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

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Abstract

Using new data on entry plans into the American casino industry, I find that incumbent firms invest in physical capacity when threatened with a nearby entry plan, and these strategic investments deter eventual entry. Consistent with an entry deterrence motive, incumbents respond to the threat of entry during planning when entry is uncertain, but do not invest in physical capacity when entry is assured. Further, a standard deviation increase in incumbent strategic investment is associated with a 0.147 greater probability of failure of the entry plan. Strategic capacity investments are particularly effective in deterring relatively inexperienced entrants. These findings show that investments in deterrence are viable, especially when new entrants face significant other barriers to entry.

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"So in war, the way is to avoid what is strong, and to strike at what is weak."
- Sun Tzu in *The Art of War*

Competition from new entrants has important implications for strategic behavior of incumbent firms. In this vein, an important theoretical literature beginning with Spence (1977) and Dixit (1979) outlines conditions under which incumbent firms will deter the entry of a rival by making preemptive strategic investments. More generally, economists have long sought to understand the implications of barriers to entry (Wallace, 1936; Bain, 1956; Stigler, 1968), and strategic entry deterrence models yield insight into the extent and nature of these entry barriers.

Despite the significant theoretical attention, empirical evidence on entry deterrence has emerged only recently because of the inherent difficulty in distinguishing strategic deterrence motives from other rationales to invest. In this emerging literature, scholars have documented deterrence using strategic alliances, advertising to manipulate the size of the market, and preemptive aggressive pricing (Goolsbee and Syverson, 2008; Ellison and Ellison, 2011; Goetz and Shapiro, 2012). Nonetheless, important gaps remain between the mechanisms outlined in rich theoretical literature and what is known empirically about strategic entry deterrence. In particular, previous work offers limited insight into factors that influence the success of entry deterrence. Also, despite the fact that many entry deterrence models posit that irreversible investments in capacity can be used to preempt new entry (e.g, Dixit 1979, 1980; Maskin 1999; Huisman and Kort 2013), there is little empirical evidence of capacity investments as an entry deterrence tool.

This paper fills this gap by studying capacity investments by incumbent casinos in response to entry plans, which become known well before actual entry. My contribution is to use industry sources to construct a data set on these entry plans and incumbent investments (from March 2003 to August 2012), and use them to study the nature and success of entry deterring investments. Entry plans are useful to study entry deterring investments because they distinguish the timing of entry threats from actual entry, a central concern in empirically documenting entry deterring investments (Goolsbee and Syverson, 2008). In addition, these entry plans become known before the potential entrant fully committing to enter the market as the potential entrant develops a network of vendors and suppliers. Due to the unique timing of information about entry, incumbents can respond to the threat of entry in time to influence the eventual entry decision of the potential entrant.[1]

In the casino industry, capacity is determined by casino floor space. In practice, casinos precommit to a scale of operation by choosing the size of the casino floor. Then, given the choice of floor space, vendors compete to fill the casino floor with product offerings. From this perspective, floor space is the key strategic variable that casinos use to compete with other properties.

[1]Beyond the information structure, the casino industry during this time offers a large number of entry events because there has been significant entry into the market for casino gambling. The casino industry has a great deal of geographic dispersion with casinos operating in 41 states.

Moreover, expanding casino floor space is a costly-to-reverse commitment to compete more aggressively with other casinos in the future, which makes pre-entry expansions of casino floor space ideal for deterring entry of a new rival.[2]

In support of this logic, I find that incumbents expand floor space in response to nearby entry plans, and that these capacity expansions appear to decrease the entry plan's likelihood of success. Specifically, my estimates imply that incumbent casinos expand capacity by 13 to 16 percent of casino floor space in response to the threat of entry, and that entry plans are half as likely to succeed if incumbent capacity expansion is high rather than low.[3] This principal result contrasts with the interpretation that demand drives entry and incumbent investment outcomes simultaneously. In fact, unmeasured demand shocks would generate the opposite result because, if incumbents invest in capacity when demand is high, entry attempts should be more likely to succeed due to higher demand. The fact I find the opposite is a strong indication that these preemptive investments are strategic.

My specifications also control for unobserved demand using a difference-in-difference strategy that baselines the capacity investment response of nearby incumbents (within 100 miles) against farther away incumbents (100-200 miles away) who have a weaker incentive to respond to the threat of entry (shown in my analysis of substitution patterns between incumbent and entrant casinos). This strategy controls for unobservable regional demand and regulation shocks, but my specifications also control for time-varying demographics as well as entrant and incumbent fixed effects. Beyond enriching my main specifications, I also analyze casino demand directly using proprietary data on cash withdrawals at casinos from May 2010 to June 2012. Consistent with the interpretation that the preemptive capacity investments I document are strategic, I find that entry plans were not targeted geographically toward regions where incumbent demand was high or increasing using an analysis of cash withdrawal patrons at incumbent casinos by patrons who reside near entry plans between 2010 and 2012.

Within strategic motives to preemptively invest in capacity, it is important to distinguish empirically whether these investments are for the purpose of deterring entry by the potential rival or strategically accommodating the eventual entry of the rival. To evaluate deterrence versus accommodation, I consider whether incumbents make similar strategic investments in response to construction of new rival casino. In practice, a property going under construction implies that

[2]Aside from credibility of investment, another necessary condition for entry deterrence by excess capacity investment is that incumbents and entrants view their products as strategic substitutes (see Bulow et al. 1985). The softer competition implied by the precommitment to casino capacity helps, but it is also important that casinos are demand substitutes. In the empirical analysis, I analyze proprietary data on cash withdrawals, and conclude that incuments and entrants are, indeed, substitutes for one another.

[3]The estimates here come from the estimated survival function at 60 months after the entry plan, evaluated at one standard deviation above the mean of incumbent capacity expansion (high) versus one standard deviation below the mean of incumbent capacity expansion (low).

entry is nearly certain (i.e., deterrence is infeasible). Even though deterrence is not feasible for properties under construction, investment during this time by incumbents can influence the nature of entrant projects that involve long, often multiple-year, construction periods. Unlike my analysis of incumbent investments around entry plans, I find that incumbents do not make capacity investments around construction events. This finding suggests that capacity investments are intended to deter new entry, rather that accommodate entry or compete more effectively conditional on entry.

Beyond the analysis of incumbent capacity choices, I also investigate whether strategic investments are effective for deterring the entry of a new rival. The results from a binary logistic regression of stalled entry on incumbent capacity investment implies that a standard deviation increase in capacity investment by nearby incumbents by one year after the plan (~9800 square feet) is associated with an increase of 0.147 in the probability that the entry plan fails. My main specification defines a stalled entry to be a plan that lasts for 48 months without ever being open, but I consider robustness on this modeling choice, including using a hazard model to estimate how incumbent investments in capacity relate to the rate of entry (i.e., hazard out of the planning stage). Regardless of the approach, early capacity investments appear to be an effective way to deter – or delay, in the case of the hazard model – entry.

Another way to evaluate the nature of strategic investments is to examine how the effectiveness of strategic investments depends on the timing. Entry deterring investments cannot be effective if they are made too late to credibly signal tough competition before the potential entrant sinks the fixed cost of entry, therby committing to enter the market. Using this logic, I examine the effect of incumbent investments that are made early (by 12 months after plan), with some delay (by 24 months after plan), or late (by 36 months after plan). Consistent with the logic of deterrence, I find that failed entry is more likely when incumbents make early capacity investments, whereas later investments (both by 24 and 36 months post plan) are unrelated to failed entry.[4]

Finally, I deepen the analysis to also evaluate whether the effect of capacity installations on the likelihood of entry depends on the experience of the entrant. Experience could matter for deterrence because an experienced potential entrant has a lower fixed cost of entry (due to having learned how to run a casino in another market, contact vendors, etc.). With lower fixed cost of entry, an experienced entrant is more likely to enter, and less likely to be deterred by incumbent capacity investment. Empirically, I find that the experience of the potential entrant is important for the effect of entry deterring investments. There is a significant effect of capacity installations by incumbents on the rate of entry of inexperiended entrants, but there is no such effect for experienced entrants.[5]

[4]I cannot distinguish between two alternative interpretations of this finding. The pattern I observe could either arise from the investment choices by incumbents (deterring investments occur earlier) or heterogeneity in the effectiveness of strategic investments that depends on the timing. In either interpretation, however, the deterring investments occur earlier because that is precisely when they are effective.

[5]My empirical work uses two measures of experience: (i) whether the potential entrant has at least five casino

My findings and approach should be of interest to scholars and practitioners in business strategy, industrial organization, and financial economics. In particular, my finding that capacity investment can be used to deter entry in the casino industry complements the growing empirical literature on strategic entry deterrence. Recent work has finds evidence of preemptive price cuts (Goolsbee and Syverson, 2008; Gedge et al., 2014), strategic alliances (Goetz and Shapiro, 2012), and advertising to influence the size of the market (Ellison and Ellison, 2011) in strategically responding to entry threats. Within this set of empirical studies, my study is among the first to document empirically the use of installations of costly-to-reverse capacity to deter entry, as well as to distinguish this investment from accommodation. In fact, previous work that relied on implicit entry threats (Goolsbee and Syverson, 2008) or investments around the timing of actual entry (Lieberman, 1987) has found no evidence on the use of capacity investments to deter entry. [6]

Within the industrial organization literature, my use of entry plans complements the growing empirical literature on strategic entry deterrence (Ellison and Ellison 2011; Goolsbee and Syverson 2008; Snider 2009) because it enables me to directly evaluate determinants of the success of entry plans whereas previous work could not. Notably, the entry of low cost carriers into the airline industry has been used in a number of important empirical studies of strategic responses to entry (Goolsbee and Syverson, 2008; Snider, 2009; Goetz and Shapiro, 2012; Gedge et al., 2014; Tan, 2014). Because the threat of entry is implicit in these studies, successful deterrence is not easily measured. By contrast, the casino entry plans in my data indicate an expressed intent to enter. In addition, because some of the casino entry plans are unsuccessful – unlike entry announcements studied in Goolsbee and Syverson 2008 and Whinston and Collins 1992 – entry plans provide meaningful variation in the success or failure of explicit entry plans.

My empirical results on the heterogeneous effect of entry deterrence by entrant experience also relate to the broader literature on the determinants of strategic aggressiveness (Brander and Lewis, 1986; Chevalier and Scharfstein, 1996). Existing studies have focused on incumbents, finding that the incumbent response to entry depends on their (financial) strength (Chevalier, 1995; Khanna and Tice, 2000). Turning to entrants, my analysis builds on this literature by evaluating how variation in the strength of entrants relates to the likelihood of deterrence. Viewed more broadly, my findings on entrant strength have important implications for the nature of competition: If the

properties aside from the planned casino (5 is the nearest whole number that corresponds to the top 25 percent of entry plans by experience), and (ii) whether the potential entrant is a publicly traded casino company. In practice, publicly traded casino companies tend to own many properties, and so, the publicly traded indicator is a more restrictive measure of experience. The fact that both measures of experience lends credence to the main finding that entrants with greater fixed costs of entry are more vulnerable to entry deterring investments.

[6] The fact that I am able to empirically document this type of investment while other studies have not found an effect likely arises from the unique information environment in which credible plans become known – both to the incumbent and the econometrician – before entry is assured. In contrast to other studies of entry announcements (Whinston and Collins, 1992; Goolsbee and Syverson, 2008), many of the entry announcements into the casino industry are unsuccessful, and can be influenced by the actions of incumbents.

strength of entrants is an important determinant for who enters and there is substantial variation in entrant strength, potential competition is less effective at disciplining incumbents than if entrants are homogeneous (e.g., see Roberts and Sweeting (2013)).[7]

Finally, this paper is related to a broader literature at the intersection of industrial organization and finance that uses real links between firms to understand the determinants of firm performance (Hoberg and Phillips, 2010, 2011; Bernile and Lyandres, 2010). While I use geographic links between rivals within a single industry, notable other work in this area uses cross-industry links (Bernile and Lyandres, 2010) and text analysis of product descriptions to link rivals to one another (Hoberg and Phillips, 2010, 2011). My findings complement these analyses by showing that exploiting geographic rival linkages can be useful, especially for local industries.[8]

1 Setting and Hypothesis Development

This section motivates the empirical exercise with a discussion of the central predictions and tensions arising from a model of strategic entry deterrence and accommodation, as well as how the setting – observable plans to enter the American casino industry – can speak to the use of strategic investments for the purpose of deterrence versus accommodation.

1.1 Conditions for Entry Deterrence

Early work on strategic entry deterrence by Dixit (1980) and Spence (1977) outlined how capacity installations can be used to deter entry of a rival. In its simplest form, the viability of entry deterrence through irreversible capacity investment relies on three important elements: (a) products are strategic substitutes, (b) entrants must sink a non-negligible fixed cost of entry to participate in the market, and (c) the incumbent's investment is credible – in this case, because it is irreversible. Subsequent work theoretically examined the role of switching costs, contracting, signaling, and loyalty in facilitating entry deterrence strategies (Milgrom and Roberts, 1982; Aghion and Bolton, 1987; Klemperer, 1987). Regardless of the mechanism, the sunk cost of entry plays a central role

[7] In this respect, my work is related to findings in Roberts and Sweeting (2013) who show using an estimated structural model of mergers in the airline industry that heterogeneity in the costs of entrants matters for selection of actual entrants from the set of potential entrants, and argue this weakens the 'Potential Entry Defense' in the context of antitrust economics.

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

because the entrant having to pay the fixed cost of entry enables the incumbent to invest enough to drive the entrant's profits negative, thereby preventing entry.

Intuitively, entry deterrence is feasible only if the incumbent entry-deterring action reduces profits by the entrant. Beyond the relation of incumbent profits to entrant profit, strategic entry deterrence in its simplest form – overinvestment that deters a potential rival from entering – requires that incumbents and entrants view their products as strategic substitutes (Fudenberg and Tirole, 1984; Bulow et al., 1985).[9] The importance of strategic substitutes is robust to other features of the environment (e.g., uncertainty, dynamics). As an illustration, recent work by Huisman and Kort (2013) analyzes dynamic entry deterrence strategies under uncertainty in a real options framework. Because a notion of strategic substitutes is embedded in their model, their basic conclusions mimic the insights of a static Dixit (1980) model in that strategic overinvestment can be used to deter entry of a rival.[10]

In comparison to the well-developed theoretical literature on strategic preemptive investments (both deterrence and accommodation), the empirical literature is relatively sparse. Empirically observing entry deterrence is difficult because most industrial data sets consist of firms that have operated in the industry, and thus, have entered at some point in the past. Studies of entry deterrence that rely on data on actual entries have two limitations. First, using actual entries, the sample of entry threats is selected on those that were successful. Second, even for the selected sample of entry threats, the timing of the entry threat (as distinct from the actual timing of entry) is unknown. Both limitations make it unlikely to observe entry deterrence using data on actual entry. Not surprisingly, early empirical work using data on actual entries found limited role for entry deterring investments in capacity (Lieberman, 1987).

More recent work has overcome these challenges to identify the strategic response of incumbents to the threat of entry as distinct from actual entry (Dafny, 2005; Goolsbee and Syverson, 2008; Ellison and Ellison, 2011). These studies have yielded a number of important insights. For example, using airlines and the entry patterns of Southwest, Goolsbee and Syverson (2008) found evidence that incumbent airlines aggressively priced in response to the threat of entry, potentially motivated by preventing Southwest's entry. Subsequent work using entry by low cost carrier airlines (including Southwest) has documented that incumbents responded on other margins – e.g.,

[9] In fact, Bulow et al. (1985) show that – under strategic complements – an incumbent can deter entry by underinvesting (and credibly committing to underinvestment). Speaking to the nature of entry deterrence as underinvestment, the empirical results in Ellison and Ellison (2011) provide evidence that pharmaceutical companies underinvest in market size in order to deter entry of generics at the time of patent expiration. Beyond the basic models of entry deterrence, other scholars have considered the role of uncertainty and strategic interactions among incumbents (Gilbert and Vives, 1986; Maskin, 1999).

[10] In the real options model, Huisman and Kort (2013) draw an equivalence between entry deterrence and strategically delaying the entry of a potential rival until the demand state is high enough. This dynamic element of the model draws a theoretical equivalence between strategically delayed entry and entry deterrence. Some of my empirical tests – e.g., the hazard model evidence – mimic this theoretical equivalence.

forming strategic alliances (Goetz and Shapiro, 2012) or substituting away from service quality (Prince and Simon, 2015). Another recent empirical study of entry deterrence is Ellison and Ellison (2011), which provides evidence that incumbents in the pharmaceutical industry underinvest in advertising for the purpose of deterring entry. This finding is in line with Bulow et al. (1985)'s model of deterrence when products are strategic complements.

Taken together, the empirical literature on entry deterrence has yielded important insights into the conditions under which pricing, contracts, product quality, and advertising have been used strategically to deter entry. These techniques appear to have been used strategically around the threat of entry and actual entry. Despite the emergence of these new studies, there is limited empirical evidence of incumbents using excess capacity investment to deter entry of a rival. In addition, empirical evidence on *successful* entry deterrence is rare. In fact, in the airline industry (which has generated the data for most of these studies), entry deterring investments have had little impact on entry by low cost carriers. Relative to existing empirical work on deterrence, my findings complement existing work by establishing empirical evidence that incumbents have used capacity overinvestment to *successfully* deter entry.

1.2 Deterrence of Entry Plans

The primary empirical challenge in studying strategic responses to entry is to identify strategic investments (i.e., those made in response to the threat of entry) separately from other investments in response to actual entry or in response to changes in demand. My approach is to directly observe the timing of entry *plans* in the casino industry. As the plans occur well before the actual entry date, the strategic response to the entry plan can be more easily disentangled from other factors that motivate or enable actual entry.

I observe entry plans through a casino industry managerial contacts database, the Gambling Business Directory. The Gambling Business Directory collects up-to-date information about every casino (planned, under construction, and open), as well as the contact information of every casino manager in the United States. The purpose of the database is to put vendors in contact with casino managers, and as a result, the potential entrants enter the database when they start contacting casino vendors about a proposed casino. Because the information and plans are verified and collected by a third party, manipulation of the intent to plan is costly enough that it is not observed in the data. The Gambling Business Directory provides the status of the industry at a monthly frequency (from March 2003 to August 2012). Linking the data over time, I observe the monthly timing of entry plans and the precise location of the planned casino, which allows me to observe which incumbents face a threat to entry in their local casino market and when this threat becomes known.

Although entry plan data have been studied in the literature on strategic entry, entry plans for which deterrence is possible (as is the case here) are not common.[11] In part, this is because disclosing the intent to enter a particular location is costly, and such disclosure is usually avoidable in other industries. In the casino industry, however, the scale of investment, the importance of coordinating with vendors well in advance of entering, and the necessity of obtaining permits imply a long, unavoidably observable planning stage. Especially after the advent of the Internet, it is unlikely that a potential entrant could plan a casino without being detected and recorded in the Gambling Business Directory at a very early stage.

My direct observation of entry plans that threaten nearby incumbents is similar to other recent empirical approaches to study entry deterrence empirically. Similar to Ellison and Ellison (2011)'s study of patent expirations in pharmaceuticals and the entry threat of generics, I observe the timing of the heightened entry threat as well as incumbents who are more exposed to that entry threat using incumbents nearest to the proposed entry site. Because I also use local geography to isolate the incumbents threatened by entry, my approach also mimics other uses of industrial structure to infer heightened threat of entry – e.g., Dafny (2005)'s analysis of entry deterrence in hospital markets, and Goolsbee and Syverson (2008)'s analysis of entry threats in the airline industry.[12]

After ruling out non-strategic rationales for preemptive investment, there is another strategic reason to preemptively overinvest – strategic entry accommodation. That is, incumbents may overinvest in capacity in order to earn more profit conditional on successful entry. Because incumbents could use excess capacity installations either to deter entry or to accommodate entry, it is important to determine whether the investment is for deterrence or accommodation. I empirically distinguish deterrence from accommodation in two ways. First, I directly analyze how well strategic investments preempt new entry. Because they are designed to reposition the incumbent conditional on successful entry, investments in accommodation should be less likely than investments in deterrence to affect the likelihood of actual entry. Second, I analyze whether incumbents undertake similar investments around the time when a rival property undergoes construction. The logic of this second test is that – if investment is for the sake of deterrence – incumbents should not invest in response to a rival starting construction when eventual entry is almost certain. On the other hand, accommodative investments are just as likely to occur after the fixed cost of entry is sunk be-

[11] For example, Whinston and Collins (1992) use the announcement by People's Express Airlines to enter particular routes to motivate an event study analysis. In a different use of entry plans, Goolsbee and Syverson (2008) used announced entry plans by Southwest as precisely the kinds of entry plans that are unlikely to be deterred (and thus can use them to distinguish between accommodation and deterrence motives).

[12] A popular alternative to reduced form evidence on entry deterrence in the main text is to structurally estimate of an entry deterrence model (Chicu, 2012; Molnar, 2013). Identification in these structural estimation exercises hinges on similar considerations to those employed here. Indeed, either structural work infers entry deterrence from parameters that should respond to the threat of entry (rather than actual entry) to achieve better identification, or parameters are identified from parametric assumptions in the model. Some structural studies of entry deterrence do both. For example, Molnar (2013)'s analysis of the use of scheduling congestion externalities to deter entry in the airline industry explicitly makes use of the industrial structure, while interpreting correlations in the context of a model of entry deterrence.

cause their intention is not to deter. Other empirical studies of entry deterrence distinguish between deterrence and accommodation using similar logic.[13]

1.3 Capacity and the Nature of Competition in the Casino Industry

Competition in the casino industry takes places as a two-stage process. In the first stage, casinos select their capacity (casino floor space). In the second stage, casinos choose product offerings that maximize profit given the amount of casino floor space constructed in the first stage. In practice, the second stage is achieved through within-casino competition among casino game vendors who provide an array of table games, slot machines, and other gambling opportunities. Vendors such as International Game Technology (IGT) or Bally's compete with one another for placement of their products on the casino floor. Competition for floor space is fierce – with approximately the worst-performing one fifth of products replaced by new products each year, either routed to resale markets or destroyed in obsolescence (Bourie, 2011).

The structure of strategic interaction in the casino industry – a capacity choice in the first stage, and fierce competition in the second stage – resembles the classic setup of Kreps and Scheinkman (1983), which justifies studying strategic interaction among casinos directly using capacity choices.[14] In addition to speaking to the nature of competition, it is convenient that expanding the casino floor space is costly and difficult to reverse from the standpoint of entry deterrence theory. As a result, when an incumbent casino invests in additional casino floor space while a rival is planning to enter, it is a credible commitment to compete aggressively conditional on effective entry. From the standpoint of the theoretical literature, commitments to compete aggressively are precisely the type of investments that can deter entry.

Another useful feature of the casino industry is that gambling markets tend to be local. To this point, Figure 1 presents a density plot of the distance of patron home ZIP codes to casinos (for transactions between 2010 and 2012), which I compute using a proprietary casino cash withdrawal data set.[15] According to the plot, approximately 75 percent of casino patrons reside within 100

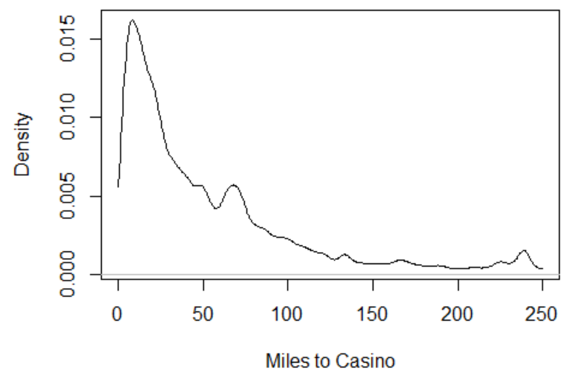
[13] For example, to isolate accommodation motives, Goolsbee and Syverson (2008) focus on a subset of Southwest routes for which entry was announced (and thus, virtually assured). To focus on deterring investment, Ellison and Ellison (2011) focus on medium-sized pharmaceutical markets for which the likelihood of entry by generics can be influenced by strategic investments (large markets will certainly have generic entry, while small markets will certainly have no entry). Finally, Dafny (2005) uses similar logic to study entry deterring investments, which result in a non-monotonic relationship between market potential and number of potential entrants (noting a discrete jump when a monopolist incumbent faces at least one potential entrant).

[14] The softer competition implied by pre-committing to capacity rather than competing directly on casino product offerings suggests that casino capacity choices are strategic substitutes. Technically, the strategic substitutes condition also requires that incumbent and entrant demand are substitutes (i.e., market expansion by the new entrant is dominated by competitive effects). Using data on cash withdrawals from incumbent casinos near successful entries, I also establish this fact in Section 2.

[15] These data are provided in a proprietary and confidential manner to the author, with respect to sharing the identities

miles of the casino, a pattern of visitation that implies that competition is stronger locally. On the basis casino demand is local, my empirical exercise analyzes the strategic response to the threat of entry by geographically proximate incumbents.

Figure 1: Density Plot of Patron Distance to Casino



Note: This plot is censored at the 90th percentile distance to casino for clarity of exposition. Source: proprietary casino ATM withdrawal data.

1.4 Testable Hypotheses

Given that competition across casinos primarily occurs on the basis on casino capacity, my evidence credibly speaks to theories of entry deterrence using excess capacity (e.g., Dixit 1979, 1980; Huisman and Kort 2013). As long as the incumbent and entrant casino are strategic substitutes (a condition I verify empirically using cash withdrawals at casinos), these models yield the central prediction:

Hypothesis 1 *Incumbents Invest in Deterrence*. Incumbent casinos expand capacity in response to nearby entry plans (in the same geographic market).

Consistent with the logic of Ellison and Ellison (2011) and Goolsbee and Syverson (2008) in distinguishing between deterrence and accommodation, the entry plan must be an intent to enter that is uncertain in order for incumbent responses to it to reflect deterrence. In support of using entry plan data for understanding strategic deterrence, the entry plans in my data occur before the potential entrant sinks the fixed costs of entry, but after the plan becomes a serious intent to enter. Indeed, approximately half of the entry plans do not result in an eventual entry.

of the patrons and casinos covered in the data set. These proprietary data allow me to identify patron transactions and home ZIP codes for 8.5 million withdrawal transactions.

Hypothesis 2 *Strategic Investments Deter Entry*. When nearby incumbents expand capacity strategically, the likelihood that the entry plan fails is greater.

This hypothesis – which states that entry deterrence is effective – distinguishes the prediction of strategic entry deterrence from an alternative hypothesis in which entry plans and incumbent investments are both motivated by unobserved demand shocks. If entry behavior and investments were motivated by an expansion of demand, we should expect the opposite: when incumbent expand capacity, entry will be more likely.

Hypothesis 3 *Incumbents do not Invest in Deterrence when Entry is Certain*. Incumbent casinos do not expand capacity in response to nearby construction projects (in the same geographic market).

This hypothesis distinguishes between strategic entry deterrence and accommodation. Strategic investments when investment in capacity is unlikely to influence the likelihood of eventual entry cannot deter, and thus, their principal motivation is to accommodate new entry. Dafny (2005), Ellison and Ellison (2011) and Goolsbee and Syverson (2008) conduct similar tests of strategic investment when deterrence cannot be effective in order to distinguish deterrence and accommodation incentives.

Hypothesis 4 *Earlier Investments are More Effective at Deterring Entry*. The likelihood of entry deterrence is greater if capacity installations are made earlier in the entry plan.

For entry deterrence to be effective, the incumbent needs to make the capacity investment early enough in the entry plan so that the entrant receives the credible signal prior to sinking its fixed costs of entry. If the capacity investment arrives too late (i.e., by the time the entrant has already broken ground), it will be ineffective at deterring the new rival's entry.

Hypothesis 5 *Strategic Investments Deter Entry of Less Experienced Rivals*. When nearby incumbents expand capacity strategically, it reduces the likelihood of less experienced entrants.

The rationale for this hypothesis is that the efficiency of operating in the casino industry may depend on learning by doing (Benkard, 2000). Potential entrants who are experienced in running other casino operations have less to learn during the planning and construction phases, and are thus, less likely to be deterred from entering.[16]

[16] This prediction together with Hypothesis 3 seems to imply that incumbents would simply not respond to the threat of entry by an experienced entrant. This implication is not quite true. In practice, there is a set of experienced entrants who can be deterred, and to the extent that experienced entrants are stronger, it will take larger investments to deter them. This implies that (i) conditional on deterrence, incumbents invest more in deterring experienced entrants,

2 Data

This section describes the two main data sources used in the empirical exercise, and provides evidence of stylized facts that support analyzing entry deterring investments in the context of the casino industry.

2.1 Casino Plans, Locations and Attributes

The primary data source is the Gaming Business Directory, which contains comprehensive casino industry information about every casino 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.[17]

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. Among the 100 entry plans initiated prior to 2010 (out of 134 total), 54 of the entry plans never opened.

Beyond observing the monthly timing of planning, construction and entry by following records over time, each record also provides the precise location of every property (latitude and longitude). Using this information, Figure 2 portrays the geographic dispersion of the casino properties in the American casino industry using location data from the Gambling Business Directory (Casino City Press, 2012). 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, essentially every state with an incumbent.[18]

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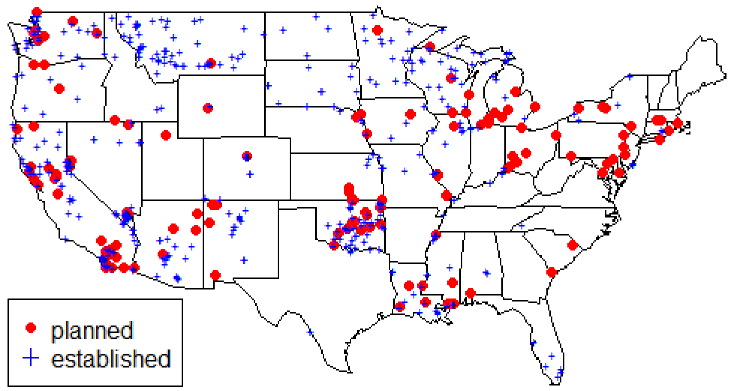
but (ii) there is a lower likelihood of wanting to deter an experienced entrant. Putting (i) and (ii) together, there is an ambiguous unconditional prediction on whether incumbents respond more or less to experienced entrants. I have performed some tests to distinguish (i) and (ii), but these tests run into power issues, especially in detecting greater investment for incumbents conditional on deterrence. Partly, this theoretical ambiguity can explain the ambiguous relationship between entrant strength and observed incumbent investments (see Appendix Table 17).

[17]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 web page, 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.

[18]Cookson (2014) provides a more detailed history of casino gambling in the United States. For even more detail,

Figure 2: Geographic Dispersion of American Casino Industry

Note: This figure depicts the locations of entry plans (denoted by red dots) and incumbent casino properties (denoted by blue crosses) across the United States. By August 2012, there were 41 states with casinos, indicating considerable geographic dispersion.



Beyond the location and timing information, 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. The data also provide the identity of the owner of each casino property, which allows me to determine whether the entrant is experienced and identify whether the incumbent is a publicly traded casino firm. Aside from providing information about the nature of incumbents, the level of detail and characteristics of the potential entrant's plan can also be informative of the nature of entry deterrence.

To better understand the nature of the entry plan data, consider Table 1, which reports selected summary statistics on entry plans initiated prior to 2010. Even in tabular form, Table 1 reveals much information about the propensity of incumbents to deter entry, the strength of potential entrants, and the role of capacity expansion. In particular, incumbents near eventually stalled entry plans expand capacity by more than incumbents near compoleted entry plans (whether measured at 12, 24, or 36 months after the entry plan). In addition, consistent with the hypothesis that high-cost entrants are easier to deter, experienced entrants (those with five or more properties) are much more likely to complete their entry plan than inexperienced potential entrants (20 out of 23 plans by experienced entrants are successful). Similarly, entry plans initiated by publicly-traded casino firms, which tend to have greater experience in the industry, are successful 85 percent of the time

see Rose (1991).

(17 out of 20 plans) in my sample.

Table 1 also reports means and counts of other characteristics of incumbents, plans, and the entrant's market to shed further light on what motivates entry plans and investments by incumbents.[19] In particular, the median stalled plan and the median completed plan are initiated at very similar times (February 2006 versus March 2006), indicating that differences between stalled and completed entry plans are unlikely to be driven by macroeconomic factors. Stalled and completed entry plans do not appear to be different on demand because both income per capita and population are similar for for the two types of plans. Moreover, incumbents near stalled and completed entries own a similar number of properties, and the number of incumbent casinos is similar across stalled and completed plans. Among these other characteristics, the only notable difference is that the distance to Las Vegas is greater for completed entries. In my specifications that evaluate incumbent capacity investments and their success, I control for these alternative characteristics, and noting the difference in distance to Las Vegas, I examine whether the results hold dropping mature markets (Nevada, Atlantic City, Las Vegas).

2.2 Substitutability between Entrants and Incumbents

I supplement my main data set on the location and timing of entry plans with a proprietary, transaction-level database of cash withdrawal transactions at casinos throughout the United States from May 2010 to June 2012. For each transaction, I observe a patron identifier, the patron's home ZIP code, a casino identifier, the amount withdrawn, the method of withdrawal, and a time stamp for the transaction. In the context of providing supplemental information on entry deterrence, the cash withdrawal data allow me to construct ZIP code $\times$ casino $\times$ month measures of casino demand by summing transaction amounts across patrons from a particular ZIP code and particular month.

This is useful because, beyond local markets and irreversible capacity investment, it is instructive to evaluate how incumbent casino demand responds to a successful entry event. Moreover, it is also useful to establish that entrant casinos reduce demand for incumbent casinos by a greater amount for patrons who are closer to the entrant casino. To address both of these points, I estimate the specification using ZIP $\times$ potential entrant $\times$ month observations:

[19] In addition to the features discussed in the main text, the counts of number of owners and number of states by stalled versus completed entry plans highlights the fact that there is plenty of within state and within owner variation in the success of entry plans (i.e., there is considerable overlap between the states and owners in which there are entry successes and failures). This geographic pattern suggests that differences across geographic markets are not driving the patterns in the data. Nonetheless, my empirical analysis is careful to rule out geography as a driver of outcomes, dropping mature markets – Las Vegas and Atlantic City – in robustness checks.

$$log\left(1+cash_{ijt}\right) = \gamma_i+\gamma_j+\gamma_t+\beta_1 post_{it}+\beta_2 dist_{ij}+\beta_3 post_{it}\times dist_{ij}+\varepsilon_{ijt} \quad (1)$$

where $cash_{ijt}$ is the total cash accessed at incumbent casinos by patrons who reside in ZIP code j, which is within 100 miles of entering casino i, aggregated over all transactions in month-year t. Incumbent casinos are casinos that reported cash access transactions prior to any of the opening dates in the sample. The variable $post_{it}$ is an indicator that equals one if the observation occurs after casino i's entry date, and is zero otherwise, $dist_{ij}$ is the distance from casino i's precise location (latitude-longitude) to ZIP code j's geographic centroid. The coefficient of interest is the coefficient on the interaction β_3, which is positive if patrons farther from the casino substitute less strongly away from their existing gambling options. To focus on the influence of the entering casino i, the sample is restricted to a one-year window around the month of opening (-6 months to +6 months). This narrow window reduces the extent of truncation at the edges of the 26-month sample. Standard errors in parentheses are double clustered by ZIP code and date (month-year).

Table 2 presents the results from estimating equation (1) using an increasingly rich set of fixed effects. Regardless of the specification, the coefficient estimate on $post_{it}\times dist_{ij}$ is positive, indicating that the effect of a successful entry on incumbent demand diminishes (i.e., becomes less negative) the farther the patron is from the successful entrant's location. For incumbents that compete on casino capacity, my estimates of equation (1) have two important implications: (1) casino markets and the threat of entry is local with the most intense threat to incumbent casino demand occurring closer to the potential entrant, and (2) the successful entry by a new rival reduces incumbent demand in a manner that suggests entrant and incumbent capacity choices are strategic substitutes. In addition to the tests presented in Table 2, I have conducted several robustness tests on this specification including estimating the $post_{it}\times dist_{ij}$ effect for smaller windows around the entry event, as well as estimating a null effect on pre-entry placebos and evaluating the impact of including ZIP codes within 200 miles instead of 100 miles.[20] It is a robust feature of the casino market that incumbent demand decreases post entry and decreases most strongly near the entry site.

[20]These results are presented in Tables 13, 14 and 15 in the Appendix. From the specifications that also include gambling activity between 100 and 200 miles from the proposed entry site, substitution away from incumbent casinos is weaker outside of 100 miles. This finding provides an additional rationale to baseline the investment choices of nearby incumbents (those within 100 miles) against those made by farther incumbents (those between 100 and 200 miles away).

2.3 Sampling Frame and Identification of Deterrence

The Gambling Business Directory encompasses more properties than are meaningful to include in a casino industry data set. In particular, there are a significant number of properties for which the primary business is not casino gambling – i.e., in Montana, it is common for small casinos to be attached to convenience stores and gas stations. Given how different this type of casino is from the typical casino in the industry, it would be surprising if such a property were to expand its casino operations in order to deter the entry of a pure casino rival nearby. Thus, I impose a number of filters on the original Gambling Business Directory data to ensure that the data cover casinos for which casino gambling and entertainment is the primary source of business: (a) the casino has greater than the 10th percentile number of slot machines and casino size (square feet), and (b) the casino has at least one table game.

Further, I restrict the sample to entrants and incumbents where the potential entrant makes a plan within 100 miles of the incumbent (and as a control incumbents within 200 miles from these potential entrants). In addition, to identify the incumbent response to the entry plan, it must be the case that data on the incumbent property exist at some point 12 to 18 months prior to the entry plan, as well as at some point 24 to 30 months after the entry plan. From the total of 134 entry plans in the data set, these sampling restrictions reduce the total number of potential entrants to 100 potential entrants. The resulting sample is an unbalanced panel with 25,775 entrant-incumbent-date pairs (100 entrants, 272 incumbents, over the course of 98 months).[21]

3 Evidence on Entry Deterrence

This section provides evidence on the nature of strategic investments made by incumbents around the arrival of nearby entry plans. Throughout this analysis, I exploit the local nature of competition in the casino industry, focusing on the response of nearby incumbent casinos who face the strongest competitive threat. Specifically, when a new casino is planned within 100 miles of an incumbent, does that incumbent expand casino floor space (Hypothesis 1)? Further, I baseline my estimates of

[21] Throughout the empirical analysis, I consider three additional samples: (1) the sample of first construction events (44 potential entrants break ground during the sample), which is defined analogously to the sample of entry plans (100 potential entrants make explicit entry plans that threaten incumbents within 200 miles between March 2003 and August 2012), (2) plans and successful opens between 2010 and 2012 to exploit the casino cash withdrawal data set (13 entry plans and 21 realized successful entries), and (3) entrant-level samples where I classify failed entry attempts, and estimate the effect of capacity adjustments by incumbents to deter entry. In this last set of estimation samples, some classifications must drop observations for sample truncation reasons, but in the fullest of these estimated in the hazard model, there are 109 potential entrants for which capacity adjustment by one year after the plan can be measured (this sample has more entry plans than the estimation sample in the first part of the paper because the timing only requires there to be 12 months of post plan data, rather than 30). To avoid confusion about the level and/or sample selection used, each regression table reports the number of entrants, incumbents, and ZIP codes used in the analysis (when each is appropriate).

the strategic response of nearby incumbents against the contemporaneous response of incumbents between 100 and 200 miles away. These more distant incumbents may still experience the threat of entry, but they have a weaker strategic incentive to respond to the threat of entry. Because incumbents between 100 and 200 miles from the proposed site share unobservables (i.e., local regulation, changes in regional economy, etc.), the observed difference between nearby incumbents (within 100 miles) and those farther away (100-200 miles) more likely arises from a strategic response to entry plans than the raw change in capacity.[22]

3.1 Strategic Responses to Entry Plans

My main empirical tests are from a difference-in-difference specification in which I analyze capacity choices of established incumbents observed 18 to 12 months before, and 24 to 30 months after the entry plan:[23]

$$casino.size_{ijt} = \gamma_j + \gamma_i + \beta_1 post_{ijt} + \beta_2 nearby_{ij} + \beta_3 post_{ijt} \times nearby_{ij} + X_{ijt}\Gamma + \varepsilon_{ijt} \quad (2)$$

where i indexes incumbents j indexes potential entrants, $after$ equals 1 if $t = \{+24, 25, ..., 30\}$ and 0 if $t = \{-18, -17, ... -12\}$, *nearby* equals 1 if the incumbent is within 100 miles of the proposed site,X_{ijt} are market and incumbent characteristics (i.e., income and population demographics, average characteristics of incumbent casino properties, and interactions with $nearby_{ij}$ and $post_{ijt}$) γ_j are entrant fixed effects, and γ_i are incumbent property fixed effects. 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.[24]

[22] 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.

[23] The timing when the incumbent learns of the intent of a rival to enter may be earlier than observed in my data. To address this concern, I adopt a doughnut strategy with a wide event window. In this way, my specifications employ a wide event window to allow incumbents to have better knowledge of the entry plan than the econometrician, and also to allow for some construction delay.

[24] Incumbents who are between 100 and 200 miles away are similar on most dimensions, but different on a couple. In particular, far incumbents have smaller hotels and convention centers than nearby incumbents. The owners of far incumbents also own fewer properties than the owners of near incumbents. Despite these differences, near and far incumbents are remarkably similar on casino floor space, slot machines, number of table games, number of poker tables, restaurants, entertainment venues, parking spaces and employees. These similarities suggest that the demand and regulatory environment is similar for the two groups. See Table 12 in the Appendix. Nonetheless, a reader may express skepticism that these two groups are well matched. For this reason, I include a rich set of incumbent, potential entrant, and market controls and fixed effects to alleviate this issue. Throughout the paper, I suppress reporting the results for the full set of controls for clarity of exposition. Log files with those additional results are available on request from the author.

Table 3 presents the results from estimating this difference-in-difference specification, showing robustness to incumbent and potential entrant fixed effects, demographic control variables, market characteristics, time trends, and double clustering by incumbent and entrant property. Across specifications, I find robust evidence that nearby incumbents respond strategically to the threat of entry by expanding their casino floor space. Moreover, my difference-in-difference estimates imply the expansion of capacity by nearby incumbents is significantly greater for nearby incumbents who face the strongest competitive threat from the entry plan. The effect size ranges from 6500 square feet to 7900 square feet (13 to 16 percent of the initial size of casinos), and is statistically significant at the five percent level in the specification with the richest set of controls (i.e., controls for regional demographic variables, market controls and year dummies interacted with *nearby* and *post*, as well as potential entrant and incumbent property fixed effects), while exhibiting similar statistical significance across specifications.

The effects I find in the main specification are not predominantly a Las Vegas phenomenon, nor are they driven by Nevada or Atlantic City. Table 4 presents estimates from analogous specifications where observations from incumbents within 25 miles of Las Vegas, Nevada, and New Jersey are excluded from the estimation. The economic magnitude of the strategic response of incumbents remains (and in many cases becomes stronger), and the results are typically statistically significant, and if not, they have p-values below 0.15 across specifications.[25] Taken together, the strategic response to the threat of entry by expanding casino floor space seems to be robust.

3.2 Deterrence versus Accommodation

Although the excess capacity investments documented in Tables 3 and 5 appear to be strategic, incumbents could use excess capacity investments to accommodate new entry rather than deter it. To distinguish accommodation from deterrence, I also evaluate how incumbents respond to the threat of entry when entry is (nearly) guaranteed. In this case, there is no point to make investments for the sake of deterrence, and thus, the strategic investments can be thought to be made to accommodate new entry (Hypothesis 3). Dafny (2005), Ellison and Ellison (2011) and Goolsbee and Syverson (2008) conduct similar tests to distinguish deterrence and accommodation.

In the case of pre-entry behavior in the casino industry, entry is essentially assured once the potential entrant breaks ground on the construction of the new project. By this point, the entrant has committed to enter, and investments made by the incumbent cannot be for deterrence. To examine whether incumbents invest to accommodate new entry, I evaluate a difference-in-difference specification that is similar to equation (2), but centered on construction events rather than entry

[25] This amount of robustness is fairly remarkable, especially in the specifications where all incumbents in Nevada are dropped – in that case, we lose nearly half of the sample observations, and it is understandable that the tests would lose some power.

plans (i.e., $post_{ijt}$ equals one after the potential entrant breaks ground on the new project).

Table 5 presents the estimates from this difference-in-difference specification. In contrast to the robust expansion around the first planning, incumbents do not seem to respond to the construction of a new rival's property at all. Across specifications, none of the difference-in-difference estimates are statistically significant. Moreover, the magnitude of the response is small in comparison to expansion of incumbent properties around planning, which suggests the difference in significance does not have to do with lack of power. Indeed, the standard errors are similar in magnitude to the standard errors in Table 3. The fact that incumbents do not make strategic investments around construction events, but make significant expansions of capacity around planning events, suggests that strategic investments were made for the purpose of deterring rivals rather than for the purpose of strategic accommodation.

3.3 Deterrence versus Demand

In the main specification, the controls for income and population, market characteristics and the fixed effects for both incumbent and entrant suggest that the estimates I obtain are not driven by demand. Moreover, the fact that I baseline my estimates against regional casinos that are not within 100 miles also helps. Nonetheless, it is worth directly examining whether entry plans were made in locations with excess demand for casino services from incumbents. To examine this possibility directly, I return to the casino cash withdrawal data set. Recall that the casino cash data run from May 2010 to June 2012, which limits the number of entry plans I can evaluate to the 13 entry plans that occurred during that window.[26] Nonetheless, I can identify from within-plan variation of casino demand of patrons who reside near the entry plan.

At the ZIP-plan-month level, I can construct a measure of demand, and evaluate whether these plans were centered on locations that had greater demand at the time. Specifically, I estimate a specification of the form given in equation (1), but centered on the 13 entry plans instead of the 21 successful opens between May 2010 and June 2012.

$$log\left(1+cash_{ijt}\right) = \gamma_i+\gamma_j+\gamma_t+\beta_1 post_{it}+\beta_2 dist_{ij}+\beta_3 post_{it}\times dist_{ij}+\varepsilon_{ijt} \tag{3}$$

In this specification, beyond the interpretation of the difference-in-difference coefficient β_3, β_1

[26] The fact that there are only 13 plans covered by the casino cash data implies that I cannot use the casino cash data to construct a measure of casino demand at the instance of the plan to use as a control in my main specification. Nonetheless, I can use the data to conduct falsification tests of the form presented here, and the demographics and characteristics controls help considerably with the unobserved demand critique. Moreover, the results in the next section on the success of entry deterrence also suggest that unobserved demand is not a major driver of the results. To the extent that it is an issue with the results on the success of entry, it would only make the results stronger to more completely control for unobserved demand.

reveals whether there is a trend in casino demand in the region around the announcement of the entry plan, and β_2 indicates whether the entry plan is targeted toward (negative) or away from (positive) areas where there is high demand for incumbent casinos. Table 6 presents estimates from this specification. In contrast to an unobserved demand These estimates indicate not much evidence of the plans being geographically targeted (i.e., $\beta_2 \approx 0$). Although this result is not estimated for all 100 plans with a viable incumbent nearby, it suggests that an increase in incumbent demand was not the rationale for the entry plan (concurrent with the investment around the same time).[27]

4 Success and Timing of Strategic Investments

This section provides evidence on the effectiveness of entry deterrence, the timing of incumbent investments, and heterogeneity in effects on potential entrants. Broadly, I find that when nearby incumbents expand capacity around the arrival of an entry plan, the plan to enter is less likely to succeed. 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* greater strategic investment by incumbent casinos, yet the results in this section robustly point to a negative relationship 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.

4.1 Do Excess Capacity Installations Affect the Likelihood of Entry?

To evaluate how capacity adjustment by incumbents affects the succcess of entry (Hypothesis 2), I estimate the likelihood of unsuccessful entry using the binary logistic regression specification:

$$\log\left(Odds\left(stalled_j\right)\right) = \beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma + \varepsilon_j \qquad (4)$$

where $stalled_j = 1$ if the entry plan is unsuccessful. In the data, lack of success is indicated by a stale record that is no longer updated. Thus, my main definition of $stalled_j$ is equal to one if the plan is observed for 48 months without opening during the data. To use this classification, I

[27] As complementary evidence to this point, I have also conducted a long-run event study that estimates the impact of a deterred entry plan on the stock market value of publicly-traded casino firms. In this event study, the announcement of a plan harms incumbent firm value while the withdrawal of the plan causes the incumbent firm value to recover. If demand were the rationale for the plans or the failure of plans, the result would have gone the other way. Consistent with this being deterrence rather than demand, these effects are more pronounced in markets where incumbent properties are more exposed to the threat of entry. Table 16 in the appendix reports results from this event study.

restrict the estimation sample to observations that could be classified as stalled or not (i.e., at least 48 months of data for the main definition of stalled). The dependent variable of interst is $CapAdj_j$ which is the increase in the average casino floor space of incumbents within 100 miles of the entry plan by one year after the entry plan (relative to the baseline of 12 months prior to the entry plan).[28]

My specifications also control for the initial capacity one year prior to the entry plan ($CapInit_j$), the number of incumbents, and X_j, which contains a host of other covariates to capture differences in the entry plan, and incumbent/market characteristics. In particular, I include a dummy variable for whether the entry plan was initiated prior to 2007, a dummy variable for whether the entry plan is detailed,[29] controls for whether the entrant is experienced (i.e., has five other properties), as wel as publicly traded. On the incumbent side, I control for the average number of properties owned by nearby incumbents, as well as for average number of slot machines, parking spaces, employees, convention center square footage, and number of hotel rooms for incumbent casinos within 100 miles.

Table 7 presents estimates of marginal effects evaluated at the mean from estimating the binary logistic equation (4). In the main specification, a standard deviation increase in the capacity adjustment of nearby incumbent properties leads to a 14.0 percent greater probability that the entry plan stalls (classified after 48 months). This effect is robust to controlling for entrant and incumbent characteristics, and is statistically significant at the one percent level using standard errors clustered by state.

To evaluate robustness to this choice of classification, I consider two alternative definitions of deterred entry: no entry observed after 36 months, and no entry observed after 24 months. The advantage of these shorter-horizon classifications is that they enable me to retain more observations for estimation (85 and 98 observations respectively), but the disadvantage is that these definitions raise the possibility that successful entry is misclassified as deterred entry. If the events are classified incorrectly at random, misclassifying some successful entries as deterred entries tends to reduce the observed effect of capacity installations. Indeed, this is consistent with the results in 7. Although the effect of capacity adjustment is robust to which classification I employ, the observed effect size reduces as the chance for misclassification increases. Viewed another way, if the main measure (stalled after 48 months) contains some misclassification of longer entry plans (but less than stalled after 24/36 months), this suggests the effect of capacity adjustment is greater than observed in the main specifications in columns (1) and (2).

[28] In shifting to evaluate how strategic investments affect the likelihood of entry, I drop the comparison to how incumbents 100 to 200 miles away from the entry location make investments at the same time. I do this for clarity of exposition and brevity of explanation. In the Appendix, I estimate specifications, which control for the amount of investment of these farther-away incumbents. As expected, investments made by incumbents this far away have limited effect on the likelihood of entry. See Table 18 for details.

[29] Some entry plans do not offer detailed information, whereas others do. There is limited evidence that this matters for the response of the incumbent's response to the threat of entry. See Table 17 in the Appendix.

4.2 Does the Timing of Strategic Investments Matter?

In addition to the main specifications, I also consider whether the timing (immediacy) of the capacity installations matters for their success in deterring entry. If the investment is indeed strategic and intended to deter entry, capacity installations that are too late to influence the planning behavior of the potential entrant should be less effective (Hypothesis 4). To analyze how the timing of capacity investment matters, I construct two alternative measures of capacity adjustment by incumbents: capacity adjustment by two years after the plan, and capacity adjustment by three years after the plan (again, both relative to capacity of incumbents one year prior to the plan). With these alternative measures, I estimate analogous specifications to equation (4).

Table 8 presents the alternative results with the more delayed measures of capacity expansion. As anticipated, the longer is the horizon for capacity installation, the smaller is the effect of capacity installation on the likelihood of deterring the potential entrant. Taking the specifications for which entrant and incumbent characteristics are also controlled, a standard deviation increase in capacity adjustment leads to a 14.7 percent greater chance of deterrence if capacity installations are made by 12 months after the plan, a 10.7 percent greater chance of deterrence if capacity installations are made by 24 months after the plan, and an 8.0 greater chance of deterrence if capacity installations are made by 36 months after the plan. Only the first estimate is statistically significant at conventional levels (though the 24-month estimate has a p-value < 0.15). That is, consistent with the logic of strategic entry deterrence, early investments are more effective than delayed investments.

4.3 Do Incumbent Investments Affect the Rate of Entry?

The evidence in Sections 4.1 and 4.2 depends on a classification for when an entry plan fails, which results in an inefficient use of data. An attractive method to more efficiently use data with shorter histories (because of censoring at the end of the sample) is to estimate a hazard model for the rate of transition of planned projects out of the planning stage (into construction or open). Because deterred plans become stale records that persist in the planning stage, a decrease in this hazard rate is consistent with entry deterrence. To address the effectiveness of capacity adjustments, I estimate the hazard function for the rate of transition of planned projects into the construction phase or open phase.[30] Specifically, I use a Cox proportional-hazards model with a log-linear model for the

[30] 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 A.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.

hazard function $h_i(t)$:[31]

$$h_i(t) = h_0(t)\exp\left(\beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma\right) \tag{5}$$

where the set of covariates is the same as in the binary logistic specifications, and the baseline hazard function is given by $h_0(t)$. As in the binary logistic specifications, I am interested in isolating the effect of $CapAdj_j$ on the rate of entry. In this specification of Cox proportional-hazards model, when $CapAdj_j$ increases by one, the hazard rate is multiplied by $\exp(\beta_1)$.

The advantage of the hazard model is that it more efficiently uses information on the timing of entry than the binary logistic specifications.[32] On the other hand, a decrease in the hazard rate out of planning is also consistent with capacity investment merely delaying the rate of entry rather than effectively (and permanently) deterring entry. This distinction is not as sharp as it appears. In fact, in Huisman and Kort (2013)'s dynamic model of entry deterrence under uncertainty, delay for a certain market potential and deterrence are equivalent conceptually.

Table 9 presents the estimates from the Cox proportional-hazards model for how incumbent capacity investments affect the multiplicative effect on the hazard rate. As in Table 8, the different specifications evaluate how the immediacy of incumbent investments affects the hazard rate. Consistent with the binary logistic specifications, more immediate investments are more effective at deterring or delaying entry. Using the estimates from the specification that controls for entrant and incumbent characteristics, a standard deviation increase in incumbent capacity adjustment is associated with a reduction in the hazard rate of 37.3 percent, an effect that is statistically significant at the one percent level with standard errors clustered by state.[33] By contrast an increase of one standard deviation in the incumbent capacity investment by 36 months after the entry plan is

[31] Appendix A outlines technical details of estimation the Cox proportional hazards model, including the form of the partial likelihood. 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 A presents estimates that use the Breslow approximation to assure that the qualitative results do not depend on this choice.

[32] Another advantage of the Cox proportional-hazards model is that it is semi-parametric under the assumption of proportional hazards. Without specifying the functional form of $h_0(t)$, the parameter vector $(\beta_1, \beta_2, \beta_3, \Gamma)$ is identified so long as the effect on the hazard rate does not depend on the number of months since the announcement of entry. To test this restriction, Grambsch and Therneau (1994) nest the proportional hazards model within a time-varying coefficient model for the hazard. Their form of this test is implemented in the R `survival` package using the `cox.zph()` function. In Appendix A.5, I present the result of this test, which fails to reject the proportional hazards assumption.

[33] This calculation is obtained by $0.373 = 1 - 0.627$, where the multiplicative effect on the hazard rate is 0.627. Note: the longer period over which incumbent investments can be made cannot be measured for some of the observations in the sample due. As such, the number of observations is less in columns (3) and (4). In the appendix, I evaluate whether the difference in results is due to the number of observations, or the investment horizon, by estimating the model in (1) and (2) on the sample from (3) and (4). The results are qualitatively similar. I also obtain similar results if I consider incumbent investments by 24 months after the entry plan (see Table).

only associated with a reduction in the hazard rate of 13.3 percent, an effect that is statistically insignificant. As in Table 8, timing of incumbent investment matters for its effectiveness.

As a graphical depiction of the effect and timing of incumbent investments, consider Figure 3, which portrays the survival function for low incumbent investment (one standard deviation below the mean; $s = 9812$ square feet) versus high investment investment (one standard deviation above the mean), separately for early investment (by 12 months after the plan) and late investment (by 36 months after the plan). Survival in the planning stage is equivalent to non-entry, and thus, higher values of the survival function imply more effective deterrence. As the plot shows, the likelihood of survival (deterrence) is higher when incumbents make more capacity investments (i.e. the high investment case is indicated by the blue survival function). Specifically, when incumbent investments are made early, the high investment survival probability is statistically different from the low investment case.[34] By contrast, the second panel in Figure 3 indicates that the deterrence rate is not statistically different for high investment versus low investment made by 36 months after the plan.

To better understand the magnitude of the effects of incumbent strategic investments, Table 10 reports the estimated entry success probabilities. By five years after the plan, entry plans where incumbents make large amounts of entry investment are approximately half as likely to succeed – success probability of 0.334 versus 0.662. By contrast, there no meaningful difference in entry success probabilities if investment is measured by 3 years after the entry plan (success probability of 0.406 versus 0.520, and statistically insignificant). By this measure, immediate and significant investments by incumbents appear to be successful at deterring entry.

4.4 Entrant Experience and Deterrence

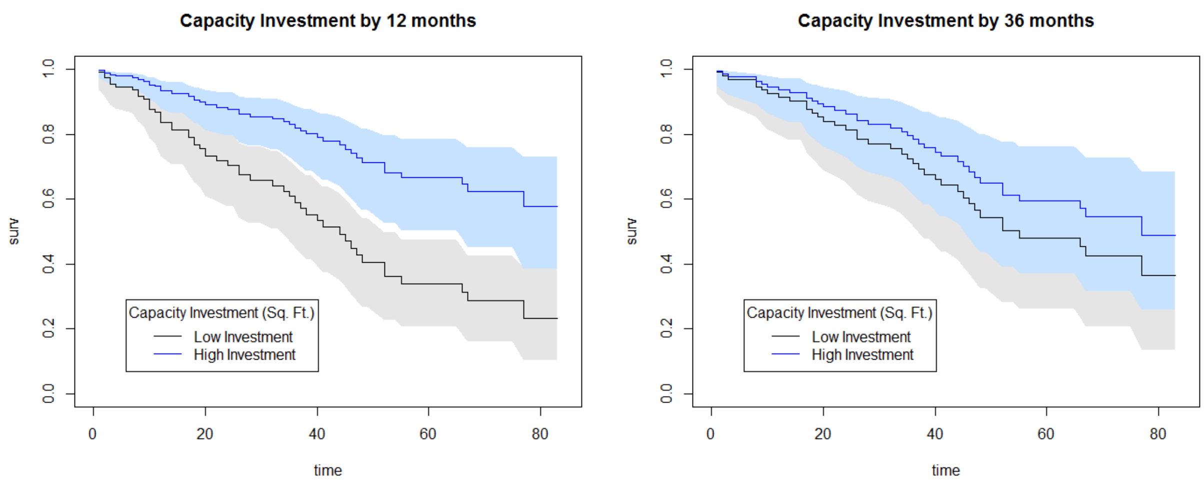
Beyond showing that deterrence is effective, entry deterrence models yield the prediction that capacity investments are more effective for entrants whose sunk cost of entry is greater. This prediction suggests that the effect of capacity adjustment on the rate of entry is less for experienced entrants (who have already sunk much of the cost of entry) than it is for inexperienced entrants with much of the sunk costs of entry into the casino industry before them. To this end, I estimate a version of equation (5) where experienced entrants (i.e., those that own at least five other casino properties at the time of entry) have a separate coefficient on $CapAdj_j$ than inexperienced entrants.[35] As alternative evidence on deterrence and experience, I separately estimate coefficients for privately run entrants (who typically have less experience in the casino industry) and publicly-

[34] This statistical significance is indicated by the non-overlapping confidence bands for much of the early investment survival function.

[35] Because I also include a main effect for *experienced*, this model is numerically equivalent to also including an interaction $CapAdj_j \times experienced$ in the Cox proportional-hazards model.

Figure 3: The Effectiveness and Timing of Strategic Investments by Incumbents

Note: This figure portrays the time series of estimated entry deterrence probabilities (i.e., the survival function) implied by the hazard model estimates in Table 9, columns (2) and (6). The entry success probabilities are computed using the fitted survival function implied by models (2) for the +12 months results and (6) for the +36 months results. 95 percent confidence bands are generated using confidence intervals for the log survival function, and translating the estimates. The fitted survival function is evaluated at the mean of other model variables, and at either "low" capacity adjustment (one standard deviation below the mean) or "high" capacity adjustment (one standard deviation above the mean)



traded entrants.

Table 11 presents the estimates from these interactive models. As expected from the entry deterrence motivation (Hypothesis 5), capacity investments by incumbents are not effective for experienced entrants, but they are effective for deterring inexperienced entrants. Specifically, for a standard deviation increase in incumbent capacity investments, the hazard rate declines by 34.7 percent, an effect that is statistically significant at the five percent level clustering by state. In contrast, experienced entrants reduce their hazard rate by 18.7 percent for a standard deviation increase in incumbent capacity investment, a statistically insignificant effect.[36] Similarly, for entry attempts by private firms, the hazard rate of entry slows by 33.2 percent (significant at the five percent level), while the hazard rate increases slightly for publicly traded firms (albeit, a statistically insignificant effect).

5 Conclusion

Strategic entry deterrence has generated such significant theoretical interest that Tirole's standard-bearing industrial organization textbook devotes a chapter to models of entry deterrence (Tirole,

[36]Table 23 in the Appendix also reports the estimates for initial capacity, and its interactions with the experience measures. Log files with the coefficient estimates on incumbent and entrant characteristics are available from the author.

1988). Nonetheless, for the classic model of entry deterrence – irreversible capacity installations that deter entry – scholars have found remarkably little evidence in support of this mechanism. This paper fills this gap between theory and evidence by constructing and using a novel data set that describes the plans of potential entrants to the American casino industry. 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; Huisman and Kort, 2013) , this paper extends the growing empirical literature on strategic entry deterrence (e.g., Goolsbee and Syverson, 2008; Ellison and Ellison, 2011; Goetz and Shapiro, 2012).

In addition, the strength of potential entrants matters for the likely success of entry deterring investments. Namely, incumbent firms are more effective in deterring inexperienced potential entrants. This heterogeneity in strategic investments is consistent with a simple model of entry deterrence, but it also provides prescriptive insight into when entry deterring investments are likely to be effective.

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.

Finally, my empirical findings appear to be more consistent with strategic entry deterrence than strategic accommodation on two dimensions. First, strategic investments are associated with a lower likelihood of entry, which would be unlikely if investments were undertaken to accommodate the new entrant conditional on entry. Second, incumbents do not make strategic investments when entry is almost certain – e.g., when a construction project breaks ground – but invest significantly around the time of an uncertain entry plan. The strategic responses studied in this paper indicate a striking degree of competition even before a rival breaks ground.

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6 Tables of Results

6.1 Summary Statistics

Table 1: Characteristics of Entry Plans

Note: This table summarizes the 100 entry plans initiated before August 2010 (to guarantee 24 months of post plan data). Stalled plans are properties that were observed for 36 or more months in the data set without appearing as an open casino. Publicly-traded entrants are planned casino properties owned by one of the publicly-traded firms in my data set. Income and population measures are from the Bureau of Economic Analysis, and are observed at the year-county level. Distance to Vegas is the Great Circle Distance from the casino property and Las Vegas. To allow incumbents to have better knowledge of entry plans than the timing in the data set, capacity expansion is taken to be relative to one year prior to the entry plan shows up in the data set.

	Stalled	Completed	Total
Capacity Expansion (1000s of square feet)			
... by 12 months post plan	6.75	4.65	5.61
... by 24 months post plan	9.16	5.77	7.43
... by 36 months post plan	10.21	7.71	9.10
Median Entry Date	Feb 2006	Mar 2006	Feb 2006
Counts			
# of Plans	46	54	100
# of Publicly Traded Entrants	3	17	20
# of Entrants with > 5 properties	3	20	23
# of Owners	24	27	38
# of States	15	19	20
Averages			
# of Properties Owned (Potential Entrants)	2.57	8.09	5.55
# of Incumbent Casinos (within 100 miles)	24.78	21.33	22.90
# of Properties Owned (Incumbents within 100 miles)	11.18	10.73	10.93
Distance to Vegas	855.06	1059.21	965.30
Income Per Capita ($ 1000s)	11.05	11.73	11.42
Population (1000s)	15.24	15.52	15.39

6.2 Cash Data: Strategic Substitution and Local Markets

Table 2: Substitution of Gambling Expenditure when a Casino Opens Nearby (2010-2012)

Note: This table presents estimates from the specification

$$log\,(1+cashwithdrawn_{ijt}) \quad = \quad \gamma_i+\gamma_j+\gamma_t+\beta_1 post_{it}+\beta_2 distance_{ij}+\beta_3 post_{it}\times distance_{jt}+\varepsilon_{ijt}$$

where $cashwithdrawn_{ijt}$ is the total cash accessed at incumbent casinos by patrons who reside in ZIP code j, which is within 100 miles of entering casino i, aggregated over all transactions in month-year t. Incumbent casinos are casinos that reported cash access transactions prior to any of the opening dates in the sample. The variable $post_{it}$ is an indicator that equals one if the observation occurs after casino i's entry date, and is zero otherwise, $distance_{ij}$ is the distance from casino i's precise location (latitude-longitude) to ZIP code j's geographic centroid. The coefficient of interest is the coefficient on the interaction β_3, which is positive if patrons farther from the casino substitute less strongly away from their existing gambling options. To focus on the influence of the entering casino i, the sample is restricted to a one-year window around the month of opening (-6 months to +6 months). This narrow window reduces the extent of truncation at the edges of the 26-month sample. Standard errors in parentheses are double clustered by ZIP code and date (month-year). $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)
post × distance (Z)	0.071^{***}	0.055^{***}	0.088^{***}	0.068^{***}
	(0.024)	(0.020)	(0.023)	(0.020)
distance (Z)	-0.114^{***}	-0.110^{***}	-0.035^{***}	-0.024^{*}
	(0.023)	(0.024)	(0.013)	(0.013)
post	-0.684^{*}	-2.531^{***}	-1.046^{*}	-3.670^{***}
	(0.411)	(0.135)	(0.569)	(0.096)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE		x		x
ZIP Code FE			x	x
N	80829	80829	80829	80829
# ZIP codes	6356	6356	6356	6356
# Entrants	21	21	21	21
R^2	0.064	0.092	0.592	0.647

6.3 Main Results, Robustness and Placebos

Table 3: Incumbent Capacity Expansion During the Planning Stage of a Nearby Rival

Note: This table presents regression results that estimate the magnitude of changes in incumbent capacity in response to nearby entry plans, according to the specification:

$$casino.size_{ijt} \quad = \quad \gamma_j + \gamma_i + \beta_1 post_{ijt} + \beta_2 nearby_{ij} + \beta_3 post_{ijt} \times nearby_{ij} + X'_{ijt}\Gamma + \varepsilon_{ijt}$$

where $casino.size_{ijt}$ is the size of incumbent casino i in square feet, near potential entrant j, at date t. To allow incumbents to become aware of the entrant's plan and respond to it, each observation is an incumbent-entrant pair at a date either 18 to 12 months prior to planning or 24 to 30 months after planning. The indicator $post_{ijt}$ equals one for post-plan observations, while $nearby_{ij}$ equals one for incumbent entrant pairs in which the incumbent is within 100 miles of the potential entrant. The regressions also control for market and incumbent characteristic controls. Market controls include the distance from Las Vegas (Great Circle distance), fraction of tribal casinos within 100 miles, fraction of casinos within 100 miles owned by private firms, and the average number of properties owned by owners of casinos within 100 miles. Demographic variables are annual county-level data for population and per capita personal income, which are taken from the Bureau of Economic Analysis. To focus on establishments for which casino gambling is the primary business, the sample is restricted to established incumbents (existing in the data as of March 2003) with greater than the 10th percentile of casino floor space (10,000 square feet) and slot machines (500 slot machines), as well as offering at least one table game. To improve robustness to outliers, the casino floor space variable was winsorized at the 0.5 and 99.5 percent level. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
post × nearby	7834.95***	6879.15*	7558.57**	6558.15**	7924.85**	7394.99**
	(2154.12)	(3592.38)	(3651.31)	(3182.90)	(3817.16)	(3578.75)
Controls × nearby & post						
Market Controls	x	x	x	x	x	x
Demographics			x			x
Year Dummies				x	x	x
Fixed Effects and Clustering						
Potential Entrant	x		x	x	x	x
Incumbent Property		x	x	x	x	x
N	25,775	25,775	25,775	25,775	25,775	25,775
# of Incumbents	272	272	272	272	272	272
# of Entrants	100	100	100	100	100	100
# of Dates	98	98	98	98	98	98
R^2	0.178	0.887	0.890	0.891	0.891	0.892

Table 4: Robustness to Mature Markets (Excluding Las Vegas and Atlantic City)

Note: This table presents regression results estimating the magnitude of changes in incumbent capacity in response to nearby entry plans, according to the specification:

$$casino.size_{ijt} \quad = \quad \gamma_j + \gamma_i + \beta_1 post_{ijt} + \beta_2 nearby_{ij} + \beta_3 post_{ijt} \times nearby_{ij} + X'_{ijt}\Gamma + \varepsilon_{ijt}$$

where variable descriptions and specification details are the same as in Table 3. The only difference is that the specification is estimated excluding incumbents from mature markets – Las Vegas, Nevada, and Atlantic City. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. †,*, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dropping Incumbents within 25 miles of Las Vegas						
post × nearby	7536.74***	6921.09*	7249.74*	6018.03**	8122.15*	7373.48*
	(2216.05)	(3968.32)	(3795.11)	(3269.89)	(4152.07)	(3988.49)
N	16,469	16,469	16,469	16,469	16,469	16,469
Dropping Incumbents in Nevada						
post × nearby	8409.29**	8442.80*	8709.66*	7147.26†	10217.70*	9351.72†
	(3313.11)	(4866.13)	(4984.13)	(4495.22)	(5704.58)	(5810.78)
N	12,084	12,084	12,084	12,084	12,084	12,084
Dropping Incumbents in New Jersey						
post × nearby	7702.62***	6901.60*	7474.86**	6350.32**	7897.46**	7230.66**
	(2160.78)	(3643.94)	(3676.78)	(3178.23)	(3868.19)	(3595.02)
N	25,400	25,400	25,400	25,400	25,400	25,400
Controls × nearby & post						
Market Controls	x	x	x	x	x	x
Demographics			x			x
Year Dummies				x	x	x
Fixed Effects and Clustering						
Potential Entrant	x		x	x	x	x
Incumbent Property		x	x	x	x	x

Table 5: Investment as Accommodation: Incumbent Capacity Expansion During a Rival's Construction Stage

Note: This table presents regression results that estimates the magnitude of changes in incumbent capacity in response to nearby construction events, according to the specification:

$$casino.size_{ijt} \quad = \quad \gamma_j + \gamma_i + \beta_1 post_{ijt} + \beta_2 nearby_{ij} + \beta_3 post_{ijt} \times nearby_{ij} + X'_{ijt}\Gamma + \varepsilon_{ijt}$$

where $casino.size_{ijt}$ is the size of incumbent casino i in square feet, near potential entrant j, at date t. To allow incumbents to become aware of the entrant's plan and respond to it, each observation is an incumbent-entrant pair at a date either 18 to 12 months prior to planning or 24 to 30 months after planning. The indicator $post_{ijt}$ equals one for post-plan observations, while $nearby_{ij}$ equals one for incumbent entrant pairs in which the incumbent is within 100 miles of the potential entrant. The regressions also control for market and incumbent characteristic controls. Market controls include the distance from Las Vegas (Great Circle distance), fraction of tribal casinos within 100 miles, fraction of casinos within 100 miles owned by private firms, and the average number of properties owned by owners of casinos within 100 miles. Demographic variables are annual county-level data for population and per capita personal income, which are taken from the Bureau of Economic Analysis. To focus on establishments for which casino gambling is the primary business, the sample is restricted to established incumbents (existing in the data as of March 2003) with greater than the 10th percentile of casino floor space (10,000 square feet) and slot machines (500 slot machines), as well as offering at least one table game. To improve robustness to outliers, the casino floor space variable was winsorized at the 0.5 and 99.5 percent level. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
post × nearby	2096.64	943.54	1206.00	−913.76	1891.82	−93.83
	(3375.89)	(3720.87)	(3516.99)	(4046.32)	(3510.94)	(4005.95)
Controls × nearby & post						
Market Controls	x	x	x	x	x	x
Demographics			x			x
Year Dummies				x	x	x
Fixed Effects and Clustering						
Potential Entrant	x		x	x	x	x
Incumbent Property		x	x	x	x	x
N	10,294	10,294	10,294	10,294	10,294	10,294
# of Incumbents	240	240	240	240	240	240
# of Entrants	44	44	44	44	44	44
# of Dates	97	97	97	97	97	97
R^2	0.207	0.920	0.923	0.924	0.924	0.925

Table 6: No Increase in Incumbent Demand Around Entry Plans (Cash Access Data, 2010-2012)

Note: This table presents estimates from the specification

$$log(1+cashwithdrawn_{ijt}) = \gamma_i + \gamma_j + \gamma_t + \beta_1 post_{it} + \beta_2 distance_{ij} + \beta_3 post_{it} \times distance_{jt} + \varepsilon_{ijt}$$

where $cashwithdrawn_{ijt}$ is the total cash accessed at incumbent casinos by patrons who reside in ZIP code j, which is within 100 miles of planned casino i, aggregated over all transactions in month-year t. Incumbent casinos are casinos that reported cash access transactions prior to any of the opening dates in the sample. The variable $post_{it}$ is an indicator that equals one if the observation occurs after casino i's plan date, and is zero otherwise, $distance_{ij}$ is the distance from casino i's precise location (latitude-longitude) to ZIP code j's geographic centroid. The coefficient of interest is the coefficient on the interaction β_3, which is positive if patrons farther from the casino substitute less strongly away from their existing gambling options. To focus on the influence of the entering casino i, the sample is restricted to a one-year window around the month of opening (-4 months to +4 months). This narrow window reduces the extent of truncation at the edges of the 26-month sample. Standard errors in parentheses are double clustered by ZIP code and date (month-year). $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)
post × distance (Z)	−0.039	−0.029	−0.040	−0.015
	(0.105)	(0.108)	(0.023)	(0.030)
distance (Z)	0.025	0.018	0.034	0.016
	(0.067)	(0.070)	(0.013)	(0.013)
post	-0.552^{**}	-2.416^{***}	-0.767^{**}	-3.729^{***}
	(0.226)	(0.271)	(0.355)	(0.369)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE		x		x
ZIP Code FE			x	x
N	31765	31765	31765	31765
# ZIP codes	4005	4005	4005	4005
# Entry Plans	13	13	13	13
R^2	0.074	0.092	0.672	0.709

6.4 Effectiveness of Deterrence and Heterogeneity

Table 7: Capacity Investments and Deterred Plans: Binary Logistic Regression, Marginal Effects

Note: This table presents regression results on the odds of entry deterrence of entry plans from estimating the binary logistic regression specification:

$$\log(Odds(stalled_j)) = \beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma + \varepsilon_j$$

where the variable $stalled_j$ is a dummy variable for whether the entry plan was stalled – i.e., for the first column, observed for 48 months in the data without ever being observed as open. To avoid bias from right-truncation at the end of the sample, we restrict attention to observations for which this classification is meaningful. Columns 3 through 6 estimate the model using alternative classifications of 24 months and 36 months. The $CapAdj_j$ variable is the average amount of expansion by incumbents within 100 miles (in square feet) from one year prior to one year after the entry plan, $CapInit_j$ is the average size in square feet of incumbent casino properties at the beginning of the sample window (one year prior to the plan). X_j is a vector of entrant and incumbent characteristics that potentially affect the likelihood of successful entry. Entrant Characteristics include a dummy for whether the plan was initiated prior to 2007, whether the plan contained detailed information, and number of properties owned by the entrant's firm. Incumbent Characteristics (within 100 miles) include average number of properties owned by incumbent firms, average convention floor space (square feet), average number of hotel rooms, average number of employees, average number of slot machines and average number of parking spaces at the casino property. For ease of interpretation, variables denoted by (Z) have been scaled to have mean zero and standard deviation one. To improve robustness to outliers, capacity variables were winsorized at the 0.5 and 99.5 percent level. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively.

Dependent Variable:	Stalled after 48 Months		Stalled after 36 Months		Stalled after 24 Months	
	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)	0.140***	0.147***	0.113***	0.113*	0.105***	0.083*
	(0.051)	(0.050)	(0.032)	(0.061)	(0.032)	(0.050)
Initial Capacity (Z)	0.058	0.195	0.004	0.209	0.071	0.289
	(0.077)	(0.221)	(0.058)	(0.263)	(0.090)	(0.229)
# of Incumbents	0.000	−0.004	0.000	−0.002	0.000	−0.001
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.002)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
Clustering						
State-Level	x	x	x	x	x	x
# of Entry Plans	68	68	85	85	98	98
# of States	21	21	25	25	28	28
AIC	95.58	90.01	137.14	113.20	120.23	122.52

Table 8: Timing of Investments and the Likelihood of Entry Deterrence: Binary Logistic Regression, Marginal Effects

Note: This table presents regression results on the odds of entry deterrence of entry plans from estimating the binary logistic regression specification:

$$\log(Odds(stalled_j)) = \beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma + \varepsilon_j$$

where the left hand side of the equation is the logged odds of stalled entry by the potential entrant. For this table, the variable $stalled_j$ is a dummy variable that equals one for properties observed for 48 months in the data without ever being observed as open. To avoid bias from right-truncation at the end of the sample, we restrict attention to observations for which this classification is meaningful. This table considers three different $CapAdj_j$ variables: expansion by 12 months after plan, expansion by 24 months after plan, and expansion by 36 months after plan. $CapInit_j$ is the average size in square feet of incumbent casino properties at the beginning of the sample window (one year prior to the plan). Finally, X_j is a vector of entrant and incumbent characteristics that potentially affect the likelihood of successful entry. Entrant Characteristics include a dummy for whether the plan was initiated prior to 2007, whether the plan contained detailed information, and number of properties owned by the entrant's firm. Incumbent Characteristics (within 100 miles) include average number of properties owned by incumbent firms, average convention floor space (square feet), average number of hotel rooms, average number of employees, average number of slot machines and average number of parking spaces at the casino property. For ease of interpretation, variables denoted by (Z) have been scaled to have mean zero and standard deviation one. To improve robustness to outliers, capacity variables were winsorized at the 0.5 and 99.5 percent level. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. † *, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)						
... by 12 months after plan	0.140***	0.147***				
	(0.051)	(0.050)				
... by 24 months after plan			0.068	0.107†		
			(0.062)	(0.074)		
... by 36 months after plan					0.035	0.080
					(0.087)	(0.073)
Initial Capacity (Z)	0.058	0.195	0.054	0.214	0.071	0.212
	(0.077)	(0.221)	(0.077)	(0.273)	(0.090)	(0.254)
# of Incumbents	0.000	−0.004	0.000	−0.003	0.000	−0.003
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
# of Entry Plans	68	68	68	68	68	68
# of States	21	21	21	21	21	21
AIC	95.58	90.01	93.60	90.72	93.18	90.19

Table 9: Determinants of the Hazard Rate out of the Planning Stage: Timing of Incumbent Investments

Note: This table presents regression results from estimating the Cox proportional hazards model:

$$h_i(t) \quad = \quad h_0(t)\exp\left\{\beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma\right\}$$

where the left hand side of the equation is the hazard rate of entry for entry plan i at date t. This table considers three different $CapAdj_j$ variables: expansion by 12 months after plan, expansion by 24 months after plan, and expansion by 36 months after plan. $CapInit_j$ is the average size in square feet of incumbent casino properties at the beginning of the sample window (one year prior to the plan). Finally, X_j is a vector of entrant and incumbent characteristics that potentially affect the likelihood of successful entry (same as for the binary logistic regressions). For ease of interpretation, variables denoted by (Z) have been scaled to have mean zero and standard deviation one. To improve robustness to outliers, capacity variables were winsorized at the 0.5 and 99.5 percent level. Z-Statistics based on clustered standard errors in parentheses. Standard errors are clustered at the state level. †*, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)						
... by 12 months after plan	0.794*	0.627***				
	(-1.736)	(-3.837)				
... by 24 months after plan			0.824	0.836		
			(-1.209)	(-1.017)		
... by 36 months after plan					0.876	0.867
					(-0.750)	(-0.658)
Initial Capacity (Z)	0.671	0.609	0.628	0.464	0.677	0.533
	(-1.600)	(-0.937)	(-1.426)	(-1.381)	(-1.398)	(-1.029)
# of Incumbents	1.001	0.998	1.003	0.995	1.003	0.998
	(0.351)	(-0.235)	(1.497)	(-0.504)	(1.288)	(-0.221)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
# of Entry Plans	109	109	93	93	82	82
# of Successes	50	50	39	39	38	38
# of States	28	28	26	26	24	24
R^2	0.057	0.272	0.064	0.264	0.051	0.227

Table 10: Effect of Incumbent Investment on Success of Entry Plans (Fitted Survival Function)

Note: This table presents the time series of estimated entry success probabilities implied by the hazard model estimates in Table 9 The entry success probabilities are computed using the fitted survival function implied by models (2) for the +12 months results and (6) for the +36 months results. The fitted survival function is evaluated at the mean of other model variables, and at either "low" capacity adjustment (one standard deviation below the mean) or "high" capacity adjustment (one standard deviation above the mean).

	Investment by +12 months		Investment by +36 months	
	low	high	low	high
Fraction of Successful Entries				
... by +12 months	0.165	0.065	0.086	0.062
... by +24 months	0.296	0.123	0.187	0.137
... by +36 months	0.411	0.180	0.291	0.216
... by +48 months	0.595	0.288	0.456	0.351
... by +60 months	0.662	0.334	0.520	0.406

Table 11: Determinants of the Hazard Rate out of the Planning Stage: Capacity Expansion by One Year After Plan

Note: This table presents regression results on the odds of entry deterrence of entry plans from estimating the Cox proportional hazards model:

$$h_i(t) = h_0(t)\exp\left\{\beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + \beta_4 CapAdj_j \times EntrantStrength_j + X_j'\Gamma\right\}$$

where the left hand side of the equation is the hazard rate of entry for entry plan i at date t. This table defines the $CapAdj_j$ variable as expansion by 12 months after plan, and the interaction with $EntrantStrength_j$ evaluates the heterogeneity in the ability of capacity expansions to deter entry plans (either if the entrant is experienced or publicly traded). $CapInit_j$ is the average size in square feet of incumbent casino properties at the beginning of the sample window (one year prior to the plan). Finally, X_j is a vector of entrant and incumbent characteristics that potentially affect the likelihood of successful entry (same as for the binary logistic regressions). For ease of interpretation, variables denoted by (Z) have been scaled to have mean zero and standard deviation one. To improve robustness to outliers, capacity variables were winsorized at the 0.5 and 99.5 percent level. Z-Statistics based on clustered standard errors in parentheses. Standard errors are clustered at the state level. †*, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	(1)	(2)	(3)
Capacity Adjustment (Z)	0.627***		
	(-3.837)		
Interactions with Entrant Experience Measures			
Capacity Adjustment (Z)			
... × Inexperienced Entrant		0.653**	
		(-2.420)	
... × Experienced Entrant		0.813	
		(-0.863)	
... × Non-Public Entrant			0.668**
			(-2.006)
... × Public Entrant			1.086
			(0.227)
Other Characteristics and Main Effects			
# of Incumbents	0.998	0.999	0.995
	(-0.235)	(-0.094)	(-1.033)
Experienced Entrant		3.359**	
		(2.547)	
Public Entrant			2.324**
			(2.027)
Additional Controls			
Entrant Characteristics	x	x	x
Incumbent Characteristics	x	x	x
Incumbent Capacity	x	x	x
Incumbent Capacity × Experience Measure		x	x
Clustering			
State-Level	x	x	x
# of Entry Plans	109	109	109
# of Successes	50	50	50
# of States	28	28	28
R^2	0.747	0.756	0.764

A Appendix Material: For Online Publication

A.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 A.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 A.3 presents estimates of the hazard function using the Breslow approximation to the partial likelihood. Section A.4 presents estimates of the hazard function when plans are allowed to stall during construction. Section A.5 presents the results of a test of the proportional hazards assumption.

A.2 Approximating the Cox Proportional Hazards Partial Likelihood

A.2.1 The partial likelihood with no ties

Start with the log-linear specification for the hazard function (equation (5) in the text):

$$h_i(t) = h_0(t)\exp\left(X_i'\beta\right) \tag{6}$$

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:

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

A.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 $\theta_i = \exp(X_i'\beta)$. Applying the method outlined in the previous section, the contribution to the partial likelihood at date t equals

$$\mathscr{L}_{1,2} = \left(\frac{\theta_1}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right)\left(\frac{\theta_2}{\theta_1+\theta_2+\theta_3+\theta_4+\theta_5}\right) \tag{7}$$

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.[37]

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.[38]

A.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 (7). In practice, this approximation reduces the power of the estimator, and tends to produce smaller coefficient estimates.

[37] 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.

[38] 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

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

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 $i = 1,2,3$:

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

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 indexes 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:

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

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).

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

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

A.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 results. Table 20 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 **??**), subject to small numerical differences.

A.4 Estimates using Hazard out of Pre-Entry

As I mentioned in the main text, the specifications in Table **??** 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 21 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.

A.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 22 shows the result of testing for non-proportional hazards. In all cases, we fail to reject the null hypothesis that hazards are proportional.

B Appendix Tables

Table 12: Appendix Table: Balance of Attributes for Near versus 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

Table 13: Appendix Table: Substitution of Gambling Expenditure when a Casino Opens Nearby (2010-2012), Placebo Tests for Effects Pre-Open

Note: This table presents estimates from the specification

$$log(1+cashwithdrawn_{ijt}) \quad = \quad \gamma_i + \gamma_j + \gamma_t + \beta_1 post_{it} + \beta_2 distance_{ij} + \beta_3 post_{it} \times distance_{jt} + \varepsilon_{ijt}$$

where $cashwithdrawn_{ijt}$ is the total cash accessed at incumbent casinos by patrons who reside in ZIP code j, which is within 100 miles of entering casino i, aggregated over all transactions in month-year t. Incumbent casinos are casinos that reported cash access transactions prior to any of the opening dates in the sample. The variable $post_{it}$ is an indicator that equals one if the observation occurs after casino i's entry date, and is zero otherwise, $distance_{ij}$ is the distance from casino i's precise location (latitude-longitude) to ZIP code j's geographic centroid. The coefficient of interest is the coefficient on the interaction β_3, which is positive if patrons farther from the casino substitute less strongly away from their existing gambling options. To focus on the influence of the entering casino i, the sample is restricted to a one-year window around the lagged post treatment dummy (-6,0) months and (-8,0) months. This narrow window reduces the extent of truncation at the edges of the 26-month sample. Standard errors in parentheses are double clustered by ZIP code and date (month-year). $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent level respectively.

Panel A: (-6 month, 0 month) window

	(1)	(2)	(3)	(4)
post_lag_three × distance (Z)	−0.008	−0.011	−0.012	−0.025
	(0.022)	(0.018)	(0.027)	(0.021)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE				x
ZIP Code FE			x	x
N	41892	41892	41892	41892
# ZIP codes	6093	6093	6093	6093
# Entrants	21	21	21	21
R^2	0.086	0.114	0.634	0.695

Panel B: (-8 month, 0 month) window

	(1)	(2)	(3)	(4)
post_lag_four × distance (Z)	−0.042*	−0.033	−0.030	−0.018
	(0.023)	(0.021)	(0.030)	(0.021)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE		x		x
ZIP Code FE			x	x
N	52699	52699	52699	52699
# ZIP codes	6216	6216	6216	6216
# Entrants	21	21	21	21
R^2	0.068	0.084	0.655	0.686

Table 14: Appendix Table: Substitution of Gambling Expenditure when a Casino Opens Nearby (2010-2012), Different Time Horizons

Note: This table presents estimates from the specification

$$log\,(1+cashwithdrawn_{ijt}) \quad = \quad \gamma_i+\gamma_j+\gamma_t+\beta_1 post_{it}+\beta_2 distance_{ij}+\beta_3 post_{it}\times distance_{jt}+\varepsilon_{ijt}$$

where $cashwithdrawn_{ijt}$ is the total cash accessed at incumbent casinos by patrons who reside in ZIP code j, which is within 100 miles of entering casino i, aggregated over all transactions in month-year t. Incumbent casinos are casinos that reported cash access transactions prior to any of the opening dates in the sample. The variable $post_{it}$ is an indicator that equals one if the observation occurs after casino i's entry date, and is zero otherwise, $distance_{ij}$ is the distance from casino i's precise location (latitude-longitude) to ZIP code j's geographic centroid. The coefficient of interest is the coefficient on the interaction β_3, which is positive if patrons farther from the casino substitute less strongly away from their existing gambling options. To focus on the influence of the entering casino i, the sample is restricted to narrow windows around the month of opening (-3,+3) and (-4,+4) months. This narrow window reduces the extent of truncation at the edges of the 26-month sample. Standard errors in parentheses are double clustered by ZIP code and date (month-year). $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent level respectively.

Panel A: (-3 month,+3 month) window

	(1)	(2)	(3)	(4)
post × distance (Z)	0.073*	0.059*	0.089***	0.070**
	(0.037)	(0.034)	(0.034)	(0.029)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE				x
ZIP Code FE			x	x
N	44391	44391	44391	44391
# ZIP codes	6037	6037	6037	6037
# Entrants	21	21	21	21
R^2	0.102	0.136	0.603	0.671

Panel B: (-4 month,+4 month) window

	(1)	(2)	(3)	(4)
post × distance (Z)	0.070**	0.060**	0.084***	0.074***
	(0.031)	(0.027)	(0.030)	(0.026)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE		x		x
ZIP Code FE			x	x
N	66001	66001	66001	66001
# ZIP codes	6236	6236	6236	6236
# Entrants	21	21	21	21
R^2	0.061	0.094	0.582	0.643

Table 15: Appendix Table: Substitution of Gambling Expenditure when a Casino Opens Nearby (2010-2012), Substitution Beyond 100 miles

Note: This table presents estimates from the specification

$$\begin{aligned} log(1+cashwithdrawn_{ijt}) &= \gamma_i+\gamma_j+\gamma_t+\gamma_{near}+\beta_1 post_{it}+\beta_2 distance^{100}_{ij}+\beta_3 distance^{100to200}_{ij}+\beta_4 post_{it}\times distance^{100}_{ij} \\ &\quad +\beta_5 post_{it}\times distance^{100to200}_{ij}+\beta_6 post_{it}\times over100_{ij}+\varepsilon_{ijt} \end{aligned}$$

where $cashwithdrawn_{ijt}$ is the total cash accessed at incumbent casinos by patrons who reside in ZIP code j, which is within 200 miles of entering casino i, aggregated over all transactions in month-year t. Incumbent casinos are casinos that reported cash access transactions prior to any of the opening dates in the sample. The variable $post_{it}$ is an indicator that equals one if the observation occurs after casino i's entry date, and is zero otherwise, $distance^{100}_{ij}$ is the distance from casino i's precise location (latitude-longitude) to ZIP code j's geographic centroid for ZIP codes within 100 miles of the proposed entry site. The coefficients of interest are β_4, β_5 and β_6, which capture how distance of patrons from the proposed entry site depends on distance to the casino (allowed to be different for ZIP codes within 100 miles versus ZIP codes 100-200 miles from the entry plan). To focus on the influence of the entering casino i, the sample is restricted to narrow windows around the month of opening (-6, +6) months. This narrow window reduces the extent of truncation at the edges of the 26-month sample. Standard errors in parentheses are double clustered by ZIP code and date (month-year). $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent level respectively.

	(1)	(2)	(3)	(4)
post × distance (Z)				
... within 100 miles	0.126***	0.099***	0.164***	0.129***
	(0.041)	(0.038)	(0.043)	(0.035)
... between 100 and 200 miles	−0.004	−0.021	0.012	−0.019
	(0.055)	(0.041)	(0.050)	(0.0193)
post × over100	−0.073	−0.086	−0.111**	−0.136***
	(0.083)	(0.075)	(0.051)	(0.037)
Entrant FE	x		x	
Month-Year FE	x		x	
Entrant × Month-Year FE				x
ZIP Code FE			x	x
N	257,169	257,169	257,169	257,169
# ZIP codes	14,846	14,846	14,846	14,846
# Entrants	21	21	21	21
R^2	0.037	0.060	0.588	0.642

Table 16: Appendix Table: Determinants of Cumulative Abnormal Returns for Pre-Entry Events

Note: This table presents OLS estimates of event-specific cumulative abnormal returns over the window $(-6, +36)$ months relative to entry plans. To compute stock performance, the sample is restricted to entry plans for which there is at least one property owned by a publicly-traded firm within 100 miles of the proposed entry site. Abnormal returns are computed by subtracting the casino industry average. Standard errors are reported in parentheses, and are computed using a sandwich-estimated variance-covariance matrix (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.

	(1)	(2)
stalled	0.126	0.207***
	(0.084)	(0.075)
fracprops (Z)	-0.251^{***}	-0.394^{***}
	(0.060)	(0.076)
stalled × fracprops (Z)		0.247**
		(0.085)
leverage (Z)	0.076	0.050
	(0.048)	(0.033)
Casino Size HHI (Z)	-0.195^{*}	-0.249^{*}
	(0.105)	(0.088)
R-squared	0.371	0.455
Observations (observed)	79	79

Table 17: Appendix Table: Heterogeneity by Observable Entrant and Incumbent Characteristics: Planning versus Construction Events

Note: This table presents regression results from the triple difference specification:

$$\begin{aligned} casino.size_{ijt} &= \gamma_j + \gamma_i + \beta_1 post_{ijt} + \beta_2 nearby_{ij} + \beta_3 char_{ijt} \\ &+\beta_4 post_{ijt} \times nearby_{ij} + \beta_5 post_{ijt} \times char_{ij} + \beta_6 nearby_{ij} \times char_{ijt} \\ &+\beta_7 post_{ijt} \times nearby_{ij} \times char_{ijt} + X'_{ijt}\Gamma + \varepsilon_{ijt} \end{aligned}$$

where $casino.size_{ijt}$, $post_{ijt}$, and $nearby_{ij}$ are as in Table 3, and $char_{ijt}$ is either an entrant characteristic or incumbent characteristic that may interact with the attractiveness to undertake entry deterring investments. To improve robustness to outliers, the casino floor space variable was winsorized at the 0.5 and 99.5 percent level. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. †, *, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	Entrant Characteristics		Incumbent Characteristics	
	Detailed Plan	Established Owner	Non-Public Firm	< 15 Properties
Planning Events				
post × nearby × characteristic	−5258.22	−862.02	−7795.89	−8103.09
	(5583.87)	(2748.94)	(3516.99)	(7252.89)
N	25,775	25,775	25,775	25,775
R^2	0.892	0.892	0.892	0.892
Construction Events				
post × nearby × characteristic	638.63	−6069.35***	−11890.66**	−13338.03**
	(4709.75)	(2121.72)	(4920.01)	(5547.97)
N	10,294	10,294	10,294	10,294
R^2	0.925	0.925	0.926	0.926
Controls × nearby & post				
Market Controls	x	x	x	x
Demographics	x	x	x	x
Year Dummies	x	x	x	x
Fixed Effects and Clustering				
Potential Entrant	x	x	x	x
Incumbent Property	x	x	x	x

Table 18: Appendix Table: Deterred Plans and Controlling for Investment by Incumbents 100 to 200 Miles from Proposed Entry Site (Binary Logistic Regression, Marginal Effects)

Note: This table presents regression results on the odds of entry deterrence of entry plans from estimating the binary logistic regression specification:

$$\log\left(Odds\left(stalled_j\right)\right) \quad = \quad \beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma + \varepsilon_j$$

where $stalled_j$ is the "after 48 months" classification throughout the table, $CapAdj_j$, $CapInit_j$, $N.Incumbents_j$, and entrant and incumbent characteristics X_j are the same as in Table 7. In addition the base specification, this table introduces changes in capacity by incumbents 100 to 200 miles away from the proposed location "Capacity Adjustment [100-200 mi] (Z)," as well as the difference between how incumbents within 100 miles and incumbents between 100 to 200 miles respond to the threat of entry (as of one year after the plan), "Differential Adjustment (Z)." To improve robustness to outliers, capacity variables were winsorized at the 0.5 and 99.5 percent level. Standard errors in parentheses are clustered at the level of the fixed effects for each specification, indicated in the table. † *, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	(1)	(2)	(3)
Capacity Adjustment (Z)	0.147***	0.143***	0.166
	(0.050)	(0.045)	(0.241)
Capacity Adjustment [100-200 mi] (Z)		−0.044	
		(0.159)	
Differential Adjustment [nearby-far] (Z)			0.123*
			(0.073)
Initial Capacity (Z)	0.195	0.255	0.166
	(0.221)	(0.249)	(0.241)
# of Incumbents	−0.004	−0.004	−0.004
	(0.003)	(0.004)	(0.004)
Additional Controls			
Entrant Characteristics	x	x	x
Incumbent Characteristics	x	x	x
Clustering			
State-Level	x	x	x
# of Entry Plans	68	68	68
# of States	21	21	21
AIC	90.01	91.01	90.51

Table 19: Appendix Table: Timing of Investments and the Hazard Rate of Entry

Note: This table presents regression results from estimating the Cox proportional hazards model:

$$h_i(t) \quad = \quad h_0(t) \exp\left\{\beta_1 CapAdj_j + \beta_2 CapInit_j + \beta_3 N.Incumbents_j + X_j'\Gamma\right\}$$

where the description, variables, and specification choices are the same as in Table 9. Standard errors in parentheses are clustered by state. †*, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

(a) Comparing Capacity Investment by 12 months to 36 months

	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)						
... by 12 months after plan	0.794^{*}	0.627^{***}	0.746^{***}	$0.797^{\dagger}$		
	(-1.736)	(-3.837)	(-2.767)	(-1.632)		
... by 36 months after plan					0.876	0.867
					(-0.750)	(-0.658)
Initial Capacity (Z)	0.671	0.609	0.652	0.553	0.677	0.533
	(-1.600)	(-0.937)	(-1.389)	(-0.990)	(-1.398)	(-1.029)
# of Incumbents	1.001	0.998	1.003	0.999	1.003	0.998
	(0.351)	(-0.235)	(1.200)	(-0.089)	(1.288)	(-0.221)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
# of Entry Plans	109	109	82	82	82	82
# of Successes	50	50	38	38	38	38
# of States	28	28	24	24	24	24
R^2	0.057	0.272	0.076	0.284	0.051	0.227

(b) Comparing Capacity Investment by 12 months to 24 months

	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)						
... by 12 months after plan	0.794^{*}	0.627^{***}	0.758^{**}	$0.819^{\dagger}$		
	(-1.736)	(-3.837)	(-2.387)	(-1.498)		
... by 24 months after plan					0.824	0.836
					(-1.209)	(-1.017)
Initial Capacity (Z)	0.671	0.609	0.619	0.492	0.628	0.464
	(-1.600)	(-0.937)	(-1.422)	(-1.269)	(-1.426)	(-1.381)
# of Incumbents	1.001	0.998	$1.003^{\dagger}$	0.996	1.003	0.995
	(0.351)	(-0.235)	(-1.537)	(-0.392)	(1.497)	(-0.504)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
Clustering						
State-Level	x	x	x	x	x	x
# of Entry Plans	109	109	93	93	93	93
# of Successes	50	50	39	39	39	39
# of States	28	28	26	26	26	26
R^2	0.057	0.272	0.076	0.265	0.064	0.264

Table 20: Appendix Table: Determinants of the Hazard Rate out of the Planning Stage using Breslow Approximation to Cox Partial Likelihood

Note: This table presents estimates of the Cox proportional hazards model, using the Breslow approximation to the partial likelihood. Wald Z-scores in parentheses. Z-Statistics based on clustered standard errors in parentheses. Standard errors are clustered at the state level. †*, **, and *** indicate statistical significance at the fifteen, 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, the structure of this table mimics the structure of Table 9, which uses the Efron (1974) approximation to the partial likelihood.

	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)						
... by 12 months after plan	0.793*	0.625***				
	(-1.758)	(-3.866)				
... by 24 months after plan			0.822	0.833		
			(-1.238)	(-1.048)		
... by 36 months after plan					0.874	0.864
					(-0.768)	(-0.678)
Initial Capacity (Z)	0.675	0.618	0.630	0.468	0.680	0.537
	(-1.612)	(-0.943)	(-1.435)	(-1.373)	(-0.768)	(-1.026)
# of Incumbents	1.001	0.998	1.003	0.995	1.003	0.998
	(0.387)	(-0.226)	(1.502)	(-0.510)	(1.298)	(-0.227)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
# of Entry Plans	109	109	82	82	82	82
# of Successes	50	50	38	38	38	38
# of States	28	28	24	24	24	24
R^2	0.056	0.267	0.064	0.262	0.050	0.275

Table 21: Appendix Table: Determinants of the Hazard Rate out of the Pre-Entry Stage

Note: This table presents estimates of the Cox proportional hazards model, using the Efron (1974) approximation to the partial likelihood, but instead of estimating hazard rates out of the planning stage, the estimates are for hazard rates out of pre-entry (planning or construction). 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, the structure of this table mimics the structure of Table 9, which uses the Efron (1974) approximation to the partial likelihood for hazard rates out of the planning stage.

	(1)	(2)	(3)	(4)	(5)	(6)
Capacity Adjustment (Z)						
... by 12 months after plan	0.764**	0.620***				
	(-2.074)	(-4.184)				
... by 24 months after plan			0.792	0.786		
			(-1.473)	(-1.300)		
... by 36 months after plan					0.862	0.841
					(-0.799)	(-0.760)
Initial Capacity (Z)	0.662*	0.692	0.632	0.598	0.681	0.659
	(-1.649)	(-0.718)	(-1.402)	(-1.078)	(-1.343)	(-0.844)
# of Incumbents	1.000	1.001	1.003	0.998	1.003	1.001
	(-0.085)	(0.180)	(1.177)	(-0.129)	(1.111)	(0.052)
Additional Controls						
Entrant Characteristics		x		x		x
Incumbent Characteristics		x		x		x
# of Entry Plans	109	109	82	82	82	82
# of Successes	50	50	38	38	38	38
# of States	28	28	24	24	24	24
R^2	0.058	0.290	0.058	0.257	0.045	0.271

Table 22: Appendix Table: Schoenfeld and Grambsch-Therneau Tests of Proportional Hazards

Note: This table presents the Schoenfeld and Grambsch-Therneau Tests for the validity of proportional hazards for the first Cox proportional hazards model in Table 9. A rejection of the null hypothesis (p-value below 0.05) indicates that the proportional hazards assumption is not valid. Failure to reject the null hypothesis, in this instance, implies that the proportional hazards assumption is reasonable.

	ρ	χ^2	p-value
Capacity Adjustment (Z)	-0.000	0.000	0.998
Initial Capacity (Z)	0.111	0.958	0.328
# Incumbents	0.045	0.027	0.870
Global Test		1.144	0.766

Table 23: Determinants of the Hazard Rate out of the Planning Stage: Capacity Expansion by One Year After Plan – Full Results

Note: This table presents results on initial capacity and interactions with experience measures that were suppressed in the main text Table 11. Standard errors are clustered at the state level. †*, **, and *** indicate statistical significance at the fifteen, ten, five, and one percent level respectively.

	(1)	(2)	(3)
Capacity Adjustment (Z)	0.627***		
	(-3.837)		
Initial Capacity (Z)	0.609		
	(-0.937)		
Interactions with Entrant Experience Measures			
Capacity Adjustment (Z)			
... × Inexperienced Entrant		0.653**	
		(-2.420)	
... × Experienced Entrant		0.813	
		(-0.863)	
... × Non-Public Entrant			0.668**
			(-2.006)
... × Public Entrant			1.086
			(0.227)
Initial Capacity (Z)			
... × Inexperienced Entrant		0.472	
		(-1.423)	
... × Experienced Entrant		0.907	
		(-0.127)	
... × Non-Public Entrant			0.326**
			(-2.426)
... × Public Entrant			2.004
			(1.368)
Other Characteristics and Main Effects			
# of Incumbents	0.998	0.999	0.995
	(-0.235)	(-0.094)	(-1.033)
Experienced Entrant		3.359**	
		(2.547)	
Public Entrant			2.324**
			(2.027)
Additional Controls			
Entrant Characteristics	x	x	x
Incumbent Characteristics	x	x	x
Clustering			
State-Level	x	x	x
# of Entry Plans	109	109	109
# of Successes	50	50	50
# of States	28	28	28
R^2	0.747	0.756	0.764