize entry deterrence strategies. Many of their conclusions mimic the insights of a static Dixit (1980) model (which predicts strategic overinvestment), but the dynamic element of the model draws an equivalence between strategically delayed entry and entry deterrence. Hence, Huisman and Kort (2013)'s model provides an alternative justification of my empirical specifications, which use variation in length of time in the planning stage to think about entry deterrence.

[17] In a switching cost model, the incumbent firm invests in a stock of additional loyal patrons, which has a similar effect on incumbent pre-commitment when it is combined with a switching cost (see Appendix A.4 for details). Section 6 presents some evidence that incumbents that expand capacity during the planning stage of a nearby rival are able to achieve greater loyalty.

[18] Milgrom and Roberts (1982) outline how limit pricing entry deterrence equilibria can result from a signaling model. The fact that casino capacity is a credible investment and easily observed makes capacity a useful signaling variable.

[19] One strand of this literature suggests that competition is more vigorous in markets with high levels of debt because of limited liability effects (Brander and Lewis, 1986; Maksimovic, 1988), financial predation (Bolton and Scharfstein, 1990), and the use of aggressive pricing to raise short-term cash in order to finance debt (Hendel, 1996). Other authors demonstrate that debt can lead to higher prices (softer competition) in markets where there are switching costs as in Klemperer (1987). In these models, the threat of liquidation reduces the dynamic incentive to invest in market share (Chevalier and Scharfstein, 1996). Povel and Raith (2004) present a model where the debt contract is determined endogenously in an agreement between a financially-constrained firm and an investor. In this model, high leverage causes a financially-constrained firm to behave less aggressively than an unconstrained firm.

can empirically evaluate the extent to which casino firms with high debt engage in more or less strategic entry deterrence. This part of the empirical exercise complements previous empirical analyses of the role of debt in product market competition (Chevalier, 1995; Phillips, 1995; Khanna and Tice, 2000; Pichler et al., 2008) by demonstrating that debt can influence strategic entry behavior.[20] My findings are similar to Chevalier's 1995 study of the effect of leveraged buyouts (LBOs) on supermarket prices. In particular, I find that incumbent casinos with more debt take less aggressive action to prevent anticipated entry. Beyond Chevalier, I document that this effect of debt on preemption operates through physical investment, not just prices.

3 Data

3.1 Overview of Data

The primary data source is the Gaming Business Directory, which contains comprehensive casino industry information about every property in the United States (Casino City Press, 2012). As the database is maintained for casino vendors to contact casino managers and owners, the data provide reliable information about the inputs employed by each casino property in the United States. I downloaded a monthly snapshot of the industry for every month for which the data are available through the online interface – March 2003 through August 2012.[21]

Because the database's purpose is to connect casino vendors with casino management, the first instance of a casino property in the database is a credible announcement that the organizers of the casino property are serious about competing in the casino market. There are 134 casino properties that enter the database as planned casinos. Over the 113 months of the sample, 60 of the 134 announced casinos stalled and were never opened, providing a great deal of variability in the success of potential entrants.[22] In the empirical section, I explore the extent to which incumbent responses to these entry plans is responsible for this variation.

All 90,755 casino-month observations in my sample contain information on the location (latitude and longitude) of casinos. Using the location data, I link each casino to rivals within a specified distance. For each entrant, I define the set of incumbent casinos to be those within a 100-mile radius of the proposed entry site, and as a comparison group, I isolate the set of incumbents between 100 miles and 200 miles from each proposed site. The data include information on the number of slot machines, square footage of the casino, square footage of the convention center, number of hotel rooms, number of restaurants on site, number of entertainment venues, number of parking spaces, and a listing of the games offered by that particular casino.

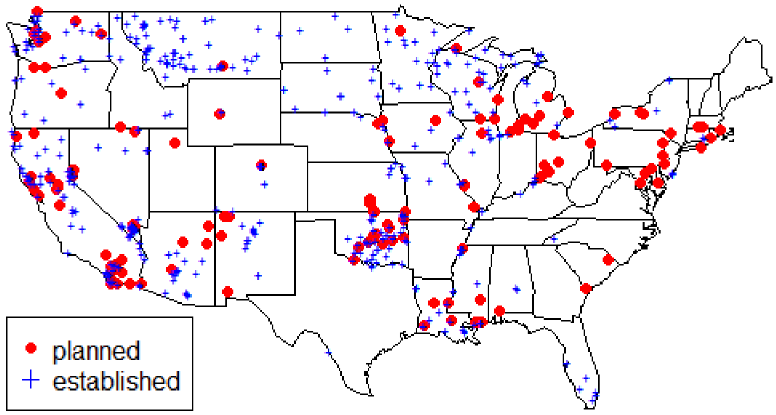
In addition, I match firm-level financial information from Compustat and the Center for Research on Security Prices (CRSP) to facilitate the study of how financial structure matters for economic performance.

[20] In addition, there have been several recent papers that have made progress on the question of whether financial leverage leads firms to be more or less aggressive by studying trade credit relationships (Lehar et al., 2011; Murfin and Njoroge, 2012).

[21] The online database is updated continuously as information becomes available. Consequently, the data could have been extracted daily in theory, but this would have been computationally burdensome without adding useful variation. According to Casino City's webpage, the database averages 1000 changes per month. At nearly 1000 distinct casinos, this amounts to one change per casino per month. Hence, it is reasonable to presume that each casino's information is refreshed monthly.

[22] Two criteria must be met to classify a planned casino as stalled: (1) the casino was never open in the data set, (2) there were at least 3 years of data on the casino.

Figure 2: Geographic Dispersion of American Casino Industry



3.2 Stylized Facts about the Casino Industry

Figure 2 portrays the geographic dispersion of the casino properties in the American casino industry. The established casinos, indicated by blue crosses on the map, are the sample of open casinos as of March 2003. The planned casinos, indicated by red dots on the map, are proposed entry sites for entry plans in my data set (March 2003 to August 2012). From the figure, not only is the distribution of incumbent properties dispersed across the United States, but the distribution of entry plans in my sample covers a significant fraction of the United States as well.

Table 1 and Figure 3 summarize the distribution of the timing of entry. For cross-tabulation statistics and simple specifications, I classify a planned casino as stalled if it was observed for more than three years, and it was never open in the 113-month sample. Although this classification is arbitrary, when I estimate the hazard model for the rate of transition out of the planning stage, none of the results depend on how I define a stalled casino. In addition, splitting the sample in this way allows me to compute simple statistics that summarize the key insights of the hazard model estimates. Moreover, the semi-parametrically estimated survival functions in Section 1.4.2 flatten out at 36 to 48 months, indicating that very few entries occur after that time. Thus, although arbitrary, the choice of requiring three years of data has some empirical justification.

For the sub-sample of publicly-traded companies, Table 2 provides a detailed view of the data on the timing of entry for the casinos that entered during the sample. Several planned casinos have been in the planning phase for more than 3 years as of the end of the sample time frame while some casinos were planned for a while and disappeared from the data set. This pattern – long planning stages with a few stalled projects – is consistent with the planning phase involving negotiation with regulators as well as coordination with vendors.

Table 1: Timing of Entry: Number of Months Spent in Planning Stage, Under Construction or Open

Full Sample	Planning Stage	Construction Stage	Open Months
Minimum	1.00	1.00	1.00
1st Quartile	8.25	4.25	73.00
Median	32.50	9.00	112.00
Mean	36.51	13.76	89.58
3rd Quartile	56.00	17.00	113.00
Maximum	97.00	62.00	113.00

Publicly Traded	Planning Stage	Construction Stage	Open Months
Minimum	1.00	3.00	3.00
1st Quartile	7.50	10.00	74.00
Median	18.00	13.00	113.00
Mean	22.04	17.81	88.32
3rd Quartile	35.00	20.00	113.00
Maximum	75.00	62.00	113.00

Note: The full sample includes 941 properties that are open at some point, 134 that are planned at some point and 82 that are under construction at some point. For comparison, the same counts for the publicly-traded subsample are 145, 27 and 21.

Figure 3: Distribution of Time a Casino Property Spends in the Planning and Construction Phases

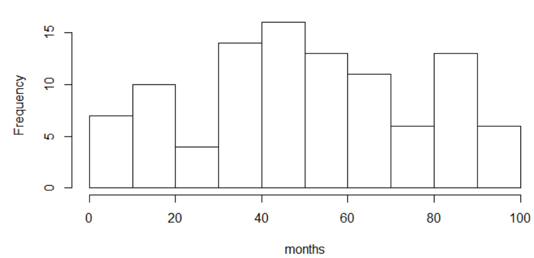
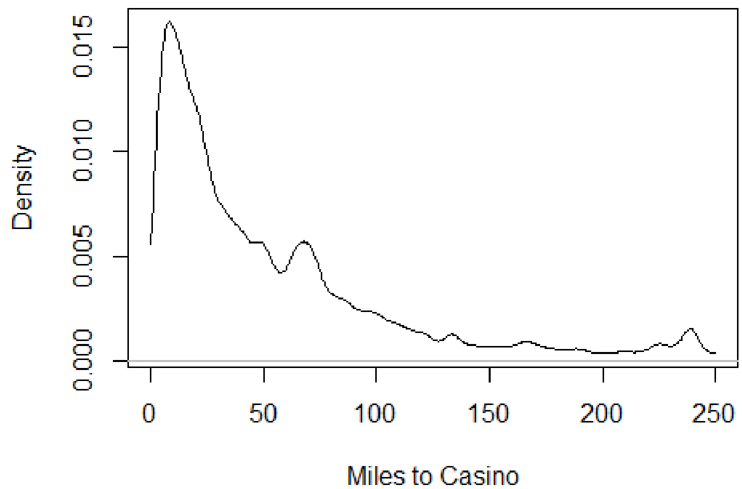


Table 2: Number of Months Entrant Properties Spent in Planning Stage, Under Construction or Open (Publicly Traded Sub-sample)

Property Id	Planned Months	Construction Months	Open Months
88000	0	3	110
534800	0	20	88
635800	0	14	76
637500	60	17	18
639000	31	5	61
639600	0	15	87
645700	13	54	30
646000	34	7	56
649400	0	43	48
651500	4	28	55
658400	26	12	37
694900	1	0	95
697800	12	25	39
701400	20	0	74
743100	29	18	44
746200	26	19	44
749800	0	6	33
759400	15	11	62
784100	28	7	42
920500	2	10	23
935600	8	21	3
765100	86	0	0
788600	18	62	0
794700	38	0	0
845700	39	0	0
849300	47	13	0
863100	36	0	0
869900	38	0	0
944200	16	13	0
961900	4	17	0
980300	8	0	0
981000	7	0	0
981300	7	0	0
1001600	2	0	0

Figure 4: Density Plot of Patron Distance to Casino



Note: This plot is censored at the 90th percentile patron distance to casino. The source is my proprietary casino ATM withdrawal data set.

Another important fact about the casino industry is that gambling markets tend to be local. Figure 4 portrays this fact by presenting a density plot of patron distance to casino that is computed using my proprietary casino ATM withdrawal data set.[23] For clarity of exposition, the plot is censored at the 90th percentile, but approximately 75 percent of patrons who make transactions at casino ATMs live within 100 miles of the casino. As will become apparent in the empirical section, the local nature of the casino industry allows me to use geographically-concentrated responses to the threat of entry to empirically measure preemptive investment.

3.3 Publicly Traded Firms and Stock Market Information

The event study in Section 5 uses stock market data. Relative to the Gaming Business Directory data, the use of stock market data introduces two empirical issues that affect the interpretation and generalizability of the event study results.

First, using stock market information restricts the sample on the basis of whether a firm is publicly traded. As Table 3 illustrates, publicly traded casino firms tend to be larger than private firms. To the extent that larger casino firms behave differently with respect to entry deterrence, this data limitation limits the scope of inference to large casino firms that resemble publicly-traded firms.

Second, stock market information is only available at the firm level, yet entries affect individual casinos. Hence, entry is likely to have a larger effect on firm value for firms that own fewer casinos. In the event

[23]These proprietary data allow me to identify patron transactions and home ZIP codes for 8.5 million withdrawal transactions. I describe this data set in more detail in Section 6.

Table 3: Comparison of Publicly-Traded Sample to Full Sample, Own and Rival Attributes

Attributes of Casinos Owned by Publicly-Traded Firms

	Whole Sample	Publicly Traded
Fraction with Hotel	0.37	0.64
Hotel Rooms	610.47	1023.32
Restaurants	2.90	5.42
Slot Machines	746.11	1291.00
Entertainment Venues	0.91	1.72
Number of Table Games	18.69	38.25
Number of Poker Tables	3.95	6.30
Casino Size (Sq. Ft.)	38405.77	51771.59
Parking Spaces	882.69	1863.30
Employees	870.21	1630.72

Average of Rival Attributes for Casinos Owned by Publicly-Traded Firms

	Whole Sample	Publicly Traded
Fraction with Hotel	0.42	0.52
Hotel Rooms	498.38	754.32
Restaurants	3.58	4.62
Slot Machines	841.28	1080.30
Entertainment Venues	1.09	1.45
Number of Table Games	21.70	31.41
Number of Poker Tables	4.87	5.43
Casino Size (Sq. Ft.)	43474.11	47350.36
Parking Spaces	1049.18	1426.21
Employees	915.49	1261.61

Note: The means in this table are computed on the casino-month level data set. Casinos in the publicly traded subsample are those for which the casino vendor database provides casino stock ticker information. The means in this table are computed by taking the mean of each attribute for all casinos within 100 miles of a casino, except for those owned by the same owner as the casino in question.

study, I account for this heterogeneity by computing the fraction of incumbent casinos affected by each entry event, and using this measure as a control variable in specifications for determinants of the effect of entry.

These restrictions on inference and interpretability only affect the results that use financial data, and hence do not affect all of the results in the paper. In particular, the attribute event windows and hazard model estimates in Section 4 rely solely on the Gaming Business Directory data, and consequently, do not restrict the sample to the larger publicly traded firms.

4 Evidence on Entry Deterrence

This section documents two key facts about how incumbent casinos respond to an entry plan: (1) Incumbents preemptively adjust casino capacity during the planning stage of rival casinos *prior* to opening, and (2) These adjustments in casino capacity appear to deter or delay entry.

4.1 Incumbent Adjustments to Casino Capacity

Using the 134 entry plans in the data set, this section investigates how incumbent casino size (in square feet) adjusts during a 37-month window around the first month of the planning stage (12 months prior to 24 months after first planning). This wide event window allows me to observe incumbent investments that occur with some construction delay, as well as investments by incumbents that learn of impending entry prior to the public announcement in my data set.[24] To ensure that composition changes in the market (due to entry) do not bias the results, I base my calculations of incumbent response to entry on the sample of established incumbents – casinos that were present at the beginning of the data set (March 2003).[25]

My strategy to identify the incumbent response to the threat of entry relies on the premise that incumbent casinos nearest to the proposed entry site have the strongest incentive to engage in entry deterrence. In particular, I measure incumbent capacity[26] in a three-year event window surrounding the 134 entry plans for incumbents within 100 miles, and as a comparison group, incumbents between 100 and 200 miles from the proposed entry site. This comparison controls for unobserved factors influencing the entry decision because incumbents between 100 and 200 miles from the proposed site share unobservables that depend on geography (local regulation, changes in regional economy, etc.), but these casinos have a weaker incentive to react to entry plans. Hence, the observed difference between nearby incumbents (within 100 miles) and those farther away (100-200 miles) plausibly reflects the strategic response to entry plans.[27]

Figure 5 portrays how incumbent casino capacity evolves around first planning of rival casinos, separately for stalled entry plans versus successful entry plans. Consistent with the theory that incumbents

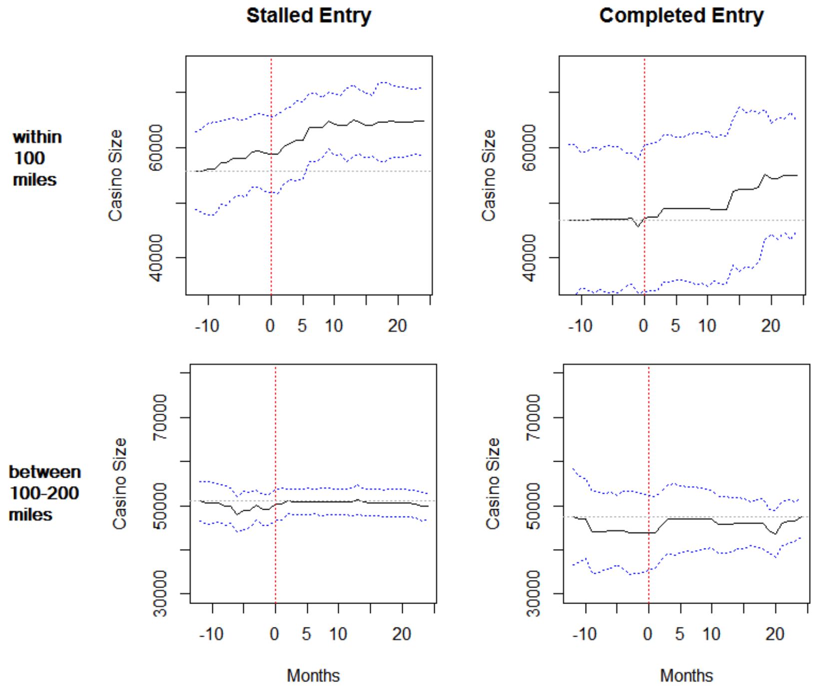
[24]In the model, the assumption is that incumbents learn of the potential entrant's plans at date 0, but this does not need to be true for my event window approach to measure strategic investments by incumbents. By observing incumbent capacity for a year prior to my observation of entry plans, I allow incumbents to have better knowledge of entry plans than the econometrician.

[25]As there is negligible exit of established casino properties from the casino industry in the sample, this sampling restriction on incumbents guarantees that the sample composition does not change.

[26]For each entry event and each lag (-12 to +24 months), I compute the average casino size of established incumbents. At each lag, I compute the median across events of average incumbent capacity. This median is my lag-level measure of incumbent capacity.

[27]To the extent that incumbents between 100 and 200 miles respond to entry plans, this difference-in-difference comparison will understate incumbent response to entry plans. Moreover, my estimate is based on the average incumbent response within 100 miles. In theory, the response of the nearest incumbents (within 50 miles for example) would be stronger still.

Figure 5: Incumbent Casino Capacity Adjustments Around Entry Plans



Note: For each lag relative to first planning, the figure plots the median of event-level data on average incumbent casino size. Pointwise 90 percent confidence bands (conducted using a bootstrapping procedure) are depicted in blue.

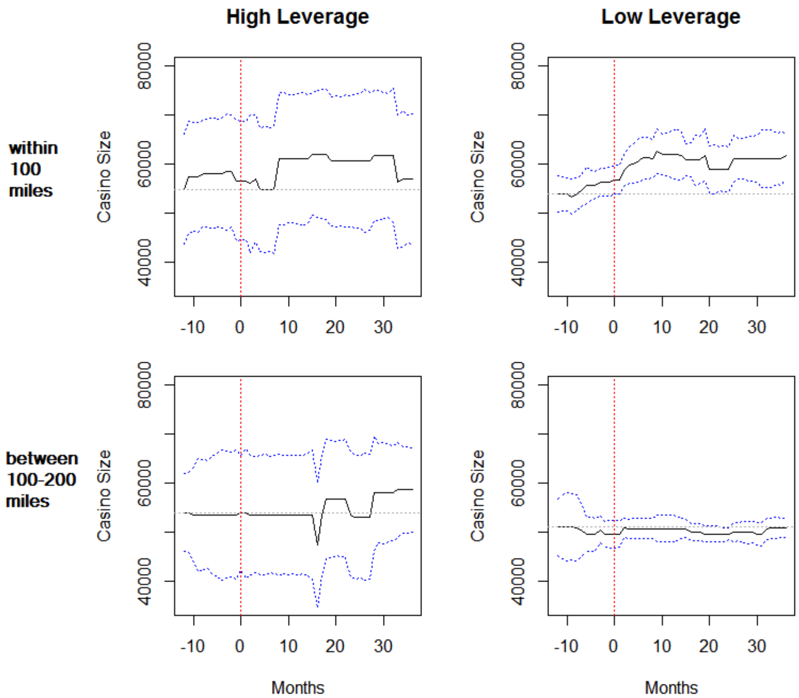
strategically adjust capacity to prevent entry, the median incumbent casino size for stalled entry plans increases much earlier than for the typical completed entry plans. Relative to casino size 12 months prior to the planning event, deterring incumbents – those near entry plans that eventually stall – expand capacity by approximately 8300 square feet (14.9%) on average by 12 months after the planning event, while incumbents near successful entry plans increase capacity by much less in this initial phase, approximately 2000 square feet (4.2%). The increase in capacity for incumbents near stalled entry plans is statistically significant,[28] while increase in capacity near completed entry plans is not. As the 100-to-200-mile incumbent panel illustrates, there is no similar pattern for incumbent casinos in the control group, which suggests that the capacity expansion we observe is a strategic response to entry plans.

Preemptive capacity expansions can be used for entry deterrence as well as entry accommodation, and this figure suggests that entry deterrence is an important motive. I consider this distinction in more detail in my entry hazard model in Section 4.2, as well as my analysis of post-entry market shares of entrants in Section 6.[29]

[28] In this context, statistically significant means that the confidence interval at 12 months after first planning does not contain the capacity at the beginning of the event window. In addition, I have run a matched-pairs t-test for the difference in means between the initial capacity and capacity at 24 months after first planning. This difference in means is statistically significant at the one percent level with a t-stat of 4.46. More rigorously, Section 4.1.3 presents difference-in-difference tests based on the fact that the nearest incumbents have the strongest incentive to respond to entry.

[29] For stalled entry plans, incumbents begin to adjust capacity slightly prior to the planning event. For completed entries, incumbents adjust capacity, but at approximately a year lag relative to incumbents of failed entries. The model does not speak to the timing of capacity adjustments, but it is intuitive that capacity adjustments for entry deterrence need to be made earlier in order to signal to the entrant that there is no room to make profit. To be more effective as an entry deterrent, these capacity adjustments should be

Figure 6: Leverage and Capacity Adjustments



Note: For each lag relative to first planning, the figure plots the median of event-level data on average incumbent casino size. Pointwise 90 percent confidence bands (conducted using a bootstrapping procedure) are depicted in blue.

4.1.1 Leverage and Capacity Adjustments

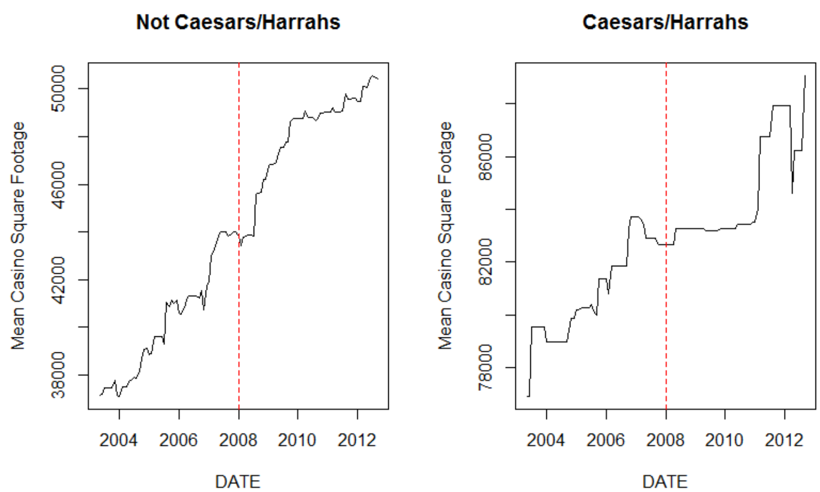
To explore the extent to which debt matters for an entry deterrence strategy, I use the debt-to-assets ratio as a measure of leverage[30] of the publicly-traded firms in the sample. To construct an attribute event window plot similar to Figure 5, I split the sample of entry plans into high incumbent leverage and low incumbent leverage using the median debt-to-assets ratio of incumbents (0.652).

According to Figure 6, low leverage incumbent firms expand capacity much more than high leverage firms. At the median, low leverage incumbent firms expand capacity by nearly 30 percent from one year before the first planning event to one year after. In contrast, high leverage incumbent firms do not adjust capacity appreciably. Similar to my other results on capacity adjustment, the comparison with incumbent casinos that are 100 to 200 miles away alleviates the concern that geographic determinants of casino firm leverage (rather than financial constraints) drive this result. In other words, it appears that leverage itself – rather than market-specific factors – affects how incumbents respond to entry plans.

made before the entrant commits too much to the project (before breaking ground on construction, for example). Accommodative capacity adjustments do not need to give the entrant enough warning to abandon the project, but just enough warning for the entrant to adjust its own capacity.

[30]For each entry plan, I compute the average leverage among publicly-traded incumbent firms within 100 miles.

Figure 7: The Caesars LBO and Investments in Established Casino Properties



4.1.2 Evidence from the Caesars Leveraged Buyout

Figure 6 relies on variation in the debt-to-assets ratios of publicly traded firms. Although this variation is useful for understanding the effect of leverage, focusing on publicly traded firms leaves out the casino industry's most prominent example of how debt can matter for product market strategies – the 2008 leveraged buyout (LBO) of Caesars Entertainment.[31] Ever since the LBO, Caesars has been heavily in debt with $22.5 billion in debt as of 2012. In fact, Caesars Entertainment's interest expense approximately equals its pre-tax cash flow. As financial commentator Robert Cyran put it, "That makes it hard to spruce up new casinos or build new ones."[32]

As evidence to this point, consider Figure 7, which uses the Gambling Business Directory data to compare the average size of established Caesars-owned casino properties over time to the average size of established non-Caesars casino properties. After the LBO in early 2008, Caesars casinos made virtually no expansions to their existing properties while non-Caesars properties continued to make investments (serving as a control for the 2008-9 recession).

Moreover, as Figure 8 demonstrates, the fact that Caesars Entertainment was unable to invest in its existing properties prevented Caesars from making strategic investments in response to entry plans around this time. Thus, compared to other large casino firms, Caesars Entertainment's debt inhibited it from making potentially profitable strategic investments that could ward off new and costly competition.

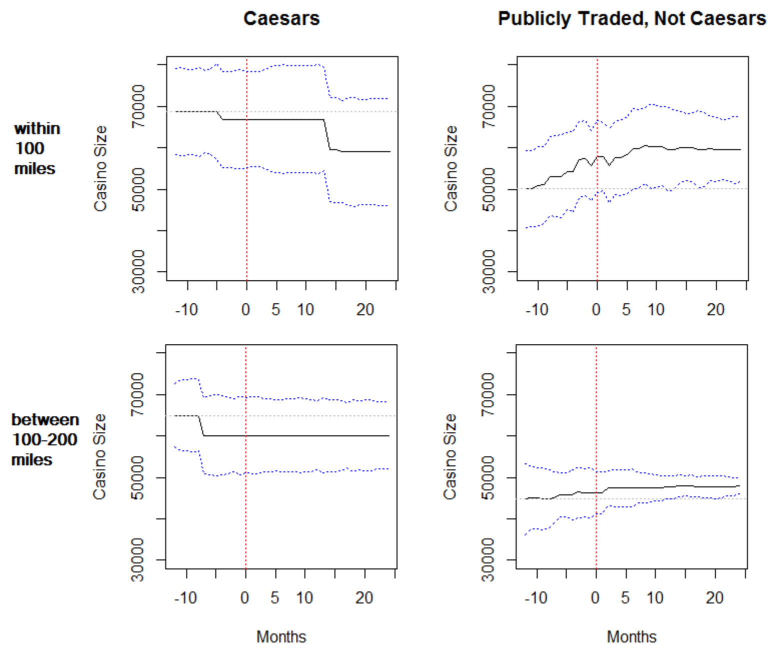
4.1.3 Fee-into-Trust Entry: Incumbent Response to High Cost Entrants

Rather than conditioning on *ex post* success of entry, another way to evaluate entry deterrence is to focus on incumbent response to *ex ante* high-cost entrants who are more likely to be swayed by incumbent capacity

[31] At the time of the LBO by Apollo Management and Texas Pacific Group, Caesars Entertainment as named Harrah's Entertainment. It was renamed after its most famous Las Vegas property.

[32] See Breakingviews commentary here. http://www.breakingviews.com/how-does-a-$31-bln-mega-lbo-become-an-$18-mln-ipo?/20047528.article

Figure 8: Strategic Investments by Caesars versus non-Caesars Casino Firms



Note: For each lag relative to first planning, the figure plots the median of event-level data on average incumbent casino size. Pointwise 90 percent confidence bands (conducted using a bootstrapping procedure) are depicted in blue.

adjustments. In particular, 41 percent of entry plans in my sample were Indian casino projects that required an involved process called a fee-into-trust transfer.[33] Despite their recent prevalence, fee-into-trust transfers of land for the purpose of Indian gaming were the exception rather than the rule until recent changes to Department of Interior policies regarding fee-into-trust applications.[34] Even with these recent changes in policy, fee-into-trust entries involve significant sunk costs of entry (significant paperwork, public hearings, applications to the Department of the Interior) that are not felt in other types of entry. According to the model of entry deterrence, incumbents should respond more aggressively to fee-into-trust entry plans than other types of entry because fee-into-trust entry plans are more likely to be deterred.[35]

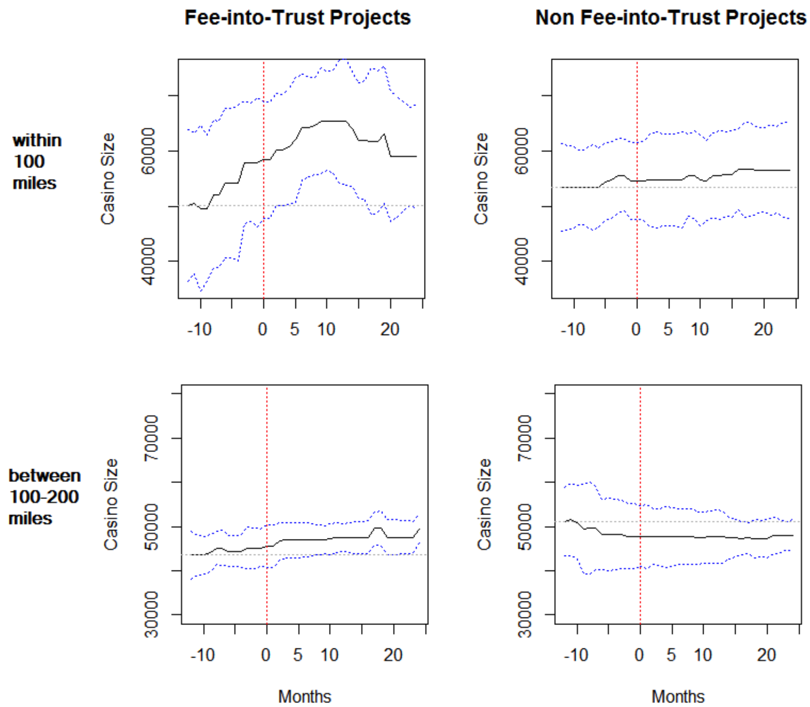
Based on Figure 9, which portrays incumbent casino capacity adjustments to fee-into-trust entry plans versus adjustments to non-fee-into-trust entry plans, incumbents respond dramatically to fee-into-trust entry plans while non-fee-into-trust projects elicit little capacity adjustment by incumbents about the time of first

[33]Fee-into-trust transfers convert non-reservation land (held in fee simple) into reservation trust land (held in trust by the Department of the Interior for the benefit of the tribe). This is significant because the Indian Gaming Regulatory Act (IGRA) requires Indian casinos to be built on reservation trust land. In addition, IGRA explicitly precludes taking land into trust for the purpose of gaming unless exceptions are met.

[34]For 120 entry plans observed prior to June 2011, I compiled the information for the fee-into-trust variable by conducting web searches for the casino name and "land trust" or "fee-into-trust." If there were news articles on the web regarding the casino's fee-into-trust application, the casino was classified as a fee-into-trust entrant. As this process requires public approval, the news coverage of the issue is comprehensive.

[35]By the time entry plans are observed in my data, fee-into-trust entries have not yet sunk a significant fraction of these planning period costs. With this timing, it makes sense to think of fee-into-trust entry plans as having higher fixed sunk cost of effective entry than non-fee-into-trust entry plans.

Figure 9: Incumbent Casino Capacity Around Entry Plans: Fee-into-Trust Projects



Note: For each lag relative to first planning, the figure plots the median of event-level data on average incumbent casino size. Pointwise 90 percent confidence bands (conducted using a bootstrapping procedure) are depicted in blue.

planning. As in Figure 5, the comparison to the non-response of incumbents that are 100 to 200 miles away from the proposed site indicates that this finding is not driven by unobserved geographic factors, but likely represents the strategic response of incumbents.

4.1.4 Difference-in-Difference Tests

I also conduct a set of difference-in-difference tests that rely on the same intuition as Figures 5 through 8 to identify a strategic effect of entry plans on incumbent capacity adjustments. To do so, I construct a data set containing the capacity choices of each incumbent within 200 miles of each proposed entry site and whether the incumbent is within 100 miles or between 100 and 200 miles from the proposed site. Further, to test whether incumbent capacity significantly increased over the event window (-12 months to 24 months), restrict the incumbent data to observations on established incumbents in those two periods relative to the entry plan.

Formally, I estimate the regression model to compute difference-in-difference estimates:

$$casino.size_{ijt} = \gamma_i + \beta_1 after + \beta_2 nearby + \beta_3 after \times nearby + \varepsilon_{ijt} \tag{1}$$

where i indexes incumbents j indexes entrants, $after$ equals 1 if $t = +24$ and 0 if $t = -12$, $nearby$ equals 1 if the incumbent is within 100 miles of the proposed site, and γ_i are incumbent fixed effects that control for unobserved characteristics of the incumbent casino owners. The coefficient of interest is β_3, which estimates the mean difference between how nearby (within 100 miles) incumbents change capacity and how incumbents farther away (100-200 miles) change capacity.

Table 4 presents the results of these difference-in-difference tests for various subsets of entry plans. The results in Table 4 generally corroborate the graphical evidence on incumbent capacity adjustment.

Most strikingly, low leverage incumbents exhibit an economically important and highly statistically significant capacity response to entry plans. Both the difference-in-difference estimate (comparison with incumbents 100-200 miles) and the triple difference estimate (additional comparison of low leverage with high leverage firms) indicate that low leverage firms are more aggressive in investing preemptively in capacity than high leverage firms. Moreover, the null results on the control group of incumbents between 100 and 200 miles from the proposed entry site suggest that this pattern of investments is not driven by unobserved regional factors such as local regulation or local demand shocks.[36]

Panels B and C of Table 4 present the results from splitting the sample by stalled entries and fee-into-trust entry plans. Although the difference-in-difference estimates are not statistically significant, the relatively large magnitude for the estimates on stalled entry plans and fee-into-trust plans is consistent with the findings of the previous sections. Indeed, for both fee-into-trust plans and stalled plans, the response of incumbents within 100 miles is statistically significant and large (5940 to 8425 square feet), but for these entry plans, there appears to be a change in capacity (albeit a smaller change in capacity) among incumbents between 100 and 200 miles from the proposed site. Taking all of these results together – especially the leverage results – the evidence suggests that incumbents respond to capacity for strategic purposes.

4.2 Relating Incumbent Capacity Adjustments to Rate of Entry

Using event-level measures of capacity adjustment from the previous section, I measure how incumbents preemptively respond to each entry event by the amount that incumbent casino capacity adjusts from 12 months prior to first planning to 12 months after first planning. This measure reflects that casino capacity takes time to install.[37] To empirically assess the role of preemptive incumbent capacity adjustments, I estimate the hazard function for the rate of transition of planned projects into the construction phase or open phase.[38] Specifically, I use a Cox proportional-hazards model with a log-linear model for the hazard function:

$$h_i(t) = h_0(t) \exp\left(X_i'\beta\right) \tag{2}$$

[36]According to Table 5, the set of incumbents within 100 miles of the proposed entry site is very similar to the set of incumbents between 100 and 200 miles of the proposed entry site. Splitting the sample by leverage, casinos owned by low leverage firms are slightly *smaller* than casinos owned high leverage firms. Hence, the large capacity adjustments indicated in the difference-in-difference estimates are even more important relative to average low leverage casino.

[37]Based on the median casino construction time of a casino of 9 to 13 months (see Table 1), incumbent plans to adjust capacity for the purpose of entry deterrence would occur before one year after first planning of a nearby rival if they were started immediately upon first planning.

[38]I estimate this hazard function to avoid the criticism that the estimates are driven by determinants of long-lasting construction projects, rather than genuine strategic interaction. In Appendix C.4, I present estimates of the hazard function for the rate of transition of planned/construction into open, and I find that the results are qualitatively unchanged, and strengthened in parts.

Table 4: Difference-in-Difference Tests for Incumbent Capacity Adjustment About Entry Plans

Panel A: Leverage

	$<$ 100 miles	100-200 miles	Difference
Low Leverage Incumbents	10600.37†	-3338.18	14920.74**
	(5902.89)	(2381.40)	(6541.61)
High Leverage Incumbents	583.17	6255.21*	-5321.73
	(3110.62)	(2723.75)	(3592.61)
Low Minus High Leverage	9961.90	$-$9250.71†	19613.19*
	(6676.73)	(4723.13)	(8066.07)

Panel B: Stalled Versus Completed

	$<$ 100 miles	100-200 miles	Difference
All Entry Plans	5424.79**	4011.52**	1371.10
	(1521.75)	(1386.12)	(1441.24)
Stalled Entry Plans	5915.05*	3669.64*	2201.21
	(2143.82)	(1430.87)	(2166.83)
Completed Entry Plans	4823.30**	4618.99*	208.12
	(1386.07)	(2129.30)	(1668.30)

Panel C: Fee-into-Trust Entries

	$<$ 100 miles	100-200 miles	Difference
Fee-into-Trust Entry Plans	8501.16**	4318.63**	4078.34†
	(2093.17)	(1626.28)	(2234.67)
Other Entry Plans	3828.34**	3895.45*	-41.27
	(1475.51)	(1886.95)	(1631.11)

Note: Each of estimate reported in this table is an estimate of the difference-in-difference coefficient β_3 from the regression specified in equation (1), which controls for incumbent owner fixed effects. Standard errors are clustered by incumbent property. To ensure robustness of this mean-based test to outliers, capacity values less than the 1st percentile and greater than the 99th percentile were winsorized prior to conducting the test.

Table 5: Balance of Attributes for Difference in Difference Tests

Panel A: Near and Far Incumbents

	within 100 miles	between 100 and 200 miles
Casino Size (Sq. Ft.)	46711.59	49886.58
Slot Machines	895.65	895.93
Number of Table Games	23.90	21.61
Number of Poker Tables	4.94	4.99
Convention Center Size (Sq. Ft.)	17289.32	9832.16
Hotel Rooms	513.92	288.23
Properties Owned	10.59	6.78
Restaurants	3.86	3.42
Entertainment Venues	1.20	1.10
Parking Spaces	1151.39	1087.21
Employees	981.40	809.33

Panel B: High versus Low Leverage

	Low Leverage	High Leverage
Casino Size (Sq. Ft.)	51615.88	56264.30
Slot Machines	1354.42	1486.83
Number of Table Games	35.65	45.64
Number of Poker Tables	6.26	7.19
Convention Center Size (Sq. Ft.)	28428.56	47017.55
Hotel Rooms	877.00	1090.44
Properties Owned	19.01	18.20
Restaurants	6.16	5.94
Entertainment Venues	1.65	2.34
Parking Spaces	2040.86	2247.44
Employees	1620.27	1808.30

where X_i includes characteristics of potential entrants, average characteristics for incumbents of the potential entrant, and market attributes, i indexes potential entrants, and t is time (in months) since announcement of the entry plan. Of particular interest, X_i includes measures of incumbent capacity and capacity adjustments around the time of entry plan. In addition to the size of the market, my attribute data allow me to control for the size of the planned casino (square footage, number of slot machines, number of table games, etc.) as well as other features of the entrant and and incumbent firms (number of properties owned, whether the casino property has a hotel, whether the casino is tribal, etc.).

The Cox proportional-hazards model in (2) is semi-parametric in the sense that one does not need to specify a functional form for the baseline hazard function $h_0(t)$ to estimate the effect of changes in the covariates on the hazard rate out of the planning stage. Without specifying the functional form of $h_0(t)$, the parameter vector β is identified so long as the effect on the hazard rate does not depend on the number of months since the announcement of entry. This restriction is nontrivial, but it is straightforward to test for violations in this assumption after estimating a particular hazard model.[39] Appendix C outlines technical details of estimation the Cox proportional hazards mode, including the form of the partial likelihood.[40]

Table 6 presents the estimates of the multiplicative effect on the hazard rate from the Cox proportional-hazards model. According to Column (1), an increase in incumbent casino size of one standard deviation is associated with 0.276 times the hazard rate out of the planning stage, and this estimated effect is statistically significant at the ten percent level using robust standard errors. Column (2) uses changes in incumbent casino size, which also exhibit a significant effect. A one standard deviation increase in incumbent capacity adjustment is associated with 0.730 times the hazard rate out of the planning stage, and this effect is statistically significant at the five percent level. In addition, Column (3) demonstrates that the effect of capacity adjustments persists (in fact, gets stronger) controlling for incumbent casino size. A one standard deviation increase in the casino capacity adjustment in the two-year window around the first planning event is associated with 0.675 times the hazard rate, relative to the mean increase in incumbent casino capacity. This estimate is statistically significant at the one percent level.

The entry deterrence model predicts that expanding capacity is less effective in deterring entry of stronger entrants. To test for this effect, I also estimate specifications with a dummy variable for whether the entrant is publicly traded. Publicly-traded status signifies experience in the casino industry, and thus, it is a proxy for strength of the entrant.[41] Columns (4) and (5) include this dummy variable, as well as interactions of this dummy with the incumbent capacity and capacity expansion variables. After accounting for the interaction with the publicly traded entrant dummy, the effect of large incumbent size and large capacity

[39]Grambsch and Therneau (1994) nest the proportional hazards model within a time-varying coefficient model for the hazard. The authors develop a test, and a set of diagnostics, for non-proportional hazards, i.e., that β is not constant over time. Their form of this test is implemented in the R `survival` package using the `cox.zph()` function. In Appendix C.5, I present the result of this test, which fails to reject the proportional hazards assumption.

[40]As I discuss in the appendix, the literature provides a number of techniques and approximations to the true form of the partial likelihood function from the Cox proportional hazards model in the presence of tied survival times (as is the case here). Because of its computational attractiveness and superior performance relative to other approximations, I use the Efron (1974) approximation to the Cox proportional hazards partial likelihood for all of the specifications in the main text. Appendix C presents estimates that use the Breslow approximation to assure that the qualitative results do not depend on this choice.

[41]In the model of strategic entry deterrence, recall that entrant strength depends on the magnitude of sunk costs of entry. The argument in the text is that publicly-traded firms have a lower sunk cost of entry into new markets because they already have experience with the industry.

Table 6: Determinants of the Hazard Rate out of the Planning Stage

	(1)	(2)	(3)	(4)	(5)
Incumbent Capacity Variables					
Casino Size (Z)	0.276†		0.197**	0.102*	0.115**
	(−1.815)		(−2.164)	(−2.733)	(−2.705)
Capacity Adj (Z)		0.730*	0.675**	0.820	0.698†
		(−2.749)	(−2.592)	(−1.417)	(−1.771)
Casino Size (Z) × Pub Entrant					4.666†
					(1.907)
Capacity Adj (Z) × Pub Entrant					1.884*
					(2.165)
Market Controls					
Open Casinos	0.997	0.998	1.000	0.991	0.992
	(−0.296)	(−0.166)	(−0.030)	(−0.895)	(−0.987)
Convention Center Size (Z)	0.445	0.393	0.388	0.525	0.640
	(−1.372)	(−1.318)	(−1.520)	(−1.394)	(−0.969)
Properties Owned (Z)	0.820	0.925	0.787	0.678*	0.757†
	(−1.211)	(−0.552)	(−1.435)	(−2.129)	(−1.827)
Slot Machines (100s)	1.195	0.930	1.540	0.897	0.551
	(0.342)	(−0.175)	(0.849)	(−0.207)	(−0.923)
Hotel Rooms (100s)	1.129	1.124	1.114	1.107	1.076
	(1.077)	(0.931)	(0.945)	(0.835)	(0.555)
Parking Spaces (Z)	1.127	0.465	0.829	2.312	2.031
	(0.118)	(−0.814)	(−0.192)	(0.976)	(0.736)
Employees (100s)	1.649	1.974	2.344	2.245	2.444
	(0.503)	(0.639)	(0.873)	(1.050)	(0.936)
Entrant Attributes					
Publicly Traded				2.633†	3.495†
				(1.785)	(1.944)
Casino Size (Z)	1.043	1.084	1.166	1.326*	1.438**
	(0.287)	(0.623)	(1.156)	(2.106)	(2.681)
Convention Center Size (Z)	1.770*	1.886**	1.875**	1.950**	1.949**
	(2.431)	(2.664)	(2.785)	(3.065)	(3.235)
Properties Owned (Z)	1.617**	1.757**	1.664**	1.372**	0.757**
	(3.458)	(4.706)	(4.068)	(3.040)	(3.433)
Slot Machines (100s)	1.291	1.328	1.336	1.196	1.078
	(1.319)	(1.526)	(1.575)	(0.931)	(0.343)
Hotel Rooms (100s)	0.918**	0.913**	0.917**	0.928**	0.915**
	(−2.550)	(−2.506)	(−2.572)	(−2.735)	(−3.401)
Parking Spaces (Z)	0.942	0.886	0.852	0.660**	0.723†
	(−0.375)	(−0.693)	(−1.000)	(−2.186)	(−1.650)
Employees (100s)	0.850**	0.831**	0.831**	0.829**	0.823**
	(−3.247)	(−4.351)	(−4.468)	(−4.533)	(−4.811)
R-squared	0.296	0.304	0.329	0.381	0.409
Observations	124	124	124	124	124
Number of Events	55	55	55	55	55

Note: Estimates of the Cox proportional hazards model, using the Efron (1974) approximation to the partial likelihood. Wald Z-scores in parentheses. Standard errors are from a robust variance-covariance matrix. †, $*$, and $**$ indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpretation.

Table 7: Determinants of the Hazard Rate out of the Planning Stage with Fee-into-Trust Information

	(1)	(2)	(3)	(4)	(5)
Fee-Into-Trust Entrant		0.398^{*}	0.542	0.562	0.593
		(-2.251)	(-1.444)	(-1.321)	(-1.102)
Incumbent Capacity Variables					
Casino Size (Z)	0.199^{*}		$0.252^{\dagger}$	0.167^{*}	0.158^{*}
	(-2.211)		(-1.846)	(-2.210)	(-2.161)
Capacity Adj (Z)	0.642^{**}		0.685^{*}	0.803	0.699
	(-2.833)		(-2.442)	(-1.396)	(-1.553)
Casino Size (Z) × Pub Entrant					$4.687^{\dagger}$
					(1.899)
Capacity Adj (Z) × Pub Entrant					1.651
					(1.631)
Entrant Attributes					
Publicly Traded				3.232^{*}	4.278^{**}
				(2.536)	(2.765)
R-squared	0.387	0.365	0.401	0.422	0.447
Observations	112	112	112	112	112
Number of Events	55	55	55	55	55

Note: Estimates of the Cox proportional hazards model, using the Efron (1974) approximation to the partial likelihood. Wald Z-scores in parentheses. Standard errors are from a robust variance-covariance matrix. $\dagger$, $*$, and $**$ indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpretation. Column (1) is the same specification as Column (3) of Table 6. Also, each specification in this table also includes the full set of entrant, market and incumbent controls that are reported in Table 6.

adjustments is negligible if the potential entrant is publicly traded.[42] Hence, these specifications provide evidence that entry deterrence is most effective when the entrant is relatively weak or inexperienced.

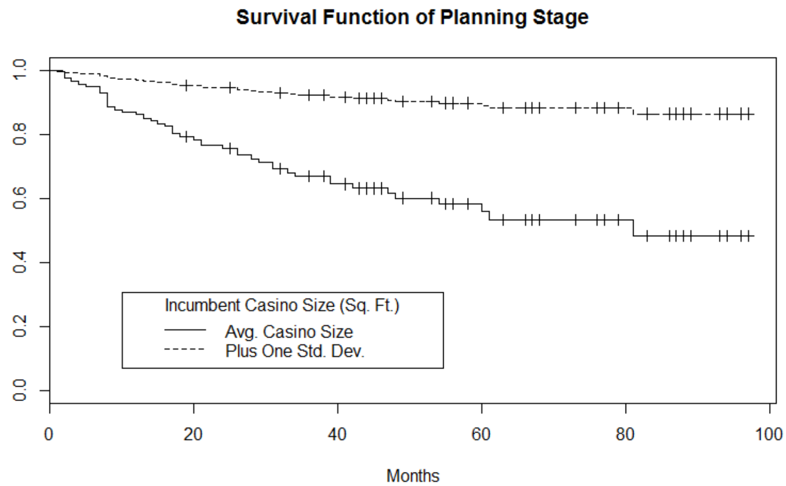
Table 7 presents similar specifications to Table 6, but conditioning on whether the potential entrant requires a fee-into-trust transfer to enter. The estimates imply that incumbent capacity and preemptive capacity adjustment have explanatory power above and beyond fee-into-trust status. For example, in column (3), incumbent casino size and capacity adjustment are statistically significant at the ten and five percent level, respectively. As predicted, fee-into-trust status by itself is associated with a lower hazard out of the planning stage. The coefficient on the fee-into-trust dummy variable is statistically and economically significant by itself, but it is not statistically significant when incumbent capacity variables are included.

As an alternative visualization of these effects, Figure 10 portrays the estimated survival function from Column (3) of Table 6, and how the estimated survival functions depends on the incumbent casino size. Consistent with my classification of stalled entry plans, the estimated survival function is essentially flat after 36 months to 48 months. 41.6 percent of entry plans transition out of planning at the average incumbent casino size compared with 13.9 percent of entry plans when incumbent casino size is one standard deviation above the mean. Taking the estimated survival probability at the 48-month mark to be the estimated fraction of deterred entries, a one standard deviation in casino size increases the estimated fraction of deterred entry plans by 47 percent.

Similar to Figure 10, Figure 11 portrays the effect of a one standard deviation increase in capacity

[42]The multiplicative effect on the hazard of a standard deviation increase in capacity adjustment is actually positive 1.31, but this effect is statistically indistinguishable from no effect (1).

Figure 10: Survival Function of Projects in the Planning Stage – The Effect of Incumbent Casino Size

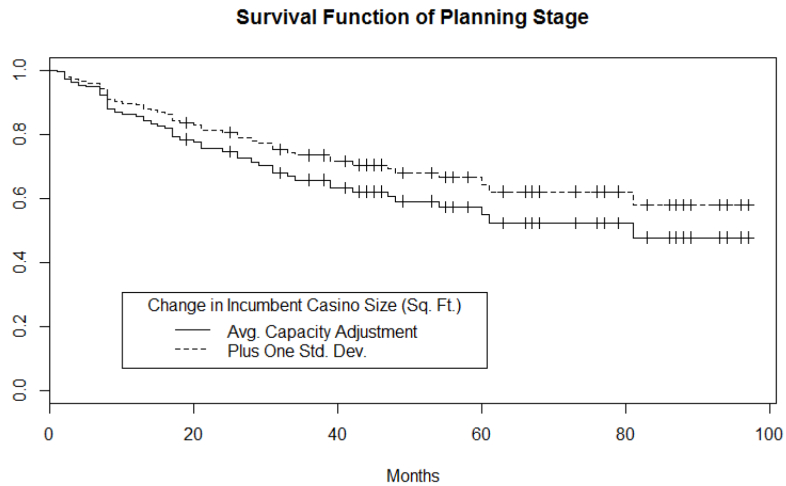


Months After Plan	Avg.	+ 1 sd
12	0.850	0.956
24	0.736	0.918
36	0.649	0.887
48	0.584	0.861

adjustment. Even though the standard deviation of capacity adjustment is smaller than the standard deviation of casino size ($9715 < 66791$ square feet), the effect of a standard deviation increase in capacity adjustment is economically important. For the average capacity adjustment, 40.9 percent of entry plans transition out of the planning stage, but for one standard deviation above the mean capacity adjustment, only 32.0 percent transition out of the planning stage. A standard deviation increase in capacity adjustment increases the estimated fraction of deterred entry plans by 15.1 percent. Both large incumbent casinos and large casino capacity adjustment lead to significantly more stalled casinos, which suggests that large capacity and capacity adjustments during a rival's planning stage are effective mechanisms through which incumbent casinos can preclude entry.

The pattern of results in this section is consistent with strategic entry deterrence; it is inconsistent with unobserved demand shocks. Additional demand would lead to a greater chance of success in entering the casino market *and* more casino capacity for incumbent casinos, yet my results robustly point to a negative correlation between incumbent capacity adjustment and likelihood of entry. Unobserved demand shocks thus imply that my estimated effect of capacity adjustments is a lower bound for the effectiveness of capacity adjustments to deter entry.

Figure 11: Survival Functions of Projects in the Planning Stage – The Effect of Incumbent Casino Size



Months After Plan	Avg.	+ 1 sd
12	0.857	0.893
24	0.746	0.807
36	0.658	0.735
48	0.591	0.680

5 The Effect of Entry using Incumbent Stock Market Performance

This section presents an event study (as in Eckbo 1983) to analyze the effect of anticipated entry on the value of incumbent casino firms. The stock market evidence provides an additional check on the nature and form of strategic entry deterrence, which complements my analysis of capacity adjustments and entry plans.

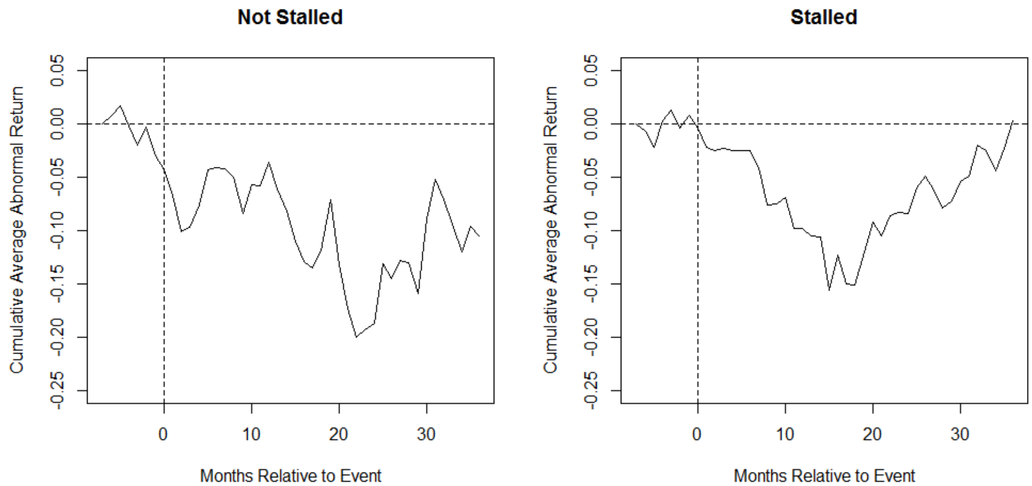
Each comparison in this section relies on changes in industry-abnormal returns for incumbent firms over a window of time surrounding entry events. After obtaining abnormal returns for each entry plan event and each lag relative to the date of the entry plans, compute average industry-abnormal[43] return at each lag by averaging across entry events. Given these calculations, the cumulative average abnormal return (CAAR) is the cumulative sum of the average abnormal returns since the beginning of the event window.

5.1 Stalled Entry Plans versus Effective Entry

To quantify the benefit of entry deterrence, Figure 12 depicts the cumulative return (CAAR) of incumbent firms separately for stalled entries and effective entries over an event window from 6 months prior to first planning to three years after first planning. Taking the difference in CAAR by the end of this event window to be the effect of entry, this comparison implies that deterring an entry event increases incumbent firm value

[43]Average industry-abnormal returns are computed by subtracting the equal-weighed casino industry average return for each month, then computing the market share weighted average of return among publicly-traded firms within the specified radius. If R_{it} is the return for firm i in month t and $\bar{R}_{it}$ is the casino industry average, abnormal return is $R_{it}^{abn} = R_{it} - \bar{R}_{it}$.

Figure 12: The Stock Market Effect of Entry Deterrence



by 10.4 percentage points, on average.

On initial news of an entry plan, incumbent firms that eventually deter entry experience a significant negative shock to stock market value. As information becomes available about the eventual failure of the nearby entry plan, the stock market value of incumbent firms returns to its initial value. This pattern of cumulative incumbent returns over the event window suggests that information about the eventual failure of the stalled entry events becomes available to the market gradually over the three-year period following the first planning event.

Figure 12 gives a measure of the average effect of entry on incumbent stock market value, but in theory, this effect should vary with incumbent firm characteristics. An obvious characteristic that matters for the effect of entry on firm value is the number of properties owned. All else equal, the stock market return for incumbent firms that own many properties will be less sensitive to an entry event than for firms that own few properties.[44] Viewed this way, this feature of how entry should relate to changes in incumbent firm value should be automatic. Splitting entry events by the number of properties incumbent casino firms own can, therefore, provide a stress test of the results.

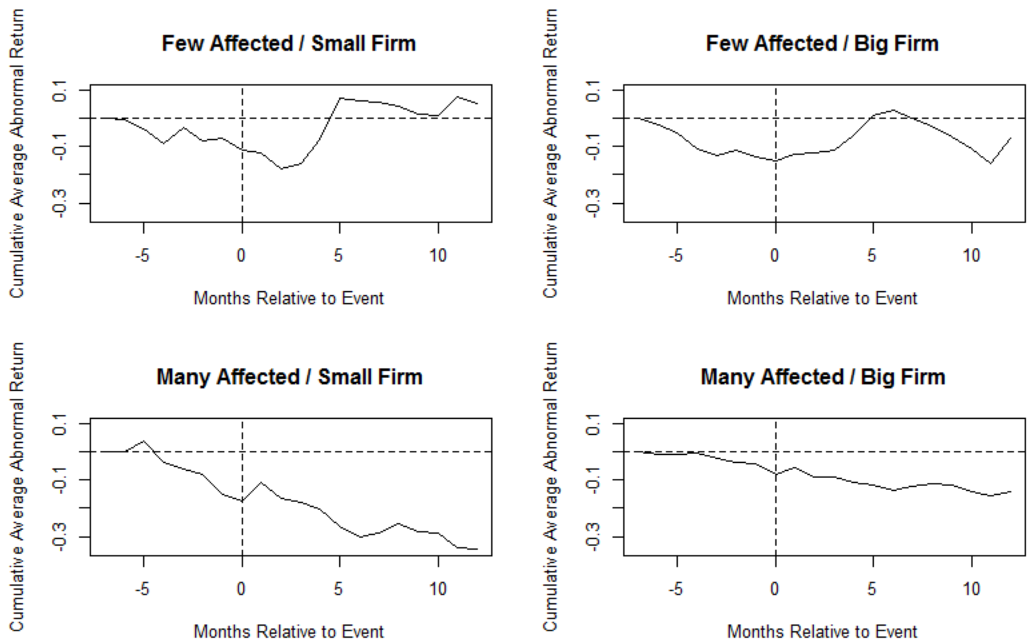
Incumbent firms also vary by the number of casinos they own near the proposed site of the potential entrant. All else equal, incumbent firms that own many properties that are affected by a particular entrant should exhibit a greater effect of entry. By this logic, firms that own few casino properties (small firms), but nevertheless, have multiple properties that are affected by the potential entrant will exhibit the greatest effect of entry.

To evaluate these hypotheses, Figure 13 splits the first opening entry events[45] into four sub-samples

[44]For example, the effect of entry on one incumbent casino should have a smaller stock market impact on a firm with 20 casino properties than it would on a casino with 4 casino properties.

[45]I used first opening events because the larger sample size facilitates breaking the stock market response into four groups. I also produced the same result using first planning events, and this is reported in Appendix C. As the plot in Figure 20 demonstrates, the same pattern as in the first opening events holds, but the magnitude is larger (CAAR: greater in magnitude than -50 percent for the many affected, small firm bin). The extremely large magnitude is due to the fact that this cell (many affected, small firm) has

Figure 13: Cumulative Average Abnormal Return by Average Number of Properties Owned and Average Number of Properties Affected (First Opening Events)



based on whether incumbent firms own fewer/more than two casinos near the potential entrant (few/many affected) and whether incumbent firms own fewer/more than 15 casinos properties (small/big firm).

As expected, the effect of entry is strongest in markets where incumbents are most sensitive to entry. Using the set of first opening events, the CAAR of incumbent firms with an average of 15 or fewer properties that also own an average of two or more affected casinos is -34.3 percentage points. In contrast, for markets where incumbents own few casinos near the entrant, the effect of entry is negligible. This pattern is consistent with both hypotheses regarding how incumbent firm value depends on sensitivity to entry. For the subset of entry events where incumbent firms own two or more affected casinos on average, entry events where firms have more than 15 properties on average yield a CAAR of -14.0 percentage points, which is a significantly smaller effect of entry than for incumbent firms with few properties.

5.2 Explaining the Effect of Entry

The relationships in Figure 13 are intuitive and the pattern of results is reassuring because stock market return measures the percentage change in firm value. To more rigorously control for heterogeneity in the effect of entry and other observable features of the market, I estimate a regression of the cumulative abnormal return (CAR) on a set of covariates that capture the heterogeneity in market characteristics:

$$CAR_i = \alpha + \beta_1 stalled_i + X_i' \beta + \varepsilon_i \quad (3)$$

very few entry plans in it (yet these incumbent firms fared extremely poorly), but the sign and order of effects correspond well to a standard intuition of how this type of heterogeneity should enter into the effect on firm value whether first opening or first planning events are used.

where CAR_i is the rival's cumulative abnormal return (CAR) for event i,[46] $stalled_i$ is a dummy variable for whether the entry plan eventually stalled, and X_i is a vector of explanatory variables that includes a Herfindahl-Hirschman Index based on ownership of casino capacity to capture market concentration effects (casino size HHI), the average fraction of incumbent casino holdings affected by the entrant in question ($fracprops$),[47] the average debt-to-assets ratio in the market ($leverage$), incumbent attributes, and entrant attributes.

The sample used to estimate (3) is a selected sample because there must be at least one publicly traded incumbent casino firm to compute cumulative abnormal return for the entry event. Publicly-traded firms tend to be larger than non-publicly traded firms (see Table 3). For this reason, the selected sample may over-represent firms that are stronger, and potentially better able to engage in entry deterrence. Because the event study relies on incumbent stock market movements to measure the effect of entry, this problem is unavoidable to some degree, but I can partially correct for selection into being publicly traded using a Heckman Selection model.

In the Heckman Selection model, my excluded instrument is the fraction of Native American casinos within 100 miles of the entrant's proposed location. Because Native American casinos are required to be owned by tribal governments, and hence not publicly traded, it is less likely that a market with a large fraction of Native American casinos has a publicly traded casino. In addition, rivals of tribal casinos tend to be far away from traditional gambling centers, and hence, are also less likely to be publicly traded. At this margin of selection, smaller publicly-traded firms operate in regional casino markets near American Indian reservations. To the extent that these small publicly-traded regional casino firms resemble private regional casino firms, the variation in the fraction of Native American casinos will help control for this selection into an incumbent being publicly traded, and may enable a wider scope of inference.[48]

Table 8 presents the results from Heckman Selection estimation of equation (3), using the pre-entry events (first planning and first construction). OLS estimates are presented as a baseline.[49] In the first column, I estimate that the benefit of entry deterrence (coefficient on $stalled$) is 13.3 percentage points of incumbent firm value, and that this effect is statistically significant at the 10 percent level. In addition, the second column results suggest that the effect of entry interacts with the leverage of incumbent firms. At one standard

[46] The rivals CAR is distinct from the CAAR. Rivals CAR is an entrant-level measure of the change in the stock market value of rival firms near that entrant over the entire event window. In contrast, CAAR is the cumulative sum of average abnormal return, which is a lag-level measure of the average return of rivals across entry events.

[47] If an entrant enters a market with two incumbent casino firms: Firm A and Firm B. Firm A owns 3 casinos in the market, but 15 casinos overall. Firm B owns 2 casinos in the market, but 4 casinos overall. Then, the measure $fracprops$ equals the casino-level average of ownership fractions in the market $\frac{0.2+0.2+0.2+0.5+0.5}{5} = 0.32$.

[48] The coefficient estimate on this variable in the selection equation is strongly negative and statistically significant (at better than 0.1 percent) across all specifications. In robustness checks not reported, I also used entrant attributes as excluded variables. These results did not differ qualitatively from the ones in Table 8, but I chose to use only the Native American casino information because it is the most valid variable to exclude from the outcome equation.

[49] The control variables exhibit a sensible pattern of results as well. The coefficient estimate on $fracprops$ is negative and strongly economically and statistically significant. In the basic Heckman Selection specification, a one standard deviation increase in $fracprops$ (sd = 25.5 percentage points) is associated with 20.8 percentage points lower rivals CAR. In addition, there is weak evidence that greater market concentration is associated with a bigger effect of entry. A standard deviation increase in market concentration (HHI) is associated with a decline in cumulative abnormal return of between 19.1 and 30.3 percentage points in the OLS regressions. On the other hand, these coefficients are imprecisely estimated and the estimated effect is much smaller in the Heckman Selection specifications.

deviation below the mean of incumbent leverage, the effect of entry deterrence is 17 percentage points greater (29.8 percentage points versus 12.8 percentage points). This difference is statistically significant at the one percent level.

This finding suggests an intuitive pattern of entry deterrence benefits. Low leverage firms that expand capacity during the planning stage, but are unsuccessful in deterring entry, experience a bigger adverse effect of entry because they have invested resources in preventing entry. In particular, the main effect on leverage implies that low leverage is associated with a larger baseline effect of entry, 11.3 percentage points greater than the average incumbent casino for one standard deviation below the mean of leverage. Because of the interaction with stalled, this coefficient estimate represents the effect of *actual* entry on low leverage incumbent casino firms. This larger effect of actual entry is consistent with attempted and failed entry deterrence. Moreover, the regression estimates in Table 8 suggest that failed entry deterrence is worse than no attempt at all,[50] and that effective entry deterrence is better than no attempt, which is a sensible pattern of results.

6 Evidence Using Patron Withdrawal Data

The analysis thus far has focused on how incumbent attributes change in response to the threat of entry by a geographically-close rival. Although compelling, this approach focuses on only one strategic variable (capacity) when incumbent casino firms have other strategic variables at their disposal (promotions, reinvestment in quality, patron loyalty). This section deepens the previous analysis by incorporating proprietary data on patron withdrawals at casinos.

6.1 Patron Visitation Data[51]

The patron visitation data span 26 full months from May 2010 until June 2012.[52] These visitation data are proprietary data on individual-day cash withdrawals from casinos within the United States, which report the date and time of the cash withdrawal, the requested amount, a unique patron identifier, and a unique casino identifier. In addition to this transaction information, the data provide information on the patron's gender, age and home ZIP code.[53]

The patron data have several useful features for complementing my analysis of changes of incumbent casino attributes. First, the data can be used to construct approximate market shares, which I use to evaluate the extent to which entrants were more effectively accommodated by financially unconstrained incumbents. Second, the data allow me to track patrons over time and at different casinos. Hence, they are amenable to constructing casino-specific measures of loyalty. Using these measures, I am able to provide evidence

[50]In this description, what I am calling "entry deterrence" is stalled entry plan, which is technically the data realization of a successful entry deterrence strategy.

[51]DISCLAIMER: All information, data, reports and other information used herein was provided to the author in a proprietary, confidential and anonymous manner with respect to the identification of any particular casino or patron.

[52]Appendix B provides a more detailed description of the patron data. July 2012 data are only for a partial month. Hence, these are dropped whenever I aggregate to the monthly level.

[53]The data include a casino file that reports casino attributes for the casinos covered by the data set, and allows me to merge the cash withdrawal data with my own casino data.

Table 8: Determinants of Cumulative Abnormal Returns for Pre-Entry Events

Panel A: Heckman Selection Estimates

	(1)	(2)
stalled	0.133†	0.128†
	(0.084)	(0.072)
leverage (Z) × stalled		−0.170**
		(0.060)
fracprops (Z)	−0.208**	−0.226**
	(0.052)	(0.050)
leverage (Z)	0.059†	0.113**
	(0.035)	(0.038)
Casino Size HHI (Z)	−0.112	−0.118
	(0.089)	(0.084)
Inverse Mills Ratio	−0.326**	−0.287*
	(0.112)	(0.111)
R-squared	0.415	0.472
Observations (observed)	79	79
Observations (censored)	62	62

Panel B: OLS Estimates

	(1)	(2)	(3)	(4)
stalled	0.126	0.118	0.115	0.065
	(0.084)	(0.081)	(0.094)	(0.109)
leverage (Z) × stalled		−0.242**	−0.233**	−0.246**
		(0.084)	(0.089)	(0.095)
fracprops (Z)	−0.251**	−0.265**	−0.243**	−0.253**
	(0.060)	(0.056)	(0.066)	(0.067)
leverage (Z)	0.076	0.153**	0.189*	0.178*
	(0.048)	(0.052)	(0.076)	(0.075)
Casino Size HHI (Z)	−0.195†	−0.191*	−0.252	−0.303
	(0.105)	(0.097)	(0.175)	(0.212)
Incumbent Attributes	No	No	Yes	Yes
Entrant Attributes	No	No	No	Yes
R-squared	0.371	0.439	0.467	0.500
N	79	79	78	78

Note: For Panel A, estimates and standard errors are from the outcome equation of a Heckman two-step procedure to account for sample selection. Panel B estimates using OLS regression with heteroskedasticity-robust standard errors (hc3). †, *, and ** indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpreting the estimates. All regression specifications also include a dummy variable for the type of entry event: first planned and first constructed in both the selection and outcome equation. To satisfy the exclusion restriction, the selection equation controls for the fraction of Native American casinos within 100 miles because Native casinos are required to be owned by tribal governments, not publicly traded.

linking capacity investments to dynamic demand (loyalty, switching costs as in Klemperer, 1987), which provides significantly more detail on the nature of entry deterrence.

6.2 Entrant Market Share After Entry

One question related to capacity expansion is whether incumbent pre-investment prior to the entry of a rival can help mitigate the loss of market share to the new rival conditional on entry. In other words, do incumbents preemptively invest in capacity in order to accommodate a new entrant? To assess this question, I use the patron withdrawal data to compute approximate market shares for successful entrants and relate these market shares to the incumbent capacity response in the two year window around the first planning of the nearby entrant. Formally, I estimate the regression model:

$$marketshare_{it} = \gamma_t + \gamma_s + X_i'\beta + \varepsilon_{it} \tag{4}$$

where γ_t are month-year fixed effects, γ_s are state fixed effects, and X_i is a vector of covariates including incumbent capacity investment, average debt-to-assets ratio of incumbents, the average size (square feet) of incumbent casinos, and the size (square feet) of the proposed casino.

Table 9 presents estimates for this regression model. In these specifications, the coefficient estimate on capacity expansion in the two year window around first planning is not statistically significant. This suggests that preemptive capacity expansions by incumbents – though useful for preventing and delaying effective entry – are not useful for accommodating a new entrant by reducing its post-entry market share. The event window evidence in Section 4.1 hinted at this null finding. As we saw in that section, incumbents that accommodate a successful entry expand capacity later relative to first planning than incumbents near rivals that eventually stall.

Table 9 also suggests that the financial strength of incumbents and entrants matters a great deal for the market share that the new entrant eventually acquires. A standard deviation increase in the average debt-to-assets ratio of incumbents is associated with between 8.1 and 10.6 percentage points greater market share, all else equal. Similarly, publicly-traded entrants acquire greater market share upon successfully entering. The specification in Table 9 implies that a publicly-traded entrant acquires 7.8 to 8.6 percentage points more market share than entrants that are not publicly traded, all else equal.

Relative to my findings on entry deterrence, these results suggest that preemptive capacity adjustments around the initial announcement of entry plans are not used by incumbents for the purpose of accommodating entry. Nevertheless, the fact that entrants obtain significantly greater market share if incumbents are highly leveraged suggests that the financial strength of incumbents is important for accommodating the entry of a new entrant. Together with my findings on entry deterrence, this finding strengthens my evidence that financially constrained firms behave less aggressively in the product market.

Table 9: Determinants of Post Entry Entrant Market Share (2010 – 2012)

	(1)	(2)	(3)
Incumbent Attributes			
Casino Size (Z)	0.060	0.097	0.105
	(0.052)	(0.066)	(0.081)
Capacity Adjustment (Z)	0.011	−0.011	−0.011
	(0.031)	(0.029)	(0.036)
Liability to Assets Ratio (Z)	0.081**	0.104**	0.106**
	(0.017)	(0.033)	(0.038)
Fraction of Native Casinos			0.034
			(0.063)
log(Open Casinos)	−0.037	−0.025	−0.022
	(0.031)	(0.029)	(0.035)
Entrant Attributes			
Casino Size (Z)	0.066**	0.068**	0.070**
	(0.007)	(0.010)	(0.014)
Publicly Traded		0.078*	0.086*
		(0.036)	(0.037)
Fee into Trust Entrant			−0.000
			(0.046)
Month-Year Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
R-squared	0.771	0.781	0.781
N	466	466	466

Note: Standard errors are clustered by state. †, *, and ** indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpretation.

6.3 Patron Loyalty and Incumbent Capacity

To use the casino visitation data to measure loyalty, I define a loyal patron for casino j at date t as a patron who has had more than three transactions at casino j before date t and more than five transactions overall, but has not (yet) had a transaction at another casino j'. For each casino-date, I compute the fraction of transactions by loyal patrons as my measure of loyalty. As this measure of loyalty depends on the length of the history of patron activity, I demean this fraction of loyal customers by date (call the demeaned version $fracloyal$) to use this measure to classify whether a casino is high loyalty or low loyalty.

Given the role that loyalty plays in models of financial predation (Bolton and Scharfstein, 1990; Chevalier, 1995), it is natural to ask how casino capacity is related to casino loyalty. On the overlap between the casino attribute data and casino visitation data (2010-2012), casino capacity is strongly positively related to this measure of casino loyalty. High loyalty casinos[54] have an average casino size of 72,295 square feet, compared to 49,256 square feet for low loyalty casinos.

This relationship holds up when I use variation within casino property, as well. In a regression of $fracloyal$ on casino size (see Table 1.10), I find a positive relationship between capacity and loyalty that

[54] For splitting the sample into high and low loyalty casinos, I compute the average $fracloyal$ for each casino in my data set. Using this average, I classify a casino as high loyalty if the average is greater than zero, and low loyalty if the average is less than zero. Because $fracprops$ is demeaned by month, zero is an appropriate reference point at which to distinguish high loyalty casinos from low loyalty casinos. The histogram of casino mean loyalties spans approximately from -0.2 to 0.2, and has an approximate bell shape.

Table 10: Determinants of Casino Loyalty (2010 – 2012)

	(1)	(2)	(3)	(4)
Own Attributes				
Casino Size (Z)	0.008**	0.013**	0.013*	0.012†
	(0.001)	(0.002)	(0.005)	(0.007)
Market Attributes				
Leverage of Competitors (Z)				0.027*
				(0.012)
Number of Competitors				0.001
				(0.004)
Property Fixed Effects	No	No	Yes	Yes
R-squared	0.009	0.035	0.283	0.165
N	8979	832	832	306

Note: Standard errors are with heteroskedasticity-robust standard errors (hc3). †, *, and ** indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpretation.

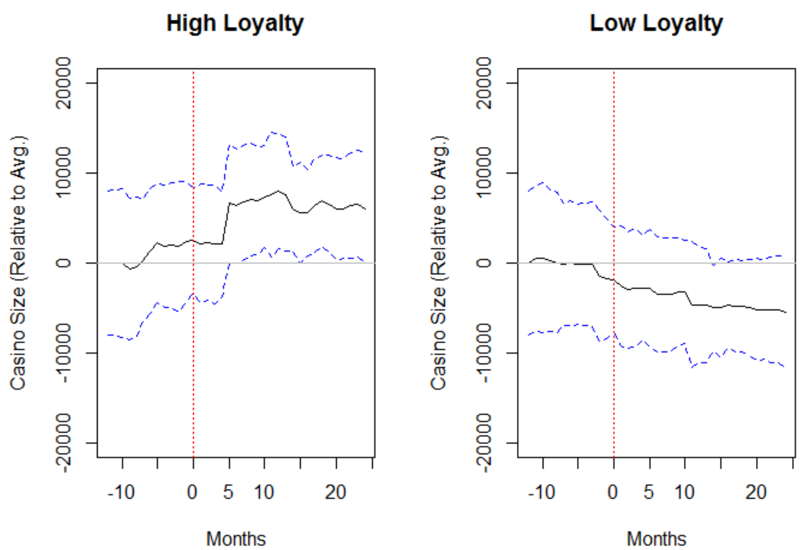
is robust to casino property fixed effects, the leverage of other firms in the market and the number of open casinos within 100 miles. In the fixed effects specifications, the coefficient is identified from the co-variation between changes in casino size and changes in casino loyalty within casino property.

The fixed effects structure in Table 1.10 rules out that the relationship between loyalty and capacity is due to permanent unobserved factors that vary at the casino property level. Nevertheless, these changes in loyalty and capacity may exhibit a simultaneous influence on one another. One technique to mitigate this concern is to evaluate whether capacity adjustments in response to entry earlier relate to casino loyalty later. To do this, split the incumbent's capacity response to entry plans (observed from March 2003 to March 2010, prior to measuring loyalty in May 2010 - June 2012) using the classification of high and low loyalty casinos. If we observe that casinos that ultimately had high loyalty were also the casinos that adjusted capacity in response to entry plans, the timing strongly suggests that capacity adjustments are useful for fostering loyalty.

As Figure 14 illustrates, casino properties that had high loyalty in 2010-2012 were precisely the incumbent casinos that responded to entry plans by expanding capacity. This difference between the responses of high loyalty and low loyalty casinos is statistically significant. Combined with the evidence from the hazard models (Section 4.2) that capacity adjustments lead to more deterred entry, this finding is evidence that casino capacity adjustments described in this paper likely lead to greater patron loyalty and more deterred entry, which is consistent with a Klemperer (1987) model of entry deterrence.[55]

[55] An implicit assumption to behind this conclusion is that casino loyalty is not some permanent feature of the casino property itself. It is plausible that the casino must invest to generate casino loyalty, and it appears that these investments in loyalty are at least accompanied by investments in the casino's physical capacity. Table 1.10 supports this interpretation because it demonstrates that contemporaneous changes in capacity are related to casino loyalty.

Figure 14: Capacity Adjustments to Entry plans (2003-2010), split by realized incumbent loyalty (2010-2012)



Note: For each lag relative to first planning, the figure plots the median of event-level data on average incumbent casino size, after using a regression of casino size to residualize by date fixed effects, per capita income in the county, population in the county, as well as the squares of these variables. Each series is adjusted so that the starting point is zero. This is to facilitate comparisons of capacity adjustments. Pointwise 90 percent confidence bands (conducted using a bootstrapping procedure) are depicted in blue.

7 Conclusion

Using a new data set that describes the plans of potential entrants, I find that incumbents respond preemptively during the planning stage of a rival casino by expanding capacity, and that these capacity expansions are effective in deterring entry. In finding empirical support for entry deterrence through capacity investments (Dixit, 1979, 1980) and loyalty programs (Klemperer, 1987), this paper extends and synthesizes the empirical literature on strategic entry deterrence (Goolsbee and Syverson, 2008) with the literature on how capital constraints affect the product market (Chevalier, 1995).

My results suggest that debt matters for the type of entry deterrence strategy adopted by incumbent firms. In particular, high-leverage incumbents do not respond to entry plans by expanding capacity (either for entry deterrence or accommodation), while low-leverage incumbents do. Moreover, based on a comparison to the response of similar incumbents far from the proposed entry site, these differences in capacity adjustments by leverage reflect the effects of financial constraints rather than geography or market-specific factors that relate to leverage. These results provide new evidence on how the capital structure of firms can relate to firm behavior in the product market.

The findings here suggest that excessive debt softens competition, and hence, my findings are similar in flavor to what Chevalier (1995) finds in the context of leveraged buyouts and supermarket prices. Going beyond Chevalier (1995), my casino visitation data allow me to directly observe customer loyalty as a channel for financial predation and entry deterrence. My finding that incumbent capacity adjustments likely facilitate customer loyalty lends empirical credibility to a large class of financial predation models (for example, Bolton and Scharfstein (1990)) that rely on loyalty in customer demand to support predatory pricing as an equilibrium outcome.

Importantly, my evidence for entry deterrence contrasts starkly with the pattern implied by unobserved demand shocks. In a simple model of competition and entry, an increase in casino demand implies a positive relationship between effective entry and incumbent capacity adjustments because more demand increases both the likelihood that an entry plan succeeds and the capacity of incumbent casinos. I find the opposite – when incumbents expand capacity, entry plans fail more regularly.

My event study corroborates this result. Unobserved demand shocks would imply greater stock market return for incumbents near successful entry plans than incumbents near failed entry plans. Nevertheless, I find that incumbents within 100 miles of failed entry attempts experience virtually no stock market effect while incumbents near successful entry attempts experience an average drop of 10.4 percentage points. Holding constant market, entrant, and incumbent heterogeneity in a regression of cumulative industry-abnormal returns, I estimate that the equity value of incumbent firms is 13.3 percent higher when entry is deterred successfully. This effect is economically important as well as statistically significant. To the extent that unobserved demand shocks are present, they partially mask the effects that I document. Hence, my estimates of entry deterrence represent a lower bound both for the effectiveness of capacity adjustments to deter entry, and the effect of entry on incumbent firm value.

More generally, my use of stock market information to analyze the American casino industry allows me to directly study competition in the American casino gambling industry, independent of using product market information (i.e., how incumbents expand capacity, the effectiveness of entry deterrence, the relationship to patron loyalty). The results from this paper suggest that the stock market event study approach can be fruitfully applied in empirical studies of entry and in industrial organization more generally. Not only can stock market information help address questions that are intractable in settings that lack product market data, but just as Whinston and Collins (1992) argued more than 20 years ago, stock market information can provide another useful input to understanding the sources and consequences of competition. In particular, structural studies of firm value could benefit by incorporating movements in stock prices. If this study is any indication, there is great potential for using stock market performance information to empirically address classical industrial organization questions.

A Model of Strategic Entry

A.1 Timing and Notation

The model formalizes the interaction between a potential entrant and an incumbent in a strategic entry deterrence game, which is preceded by a planning period. The model allows for two sources of failed entries: potential entrants who learn through a planning stage that entry is unprofitable even at the incumbent's initial capacity, and potential entrants whose attempt at entry is deterred by the capacity adjustment of an incumbent firm. After allowing for the entrant to learn its cost in a planning stage, the entry deterrence part of the model is an adaptation of the simple version of the entry deterrence model put forward by Dixit (1980). In Sections A.4 and A.5, I demonstrate how a similar set of reaction functions arises from demand with switching costs (as in Klemperer, 1987), and I show how introducing financing constraints affects the equilibrium.

The model proceeds in four stages.

1. A potential entrant begins the planning stage. Both the incumbent and potential entrant learn the entrant's marginal cost c_e, a draw from a known marginal cost distribution with continuous CDF G.

2. The incumbent – whose marginal cost c_i is known to the entrant and incumbent – chooses to adjust its capacity from its initial level of $\bar{k}_i$, choosing capacity of K. Each additional unit of capacity has an installation cost of r, regardless of when the capacity is installed. The capacity investment is irreversible, but the incumbent need not use all of it.

3. The entrant responds to the incumbent's capacity choice, either by exiting or by choosing the level of output x_e. The entrant takes the incumbent's capacity choice K from stage two as given. To enter, the entrant must pay a fixed cost f_e.

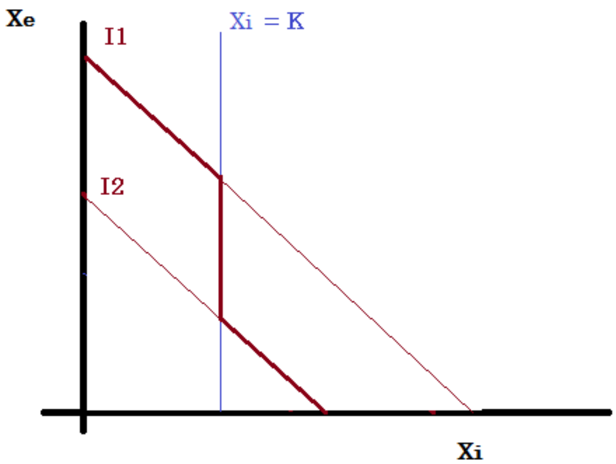
4. The incumbent selects optimal output x_i subject to its own capacity choice K and the entrant's output choice x_e. Both firms realize profits according to the reduced form profit functions $\pi^i(x_i, x_e, c_i)$ and $\pi^e(x_i, x_e, c_e)$.

Stages three and four of the entry deterrence game define a Stackelberg leader-follower game in which the entrant is the leader and the incumbent is the follower. Dixit (1980) analyzed a similar entrant-as-leader formulation as an extension of his entry deterrence model. In stage three, the potential entrant e chooses output (capacity) x_e to maximize profit $\pi^e(\cdot)$ taking into account how the incumbent will respond to the choice of x_e. In this formulation, the entrant's profit function is given by:

$$\pi^e(x_i(x_e), x_e, c_e) \quad = \quad R^e(x_i(x_e), x_e) - c_e x_e - f_e$$

where $x_i(x_e)$ is the incumbent firm's reaction function, which implicitly depends on the parameters of the problem (K, c_e, c_i and f_e), x_e is the entrant's output (capacity) choice, c_e is the entrant's marginal cost and f_e is the fixed cost of entry. The incumbent's reaction function is the solution to the profit maximization

Figure 15: Possible Incumbent Reaction Function, Conditional on Capacity Pre-Investment



problem in the fourth stage. The incumbent firm i maximizes profit given the capacity choice from stage two, denoted K, and the entrant's choice of output (capacity) x_e from stage three:

$$\pi^i(x_i, x_e, c_i) = \begin{cases} R^i(x_i, x_e) - c_i x_i & if\ x_i \leq K \\ R^i(x_i, x_e) - c_i K - (c_i + r)(x_i - K) & if\ x_i > K \end{cases}$$

In this formulation, the revenue functions $R^e(\cdot)$ and $R^i(\cdot)$ are general revenue functions that depend on the outputs of the incumbent and the entrant. As in Dixit (1980), I assume that revenue functions $R^i(\cdot)$ and $R^e(\cdot)$ are increasing and concave in own output and decreasing in rival output, and the marginal revenue functions $\frac{\partial R^i(\cdot)}{\partial x_i}$ and $\frac{\partial R^e(\cdot)}{\partial x_i}$ are decreasing in rival output. These conditions on revenue and marginal revenue guarantee that the reaction functions for both firms slope downward, and that higher marginal cost shifts reaction functions inward.

The incumbent's profit function reflects the fact that new capacity need not be installed until $x_i = K$, but to produce output greater than the installed capacity K, the incumbent must pay the marginal installation cost r for each additional unit. In this way, the capacity choice K from stage two induces the incumbent firm's reaction function to be kinked at the capacity constraint.[56]

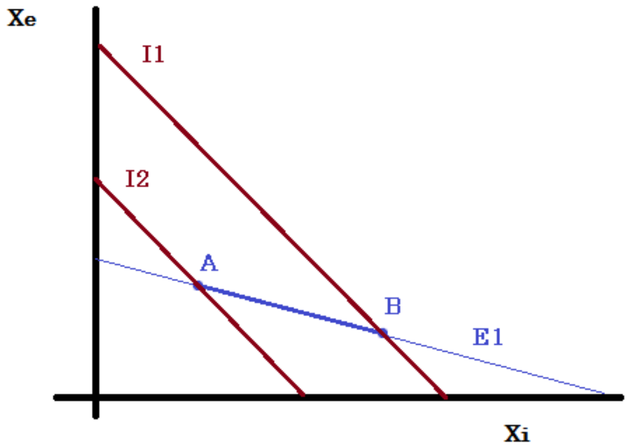
The bold line in Figure 15 depicts an example reaction function for the incumbent firm in the fourth stage of the entry deterrence game. The diagrams in this modeling exercise use linear reaction functions for expository purposes, but the derivations and results in this section do not depend on the assumption of linearity.[57] When producing output below the capacity constraint, the incumbent acts as if it is on I_1, the reaction function if it has marginal cost c_i. When producing output above the capacity constraint, the incumbent acts as if it is on I_2, the reaction function for marginal cost $c_i + r$.

Figure 16 portrays some essential elements of the entry game, where I_1 and I_2 are partial reaction func-

[56]The incumbent pays the same marginal installation cost r in stage two and stage four, but because of the timing, preemptive capacity installation can help the incumbent make a credible commitment to a particular output level. The model explores the effect of the timing of capacity investment, not any cost savings for a particular time pattern of investment.

[57]This graphical analysis of reaction functions is very much in the spirit of Dixit's original analysis.

Figure 16: Incumbent and Entrant Reaction Functions in an Entry Deterrence Game



tions for the incumbent firm and E_1 is the potential entrant's reaction function. Figure 15 is useful in understanding the incumbent's capacity choice because choosing a capacity amounts to choosing the point at which the reaction function drops vertically from I_1 to I_2. The bold segment of $E_1(AB)$ represents the set of points along the potential entrant's reaction function that possibly intersect an incumbent's reaction function with general shape portrayed in Figure 15.

A.2 Entry Accommodation

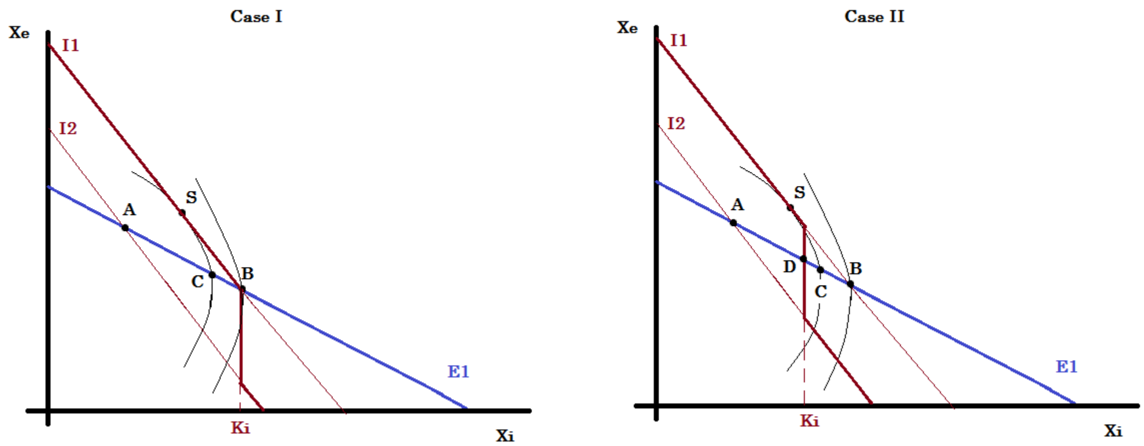
To study how the entrant's choice of x_e in stage three interacts with the incumbent's choice of capacity K in stage two, imagine that the entrant's profit in equilibrium is nonnegative regardless of K. Because profit is nonnegative, the entrant will be accommodated, but the manner in which entry is accommodated in the model is useful for understanding the scope for entry deterrence.

Conditional on entry, the entrant maximizes profit by selecting the optimal point along the incumbent's reaction function. Figure 17 displays two informative cases.

In Case I, the incumbent has capacity k_i at the level of output where I_1 intersects E_1, labeled bundle $B = \left\{x_i^b, x_e^b\right\}$ on the graph. Given incumbent capacity of k_i, the entrant optimally chooses the Stackelberg leadership point $S = \{x_i^s, x_e^s\}$, where the entrant's isoprofit curve is tangent to the incumbent's kinked reaction function. At output bundle S, the incumbent does not use all of its capacity. More importantly, the incumbent can choose a capacity level that yields a better outcome for both entrant and incumbent (namely, a lower capacity).

Case II, in second panel of Figure 17, demonstrates that if the incumbent chooses capacity so that the kinked incumbent reaction function crosses E_1 at a output bundle $D = \left\{x_i^d, x_e^d\right\}$ that the entrant prefers to the Stackelberg outcome S, the incumbent can also achieve greater profit. This capacity choice is effective if the kinked incumbent reaction function crosses at any point to the left of $C = \{x_i^c, x_e^c\}$, which yields the same entrant profit as the Stackelberg outcome. Of the outcomes that the entrant weakly prefers to C, C yields the greatest incumbent profit. For this reason, the incumbent will select capacity $K = x_i^c$ as long as the entrant

Figure 17: The Entrant's Output Choice and the Incumbent's Capacity Choice



finds it optimal to stay in the market.

As long as the incumbent's capacity exceeds x_i^s, S is a feasible output bundle for the entrant. Hence, if incumbent capacity is greater than x_i^s, the entrant can do no worse than $\pi^e\left(x_i^s, x_e^s, c_e\right)$. If incumbent capacity is less than x_i^s, the entrant does strictly better. Hence, in equilibrium, the entrant is guaranteed profit of at least the Stackelberg outcome, $\pi^e\left(x_i^s, x_e^s, c_e\right)$. This implies that a necessary and sufficient condition for the entrant to enter the market is that profit at the Stackelberg outcome is nonnegative.

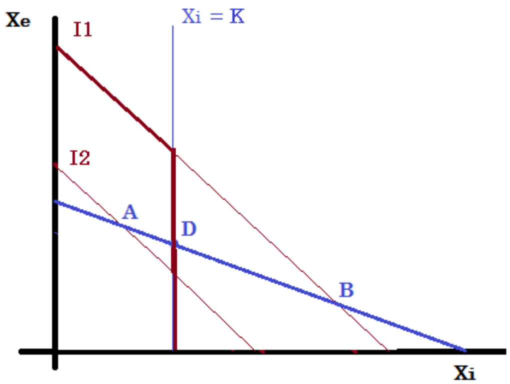
A.3 Entry Deterrence

The extent to which the incumbent can deter entry using capacity adjustment depends on whether the entrant's profit is negative anywhere along AC in Figure 17. The fixed cost of entry f_e implies that negative profit is possible at the intersection of the incumbent and entrant reaction functions. In the event that an entrant's profit is negative at some point along AC, the incumbent can choose capacity in stage two that guarantees its reaction function intersects AC at a point where the entrant receives negative profit. The entrant will choose to exit at stage three because it anticipates a loss in stage four.

To serve as a baseline, consider an incumbent that is endowed with capacity $k_i = K$, and that further investments in capacity are prohibitively expensive to make. For a particular value of K, define c^* to be the cost draw at which the entrant receives zero profit at the intersection of the incumbent and entrant reaction functions. Suppose further that this point of intersection, labeled D in Figure 18, is located to the left of the corresponding point C from Figure 17 in the previous section. In this case, c^* is the highest marginal cost draw at which the entrant would enter.

To illustrate the possibility of entry deterrence, suppose that the entrant's cost equals c^* from the example where the incumbent cannot adjust capacity, but that the incumbent can install additional capacity at a marginal installation cost of r rather than it being prohibitively costly. At the output bundle $D = \left\{x_i^d, x_e^d\right\}$, the entrant is indifferent to remaining in the market because $\pi^e\left(x_i^d, x_e^d, c^*\right) = 0$. If the incumbent chose capacity of $K + \varepsilon$, the new output bundle would yield negative profit for the entrant, driving the entrant

Figure 18: Prohibitively Costly Capacity Adjustment



out of the market. The cost of installing ε additional capacity is small relative to the gain from driving the entrant out of the market, which yields a discrete jump in profit. For this reason, the incumbent firm will deter entry that otherwise would have occurred at an entrant's marginal cost of c^*.

By this logic, the incumbent can always deter entry if the entrant's Stackelberg profits (along an unrestricted reaction function I_1) are less than zero. For c^*, the entrant's Stackelberg profit is negative because output bundle C (not pictured) is to the right of bundle D. By the envelope theorem, the entrant's Stackelberg profits are strictly decreasing in the entrant's cost draw as long as the entrant chooses a positive quantity.[58] Hence, a lower marginal cost will increase the profit of the entrant. If we continuously decrease marginal cost from c^*, there is a sufficiently-low marginal cost $c' < c^*$ such that the entrant's Stackelberg profits are zero – i.e., $\pi^e\left(x_i^d, x_e^d, c'\right) = 0$. At this marginal cost and lower, the incumbent will accommodate entry by selecting capacity to ensure bundle C is chosen.

To summarize, this model of strategic entry classifies three outcomes according to the marginal cost draw of the entrant.

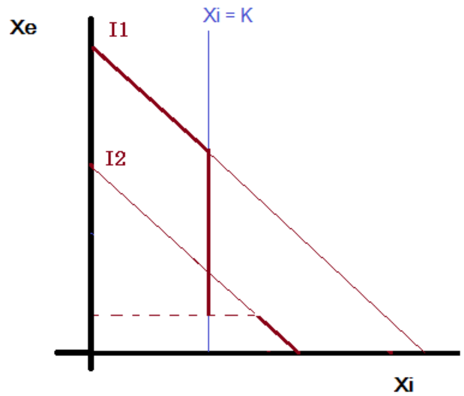
- For $c_e > c^*$, the entrant would not have made profit regardless of an incumbent adjustment of capacity. Entry is blockaded.
- For $c_e \in (c', c^*]$, the incumbent adjusts capacity in order to deter entry.
- For $c_e \leq c'$, the incumbent adjusts capacity in order to accommodate entry.

A.4 Switching Costs and Customer Base: Reinterpreting Capacity Adjustment

Instead of a capacity commitment game, suppose that customers have brand loyalty, which is embodied in paying a switching cost s to consume the product of a rival (or consume a firm's product for the first time). Entry deterrence in this setting was developed theoretically by Klemperer (1987).

[58] This is a convenient property of the entrant being a Stackelberg leader in the third and fourth stages of the strategic entry game. In math, $\frac{\partial \pi^e(x_i(x_e), x_e, c_e)}{\partial c_e} = -x_e + \frac{\partial x_e}{\partial c_e}\left(\frac{\partial R^e}{\partial x_e} - c_e\right) = -x_e^*$

Figure 19: A Possible Incumbent Reaction Function Under Switching Costs



For this model, denote inverse demand in period t as $D_t(Q)$. Firms compete on quantity (Cournot), subject to a switching cost of s, which new customers pay upon consuming one firm's product for the first time. The switching cost shifts the firm's residual demand vertically downward by s dollars per unit. Conditional on the incumbent selling to K customers in the first period, the prices in the second period are:

$$
\begin{aligned}
p_2^E &= D_2(x_i + x_e) - s \\
p_2^I &= \begin{cases} D_2(x_i + x_e) & if\ x_i \leq K \\ D_2(x_i + x_e) - s & if\ x_i > K \end{cases}
\end{aligned}
$$

Under the same assumptions about demand and marginal revenue, the incumbent reaction function can be constructed similarly to Dixit (1980). In Figure 19, I_1 is the reaction function if $D_2(Q)$ is demand for each x_i, and I_2 is the reaction function as if $D_2(Q) - s$ is demand.

Figure 19 portrays a possible reaction function in the second stage of an entry deterrence game when demand exhibits switching cost. At $x_i = K$, the incumbent faces a discrete drop in the marginal willingness to pay when it starts attempting to attract new customers. As a result, the incumbent's reaction function kinks vertically at $x_i = K$. In addition, the incumbent will not increase quantity until the switching cost reaction function I_2 evaluated at x_e yields enough new customers to offset the losses to giving a discount to the K established customers. After that point, the reaction function jumps discretely to I_2.

Relative to Dixit's capacity game, the incumbent in Klemperer's switching cost model has an incentive to milk its current customers without attracting new customers because (in many situations) attracting new customers requires reducing the price for all the incumbent's customers. If the incumbent can perfectly price discriminate between its new and old customers, there is no difference between the incumbent reactions functions in the Dixit-capacity game and Klemperer-switching cost game, and the two models give the same predictions regarding strategic entry deterrence. Nevertheless, even if the incumbent cannot perfectly price discriminate, the implications of the two models for strategic entry are similar (as described in Klemperer, 1987).[59]

A.5 Introducing Financing Constraints into the Model

Continue with the switching-cost version of the model. To introduce financing constraints into the entry deterrence model, suppose that the incumbent's marginal cost c_i is still known, but that incumbent has asymmetric information about its financing type: unconstrained or constrained. The entrant knows the proportion of unconstrained incumbents in the population p_I, but does not know if a particular incumbent is unconstrained or constrained.[60]

In period 1, the incumbent chooses how much to invest in its customer base with the possibility that it can deter the potential entrant from entering in period 2 (analogous to installing irreversible capacity). Starting from an initial customer base $\bar{K}$, the incumbent chooses K to maximize profit. Assume that new investments are financed at a marginal financing cost of $f_{weak} > 0$ for weak incumbents and $f_{strong} = 0$ for strong incumbents.[61] That is, in period 1, the cost function for a weak incumbent is:

$$C^{I}_{weak}(K) = \begin{cases} c_i K & if\ K < \bar{K} \\ c_i \bar{K} + (c_i + f_{weak})(K - \bar{K}) & if\ K \geq \bar{K} \end{cases}$$

while the cost function for a strong incumbent is:

$$C^{I}_{strong}(K) = c_i K$$

The additional financing cost induces a kink in the financially constrained incumbent's period 2 reaction function that would be, by itself, mathematically equivalent to the kink in the second stage of the Dixit (1980) entry deterrence model.

In period 1, demand facing the incumbent already has a kink at $\bar{K}$ due to the switching cost s. As a result, the additional financing cost for the constrained incumbent is equivalent to an additional switching cost that the weak incumbent must pay, but neither a strong incumbent nor the entrant must pay it to attract customers. As Klemperer noted when analyzing an increase in switching costs, this has the effect of incentivizing the financially-constrained incumbent to restrict itself to its previous customer base. In addition to introducing a bigger kink into the financially-constrained incumbent's response function, the financing cost (which totals $f_{weak}(K - \bar{K})$) is an additional cost that reduces the attractiveness of entry deterrence through period 1 over-investment in customer base.

Hence, this model of entry deterrence that incorporates financing costs for weak incumbents characterizes implies financially-constrained incumbents respond less aggressively to entry plans than do financially-

[59]The one exception is that there are circumstances in the Klemperer switching cost game where the incumbent will underinvest in its customer base. The intuition is that by underinvesting in its customer base in the first period, the incumbent can overcome the incentive to want to milk its first period customers rather than to achieve a superior second period duopoly equilibrium.

[60]This information structure makes it rational for an entrant to plan entry, but then to withdraw its plan upon observing a response that corresponds to a strong incumbent.

[61]Without loss of generality, set the financing cost to zero for strong incumbents because it is subsumed into the incumbent's cost function.

unconstrained incumbents. Accordingly, the model predicts that financially-constrained incumbents are less likely to deter entry.

A.6 Multiple Incumbents and Coordination

The model of strategic entry makes the simplifying assumption that there is one incumbent casino, but in reality, there are many incumbent casinos. Entry deterrence with multiple incumbents exhibits some classic attributes of a public good (Bernheim, 1984; Gilbert and Vives, 1986; Waldman, 1987). Because one incumbent's capacity investment benefits all incumbent firms, there is potentially a free rider problem among incumbents about how much to overinvest. As a result, without some mechanism for coordination, no firm internalizes the full benefit of entry deterrence, which makes entry deterrence less likely. Although my one-incumbent model does not explicitly account for this feature, markets where coordination among incumbents is less costly should be more likely to preemptively adjust capacity to the extent that there is a free rider problem.[62]

B Patron Visitation Data

B.1 Overview

The transaction file contains over 22 million transaction records for more than 2 million unique patron identifiers across 1070 casino properties in the United States. Not every patron or casino has a transaction in each month. As Table 11 indicates, the typical month in the sample has information on approximately 800 casinos, 400,000 patrons and more than 600,000 transactions.

Over the whole sample, the median patron visited casino ATMs 5 times and withdrew \$1092 during the sample time period. Although the median number of visits is rather low, there is a considerable mass of patrons who have visited casino ATMs frequently: 315,682 patrons visited casino ATMs more than 20 times during the 27 month time frame.

For the construction of entrant market shares and patron loyalty, I restricted the data to withdrawals (no credits or balance inquiries), and I dropped failed transactions from the data set. After cleaning, the data contain 8.5 million casino ATM withdrawals for over 1.6 million patrons. The average patron made 5.24 withdrawals (median of 3), and withdrew \$5,451 (median \$1,215). Of the 1.6 million patrons, nearly 740,000 made withdrawals at multiple casinos. On average, these switchers made 8.42 withdrawals per person (median of 6), and withdrew an average \$8,614 (median of \$2,888).

[62]Pushing back against earlier theoretical analyses of the free rider problem (e.g., Bernheim, 1984; Gilbert and Vives, 1986) in strategic entry deterrence by capacity investment, Waldman (1987) demonstrates that uncertainty about the exact amount of investment needed to deter entry can generate a free rider problem. He draws an informal distinction that models where overinvestment serves only an entry-deterring role tend to generate free rider problems while models where incumbent overinvestment can be repurposed do not.

Table 11: Summary Statistics of the Casino Visitation Data by Month

	Month-year	casinos	patrons	transactions
1	201005	839	421021	985909
2	201006	848	386740	884925
3	201007	841	422943	988621
4	201008	830	403048	933658
5	201009	823	387446	891686
6	201010	800	393256	932933
7	201011	785	344897	812122
8	201012	778	281058	638559
9	201101	762	293186	623839
10	201102	752	296118	632244
11	201103	755	319020	699273
12	201104	737	310503	685432
13	201105	755	314211	692191
14	201106	747	296686	637421
15	201107	753	334368	751381
16	201108	747	303942	665840
17	201109	746	302215	697914
18	201110	758	341286	850257
19	201111	769	320716	776238
20	201112	763	336899	857973
21	201201	780	351435	880973
22	201202	748	381612	975965
23	201203	767	424394	1154357
24	201204	759	420257	1159600
25	201205	762	444378	1290275
26	201206	760	469744	1575294
27	201207	528	51960	100766

Table 12: Transaction Amounts by Month and Match with Vendor Data

monthyear	All Transactions	Matched with Vendor	Fraction of Transactions
201005	193.91	161.37	0.83
201006	197.53	162.59	0.82
201007	237.31	194.20	0.82
201008	236.15	193.87	0.82
201009	244.89	201.66	0.82
201010	290.83	243.97	0.84
201011	292.85	249.77	0.85
201012	214.92	175.40	0.82
201101	204.86	165.40	0.81
201102	208.57	165.14	0.79
201103	253.71	198.14	0.78
201104	259.01	200.34	0.77
201105	284.26	227.16	0.80
201106	259.84	207.09	0.80
201107	310.66	248.11	0.80
201108	303.40	242.59	0.80
201109	300.52	237.32	0.79
201110	350.55	272.83	0.78
201111	346.30	268.26	0.77
201112	407.04	316.38	0.78
201201	443.35	345.78	0.78
201202	520.03	404.19	0.78
201203	692.05	530.04	0.77
201204	828.82	641.64	0.77
201205	1192.43	916.54	0.77
201206	2461.66	1910.67	0.78
201207	184.77	143.20	0.78

Note: Transaction Amounts are in $ millions.

B.2 Match with Vendor Data

The transaction file contains information on gambling venues that are not casinos (i.e., race tracks or cruise ships), and on casinos outside the United States. After dropping these non-casino observations and merging with the American casinos in the Gambling Business Directory, the final sample contains 620 of the original 1070 property codes. These 620 property codes refer to 511 distinct casinos in the United States, or 52.4 percent of the casinos in the vendor database. Table 12 depicts summary statistics on the overlap of the samples by month-year. Most of the non-overlap of the sample is due to the company not having contracts with all casinos in the American casino industry (there is 91.7 percent overlap with the data distributor's property file; the discrepancies mostly being abandoned projects or newly planned projects). The missing casinos in the transaction data tend to be smaller. That is, they are marginal casinos from the standpoint of the industry as a whole.

C Robustness Checks and Alternative Specifications

C.1 Overview

Throughout the main text, I presented the preferred specifications for each of my empirical tests. This appendix describes several specification tests, robustness checks, and alternative specifications. Section C.2 describes how to specify and approximate partial likelihood in a Cox proportional hazards model with particular emphasis on how to handle tied survival times. Section C.3 presents estimates of the hazard function using the Breslow approximation to the partial likelihood. Section C.4 presents estimates of the hazard function when plans are allowed to stall during construction. Section C.5 presents the results of a test of the proportional hazards assumption. Section C.6 presents an alternative portrayal of the heterogeneity in incumbent cumulative average abnormal return than is provided in the main text.

C.2 Approximating the Cox Proportional Hazards Partial Likelihood

C.2.1 The partial likelihood with no ties

Start with the log-linear specification for the hazard function (equation (2) in the text):

$$h_i(t) = h_0(t)\exp\left(X_i'\beta\right) \tag{5}$$

To motivate the construction of the partial likelihood, assume that event i is the only event that has a survival of t, and that $\mathscr{R}_i(X_i'\beta) = \{j \in 1,...,N\}$ is the risk set, or the set of events that have survival times as long as or longer than i. In this case, the conditional partial likelihood for observation i equals

$$\begin{aligned}\mathscr{L}_i(\beta) &= \frac{h_0(t)\exp(X_i'\beta)}{\sum_{j\in\mathscr{R}_i(X_i'\beta)} h_0(t)\exp\left(X_j'\beta\right)} \\ &= \frac{\exp(X_i'\beta)}{\sum_{j\in\mathscr{R}_i(X_i'\beta)} \exp\left(X_j'\beta\right)}\end{aligned}$$

Assuming there are no tied survival times in the entire data set and taking logs, we obtain the partial likelihood function for the sample:

$$\mathbb{L}(\beta) = \sum_{i=1}^{N}\left(X_i'\beta - \log\left(\sum_{j\in\mathscr{R}_i(X_i'\beta)} \exp\left(X_j'\beta\right)\right)\right)$$

C.2.2 Ties and the partial likelihood: an example

If there are ties in the observed survival times, the partial likelihood as constructed above is incorrect because we cannot order the two events with respect to their actual failure times.

To see why the partial likelihood is incorrect, consider a simple example in which two observations $i = 1,2$ have the survival time t, and three others $i = 3,4,5$ have survival time greater than t, and for notational convenience, denote $\theta_i = \exp\left(X_i'\beta\right)$. Applying the method outlined in the previous section, the contribution to the partial likelihood at date t equals

$$\mathscr{L}_{1,2} = \left(\frac{\theta_1}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right)\left(\frac{\theta_2}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right) \tag{6}$$

when, if we take the continuous time aspect of the Cox proportional hazards model literally, either event $i = 1$ or event $i = 2$ had a shorter survival time. Supposing that $i = 1$ had the shorter survival time in reality, the partial likelihood would equal:

$$\mathscr{L}^1_{1,2} = \left(\frac{\theta_1}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right)\left(\frac{\theta_2}{\theta_2+\theta_3+\theta_4+\theta_5}\right)$$

Similarly, if $i = 2$ had the shorter survival time, the partial likelihood would be

$$\mathscr{L}^2_{1,2} = \left(\frac{\theta_1}{\theta_1+\theta_3+\theta_4+\theta_5}\right)\left(\frac{\theta_2}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right)$$

Given this observation, one construction of the partial likelihood is to take the average likelihood of all of these possibilities:

$$\mathscr{L}_{1,2} = \frac{1}{2}\left(\mathscr{L}^1_{1,2}+\mathscr{L}^2_{1,2}\right)$$

The problem with this average likelihood (or exact) approach to constructing the partial likelihood is that it becomes computationally intractable as the number of tied survival times increases. In the simple example presented here, there are only two terms because there was one tie, but for k ties, there are $k!$ terms in this sum. For this reason, approximations to the exact partial likelihood are used in practice.[63]

An alternative solution to the problem of ties is to view time as essentially discrete, and hence, ties are natural. This approach is equivalent to estimating a conditional logistic regression in which the risk sets (risk set at t: the set of events with survival time greater than or equal to t) define the groups, and where the outcome is an indicator for whether event i's death date is t. This discrete-time approach is called the exact partial likelihood approach, and although it is an empirically valid method to handle ties, it can be incredibly computationally intensive.[64]

C.2.3 Two approximations to the partial likelihood

One approximation – the Breslow approximation – specifies the partial likelihood as if there are no ties in the data set. In other words, the contribution to the partial likelihood at date t when there are tied survival times is analogous to equation (6). In practice, this approximation reduces the power of the estimator, and tends to produce smaller coefficient estimates.

[63] Delong et al. (1994) outline a method by which the average likelihood's sum of $k!$ terms can be expressed as a single integral, which reduces the computational burden. Nevertheless, Therneau and Grambsch (2000) suggest that the extra computation is not worth it because the Efron approximation (discussed below) usually provides quite similar results.

[64] This method is readily implemented in R using the method= "exact" option in the coxph() function, but due to computational intractability, I did not run this on the data set.

Alternatively, a more attractive approximation is the Efron approximation, proposed by Efron (1974). In the context of the example in the previous section, the Efron approximation takes the form

$$\mathscr{L}_{1,2} = \left(\frac{\theta_1}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right)\left(\frac{\theta_2}{\frac{1}{2}(\theta_1+\theta_2)+\theta_3+\theta_4+\theta_5}\right)$$

One intuition for this approximation is that, in the absence of knowing which event terminated first, both $i=1,2$ have probability 1 of being included in the denominator of the first term, but only $\frac{1}{2}$ probability in being included in the second term. To see how to extend this intuition to an arbitrary number of ties, note the form of the Efron approximation to the partial likelihood for a three way-tie between $i=1,2,3$:

$$\begin{aligned}\mathscr{L}_{1,2,3} = & \left(\frac{\theta_1}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right)\left(\frac{\theta_2}{\frac{2}{3}(\theta_1+\theta_2+\theta_3)+\theta_4+\theta_5}\right)\times \\ & \left(\frac{\theta_2}{\frac{1}{3}(\theta_1+\theta_2+\theta_3)+\theta_4+\theta_5}\right)\end{aligned}$$

In this case, each tied survival event has probability 1 of being in the risk set for the first denominator, $\frac{2}{3}$ of being in the risk set for the second denominator, and $\frac{1}{3}$ of being in the risk set for the third denominator.

More generally, suppose that the set of indices for which there is a tie at survival time t is M_j (denoting the number of ties to be m), then we can express the Efron approximation to the partial likelihood contribution at survival time t as:

$$\mathscr{L}_t(\beta) = \frac{\prod_{i\in M_j}\theta_i}{\prod_{l=0}^{m-1}\left(\sum_{i=\in\mathscr{R}_i(X_i'\beta)}\theta_i - \frac{l}{m}\sum_{i\in M_j}\theta_i\right)}$$

Note that the second term in the denominator adjusts the θ_i for the events $i\in M_j$ that have survival time t in an analogous way to the two- and three-way tie examples above. Now, we can take the product across the distinct times t_j and take logs to obtain the log partial likelihood under the Efron approximation (Efron, 1974).

$$\mathbb{L}(\beta) = \sum_j\left(\sum_{i\in M_j}X_i'\beta - \sum_{l=0}^{m-1}\log\left(\sum_{i\in\mathscr{R}_i(X_i'\beta)}\exp(X_i'\beta) - \frac{l}{m}\sum_{i\in M_j}\exp(X_j'\beta)\right)\right)$$

The specifications in the main text that present estimates of the Cox proportional hazards model use this form for the log partial likelihood.

C.3 Estimates using the Breslow Approximation

Although the Efron approximation has better properties than the Breslow approximation (Hertz-Picciotto and Rockhill, 1997), a careful reader may want to see that how choice of approximation affects the main

Table 13: Determinants of the Hazard Rate out of the Planning Stage using Breslow Approximation to Cox Partial Likelihood

	(1)	(2)	(3)	(4)	(5)
Incumbent Capacity Variables					
Casino Size (Z)	$0.291^{\dagger}$		0.207^{*}	0.110^{**}	0.123^{**}
	(-1.810)		(-2.168)	(-2.740)	(-2.682)
Capacity Adj (Z)		0.732^{*}	0.679^{**}	0.820	$0.709^{\dagger}$
		(-2.447)	(-2.785)	(-1.415)	(-1.745)
Casino Size (Z) $\times$ Pub Entrant					$4.413^{\dagger}$
					(1.881)
Capacity Adj (Z) $\times$ Pub Entrant					1.802^{*}
					(2.118)
R-squared	0.288	0.296	0.321	0.373	0.398
Observations	124	124	124	124	124
Number of Events	55	55	55	55	55

Note: Estimates of the Cox proportional hazards model, using the Breslow approximation to the partial likelihood. Wald Z-scores in parentheses. Standard errors are from a robust variance-covariance matrix. $\dagger$, $*$, and $**$ indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpretation. Also, each specification in this table also includes the full set of entrant, market and incumbent controls that are reported in Table 6.

results. Table 13 presents the the main specification of the Cox proportional hazards model using the Breslow approximation instead of the Efron approximation. Based on these estimates, the pattern of results from the Breslow approximation is identical to the results I obtained using the Efron approximation (see Table 6), subject to small numerical differences.

C.4 Estimates using Hazard out of Pre-Entry

As I mentioned in the main text, the specifications in Table 6 use as the notion of survival the time it takes for a project to transition out of the planning stage. It is possible for projects to stall during the construction phase. Nevertheless, I chose to estimate the determinants of the hazard rate out of the planning stage instead of this more conventional (and correct) notion of hazard because, in this case, the estimates capture genuine strategic delay, rather than unobserved determinants of long-lasting construction periods.

Setting aside this issue, it is useful to present estimates for the determinants of the hazard rate out of the pre-entry stage as a robustness test. As the estimates in Table 14 indicate, the main results become slightly stronger when I estimate the hazard rate out of pre-entry rather than out of the planning stage. In every specification, the main effects on casino capacity and capacity adjustment become larger and their statistical significance increases. The interactions with publicly-traded entrant, however, becomes weaker and less statistically significant. Nevertheless, the effect on the hazard rate of a publicly traded entrant is estimated to be closer to zero in this specification ($1.507 \times 0.633 = 0.953$ versus 1.31 from the main text). Thus, the results of the main specification remain intact, and strengthen somewhat when I allow for plans to stall during the construction phase.

Table 14: Determinants of the Hazard Rate out of the Pre-Entry Stage

	(1)	(2)	(3)	(4)	(5)
Incumbent Capacity Variables					
Casino Size (Z)	0.218*		0.134*	0.090**	0.101**
	(−2.006)		(−2.553)	(−2.928)	(−2.883)
Capacity Adj (Z)		0.648**	0.583**	0.688*	0.633*
		(−3.289)	(−3.550)	(−2.535)	(−2.347)
Casino Size (Z) × Pub Entrant					3.032
					(1.235)
Capacity Adj (Z) × Pub Entrant					1.507
					(1.283)
R-squared	0.287	0.308	0.343	0.374	0.385
Observations	124	124	124	124	124
Number of Events	55	55	55	55	55

Note: Estimates of the Cox proportional hazards model, using the Efron (1974) approximation to the partial likelihood. Wald Z-scores in parentheses. Standard errors are from a robust variance-covariance matrix. †, ∗, and ∗∗ indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpretation. Also, each specification in this table also includes the full set of entrant, market and incumbent controls that are reported in Table 6.

C.5 Test of Proportional Hazards

Grambsch and Therneau (1994) nests the Cox proportional hazards model within a time-varying coefficient model for the hazard. In so doing, they develop a test for the proportional hazards assumption that β is constant over time. The test can be implemented for individual covariates, as well as globally for the model itself. Table 15 shows the result of testing for non-proportional hazards. In all cases, we fail to reject the null hypothesis that hazards are proportional.

C.6 Alternate CAAR Plots

When providing evidence for heterogeneous incumbent stock market returns by the fraction of incumbent properties affected, the Figure 13 used first opening events rather than first planning events. To show that the result is not sensitive to the type of entry event, I produced the same plot using first planning events in Figure 20. As I mentioned in the main text, the pattern is identical, but the magnitude of the effect of being a small firm with many properties affected by the entry event is much greater. This is due to the small sample of firms that fall into this category, and the fact that these firms performed extraordinarily poorly.

C.7 General Deterrence

A potential concern underlying the empirical exercise is that planning is deterred by previous incumbent capacity investments, and those plans that are not deterred by pre-investment are the plans that I observe in the data. Although selecting on the stronger plans would tend to bias my results against finding an effect,[65] it is worth investigating this first stage to understand the extent to which selection of this sort is important in determining the plans that we observe.

[65] A selected sample would have a greater fraction of weak entrants, which are more responsive to strategic investments by incumbents according to my hazard model estimates.

Table 15: Schoenfeld and Grambsch-Therneau Tests of Proportional Hazards

	rho	chisq	p
Incumbent Casino Size (Z)	0.041	0.111	0.739
Open Casinos	0.011	0.013	0.910
Employees (100s)	0.171	2.317	0.128
Rooms (100s)	0.238	1.639	0.200
Parking Spaces (Z)	0.053	0.238	0.625
Casino Size (Z)	0.032	0.119	0.730
Slots (100s)	-0.103	0.801	0.371
Properties Owned (Z)	-0.012	0.018	0.894
Convention Square Feet (Z)	-0.211	1.930	0.165
Incumbent Employees (Z)	-0.021	0.037	0.848
Incumbent Rooms (100s)	0.054	0.184	0.668
Incumbent Parking Spaces (Z)	-0.000	0.000	1.000
Incumbent Slots (100s)	0.034	0.098	0.754
Incumbent Properties Owned (Z)	0.048	0.080	0.777
Incumbent Convention Square Feet (Z)	-0.039	0.123	0.726
GLOBAL		6.613	0.968

Figure 20: Cumulative Average Abnormal Return by Average Number of Properties Owned and Average Number of Properties Affected (First Planning Events)

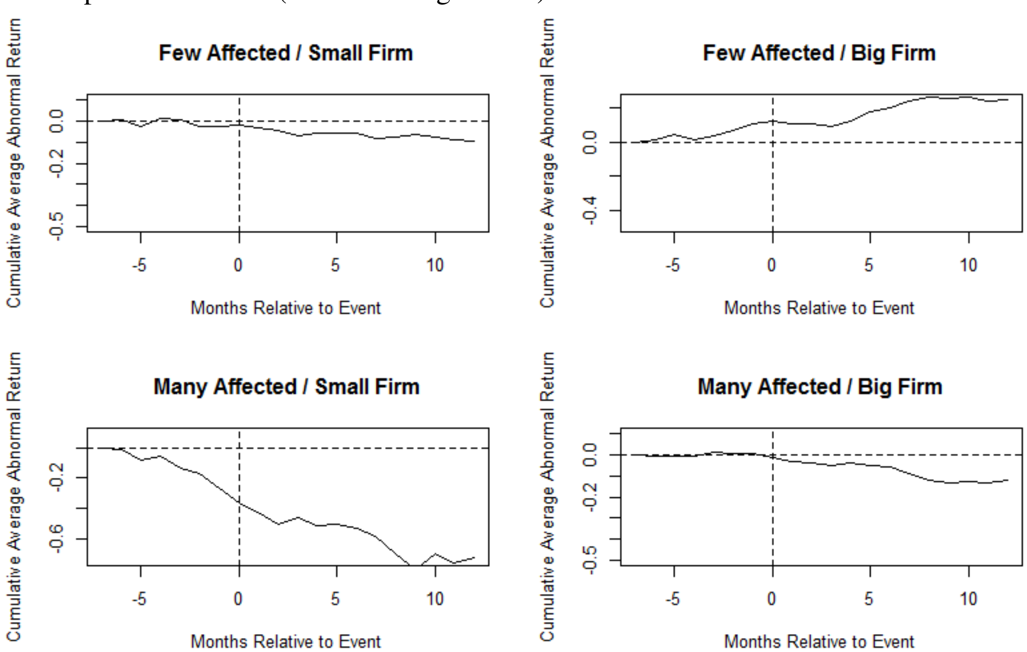


Table 16: OLS Estimates of Number of Casino Plans in Local Markets

	(1)	(2)	(3)	(4)
Existing Capacity (Z)	−0.028	−0.016	−0.018	−0.015
	(0.024)	(0.024)	(0.026)	(0.024)
Property FE	Yes	Yes	No	No
City FE	No	No	Yes	Yes
Owner FE	No	No	No	Yes
Month-Year FE	No	Yes	Yes	Yes

Note: Standard errors are clustered by property identifier. †, *, and ** indicate statistical significance at the ten, five, and one percent level respectively. Variables denoted with (Z) are standardized to have mean 0 and standard deviation 1 for ease of interpreting the estimates. All specifications also control for the number of open casinos within 100 miles of the property, and column (1) controls for a linear time trend.

One simple statistic we can compute is the correlation between casino capacity within 100 miles (as measured by average casino size of open casinos) and the number of plans within 100 miles.[66] This is weakly positive (0.14), and is mostly due to variation in whether there is a plan near the casino property.[67] This suggests that there is unobserved demand that determines both plans and incumbent casino size. We can control for this unobserved demand using a fixed effects structure:

$$plans_{ist} \quad = \quad \gamma_i + \gamma_t + \beta_1 capacity_{it} + \mathbf{X}'_{it}\beta + U_{it} \tag{7}$$

where γ_i are property fixed effects and γ_t are time fixed effects. In addition, I will control for market size (number of open casinos within 100 miles) in obtaining an estimate for the effect of existing capacity on number of casino plans nearby. Table 16 presents the estimates from various specifications of (7). As Table 16 indicates, controlling for property or locality fixed effects reverses the sign of the coefficient estimate on capacity, and renders the estimates statistically insignificant.[68] These coefficient estimates are identified from within casino property variation, and thus, there is little evidence that incumbents adjust their capacity to effectively reduce the number of nearby entry plans.

[66] For all of the calculations in this section, I restrict attention to the non-entries sample so that changes in capacity cannot be attributed to changes in the composition of firms.

[67] The correlation of casino capacity with whether there is a plan within 100 miles is 0.09.

[68] Without clustering the standard errors, the estimates are statistically significant, but clustering at the property level (as in the table) or at the State level (another specification I tried) leaves the estimates statistically insignificant.

References

Aghion, P. and P. Bolton (1987). Contracts as a Barrier to Entry. *The American Economic Review 77*(3), 388–401.

Anders, G. C. (1999). Indian Gaming: Financial and Regulatory Issues. *Annals of the American Academy of Political and Social Science 556*, 98–108.

Anders, G. C., D. Siegel, and M. Yacoub (1998). Does Indian Casino Gambling Reduce State Revenues? Evidence from Arizona. *Contemporary Economic Policy 16*(3), 347–355.

Bernheim, B. D. (1984). Strategic Deterrence of Sequential Entry into an Industry. *The RAND Journal of Economics 15*, 1–11.

Bernile, G. and E. Lyandres (2010, November). Merger Synergies along the Supply Chain. Working Paper.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile Prices in Market Equilibrium. *Econometrica 63*, 841–890.

Berry, S. T. and J. Waldfogel (1999). Free Entry and Social Inefficiency in Radio Broadcasting. *The RAND Journal of Economics 30*(3), 397–420.

Bolton, P. and D. S. Scharfstein (1990). A Theory of Predation Based on Agency Problems in Financial Contracting. *The American Economic Review 80*, 93–106.

Bourie, S. (2011). *American Casino Guide: 2011 Edition*. Casino Vacations.

Brander, J. A. and T. R. Lewis (1986). Oligopoly and Financial Struture: The Limited Liability Effect. *The American Economic Review 76*, 956–970.

Casino City Press, T. (2012, August). Gaming Business Directory. Online.

Chevalier, J. A. (1995). Do LBO Supermarkets Charge More? An Empirical Analysis of the Effects of LBOs on Supermarket Pricing. *The Journal of Finance 50*, 1095–1112.

Chevalier, J. A. and D. Scharfstein (1996). Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence. *The American Economic Review 86*, 703–725.

Cookson, J. A. (2010). Institutions and Casinos: An Empirical Investigation of the Location of Indian Casinos. *Journal of Law and Economics 53*, 651–687.

Delong, D. M., G. H. Guirguis, and Y. C. So (1994). Efficient Computation of Subset Selection Probabilities with Application to Cox Regression. *Biometrika 81*, 607–611.

Dixit, A. (1979). A Model of Duopoly Suggesting a Theory of Entry Barriers. *The Bell Journal of Economics 10*(1), 20–32.

Dixit, A. (1980). The Role of Investment in Entry-Deterrence. *The Economic Journal 90*(357), 95–106.

Dunstan, R. (1997, January). Gambling in California. Technical Report CRB-97-003, California Research Bureau.

Eckbo, E. (1983). Horizontal Mergers, Collusion, and Stockholder Wealth. *Journal of Financial Economics 11*, 241–273.

Efron, B. (1974). The Efficiency of Cox's Likelihood Function for Censored Data. *Journal of the American Statistical Association 72*, 557–565.

Ellison, G. and S. F. Ellison (2011). Strategic Entry Deterrence and the Behavior of Pharmaceutical Incumbents Prior to Patent Expiration. *American Economic Journal: Microeconomics 3*(1), 1.

Evans, W. N. and W. Kim (2008, June). The Impact of Local Labor Market Conditions on the Demand for Education: Evidence from Indian Casinos. Working Paper.

Evans, W. N. and J. H. Topoleski (2002). The Social and Economic Impact of Native American Casinos. *NBER Working Papers No: 9198*.

Gilbert, R. and X. Vives (1986). Entry Deterrence and the Free Rider Problem. *Review of Economic Studies 53*, 71–83.

Goolsbee, A. and C. Syverson (2008). How Do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines. *The Quarterly Journal of Economics 123*, 4.

Grambsch, P. M. and T. Therneau (1994). Proportional Hazards Tests and Diagnostics Based on Weighted Residuals. *Biometrika 81*, 515–26.

Grinols, E. L. and D. B. Mustard (2001). Management and Information Issues for Industries with Externalities: The Case of Casino Gambling. *Journal of Managerial and Decision Economics 22*(1-3), 1–3.

Grinols, E. L. and D. B. Mustard (2006). Casinos, Crime, and Community Costs. *Review of Economics and Statistics 88*(1), 28–45.

Hendel, I. (1996). Competition Under Financial Distress. *The Journal of Industrial Economics 44*, 309–324.

Hertz-Picciotto, I. and B. Rockhill (1997). Validity and Efficiency of Approximation Methods for Tied Survival Times in Cox Regression. *Biometrics*, 1151–1156.

Hoberg, G. and G. Phillips (2010). Real and Financial Industry Booms and Busts. *Journal of Finance 65*(1), 45–86.

Hoberg, G. and G. Phillips (2011). Text-Based Network Industries and Endogenous Product Differentiation. *Working Paper*.

Hortacsu, A., G. Matvos, C. Syverson, and S. Venkataraman (2013). Indirect Costs of Financial Distress in Durable Goods Industries: The Case of Auto Manufacturers. *Review of Financial Studies Forthcoming*.

Huisman, K. J. and P. M. Kort (2013). Strategic Capacity Investment Under Uncertainty. *Discussion Paper 2013-003, Tilburg University, Center for Economic Research*.

Khanna, N. and S. Tice (2000). Strategic Responses of Incumbents to New Entry: The Effect of Ownership Structure, Capital Structure, and Focus. *The Review of Financial Studies 13*, 749–779.

Klemperer, P. (1987). Entry Deterrence in Markets with Consumer Switching Costs. *Economic Journal 97*, 99–117.

Lehar, A., Y. Song, and L. Yuan (2011). Industry Structure and the Strategic Provision of Trade Credit by Upstream Firms. *Working Paper*.

Maksimovic, V. (1988). Capital Structure in Repeated Oligopolies. *The RAND Journal of Economics 19*, 389–407.

Maskin, E. S. (1999). Uncertainty and Entry Deterrence. *Economic Theory 14*, 429–437.

Milgrom, P. and J. Roberts (1982). Limit Pricing and Entry Under Incomplete Information: An Equilibrium Analysis. *Econometrica 50*, 443–459.

Murfin, J. and K. Njoroge (2012). Small Lending Big: The Real Effects of Trade Credit Demands on Constrained Suppliers. *Working Paper*.

Myers, S. C. (1977). Determinants of Corporate Borrowing. *Journal of Financial Economics 5*, 147–175.

Phillips, G. M. (1995). Increased Debt and Industry Product Markets: An Empirical Analysis. *Journal of Financial Economics 37*, 189–238.

Pichler, P., A. Stomper, and C. Zulehner (2008). Why Leverage Affects Pricing. *The Review of Financial Studies 21*, 1733–1765.

Povel, P. and M. Raith (2004). Financial Constraints and Product Market Competition: Ex Ante vs. Ex Post Incentives. *International Journal of Industrial Organization 22*, 917–949.

Rose, I. N. (1991). *Gambling and Public Policy*, Chapter The Rise and Fall of the Third Wave: Gambling Will be Outlawed in Forty Years, pp. 70. Institute for the Study of Gambling & Commercial Gaming.

Seim, K. (2006). An Empirical Model of Firm Entry with Endogenous Product-Type Choices. *The RAND Journal of Economics 37*, 619–640.

Seim, K. and J. Waldfogel (2010). Public Monopoly and Economic Efficiency: Evidence from the Pennsylvania Liquor Control Board's Entry Decisions. *NBER Working Paper* (16258).

Snider, C. (2009). Predatory Incentives and Predation Policy: The American Airlines Case. Working Paper.

Spence, A. M. (1977). Entry, Capacity, Investment and Oligopolistic Pricing. *The Bell Journal of Economics 8*, 534–544.

Thalheimer, R. and M. Ali (2003). The Demand for Casino Gambling. *Applied Economics 35*(8), 907–920.

Therneau, T. M. and P. M. Grambsch (2000). *Modeling Survival Data: Extending the Cox Model*. Springer-Verlag.

Waldman, M. (1987). Noncooperative Entry Deterrence, Uncertainty, and the Free Rider Problem. *Review of Economic Studies 54*, 301–310.

Whinston, M. D. and S. C. Collins (1992). Entry and Competitive Structure in Deregulated Airline Markets: An Event Study Analysis of People Express. *The RAND Journal of Economics 23*, 445–462.