

Highlights

The Economics of Bundling in Casino Markets: Theory and Evidence from U.S. Gaming Destinations

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- Integrated casino resorts are associated with reach beyond local gaming demand.
- A 10% increase in rooms is associated with $\sim 1.9\%$ more revenue in isolated markets.
- Casino resorts draw visitors from over double the distance of gaming-only venues.

The Economics of Bundling in Casino Markets: Theory and Evidence from U.S. Gaming Destinations

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ABSTRACT

When jurisdictions adopt casinos, a central design question is whether to build integrated resorts or standalone gaming facilities. We examine how bundling gaming with hotels and other amenities is associated with casino market revenue, proposing that integrated resorts act as destination-creating mechanisms. The amenity bundle extends a property's geographic reach by giving distant tourists a reason to travel. Using a gravity model across 186 U.S. gaming destination clusters drawn from a nationwide inventory of 1,014 properties, we find that resort intensity is positively associated with revenue at every level of local demand, with the proportional association concentrated in geographically isolated markets, roughly threefold larger than in dense ones. Visitor-origin data from TripAdvisor support this interpretation. Destination clusters with hotels draw visitors from over twice the distance of gaming-only markets. Low-demand jurisdictions therefore exhibit the strongest association, though bundling intensity is endogenous and we are explicit about identification.

1. Introduction

Casino markets span the full spectrum of product bundling. A single property on the Las Vegas Strip may combine 3,000 hotel rooms, a dozen restaurants, a Cirque du Soleil theater, a convention center, and a retail mall alongside its gaming floor. A convenience casino 200 miles away in the Nevada desert may contain 15 slot machines and a coffee pot. Both offer gaming, but they are not in the same business. The variation reflects a property-level choice about how much to bundle with the core service and, in multi-property destinations, a market organization in which amenities and visitor demand may spill across neighboring properties.

The industrial organization theory of bundling explains why firms facing heterogeneous consumers can increase profits by combining goods rather than selling them separately (Stigler, 1963; Adams and Yellen, 1976; Schmalensee, 1984; McAfee, McMillan and Whinston, 1989). The framework has not, however, been formally connected to casino-market analysis in the published gaming-economics literature, which has typically studied multi-product properties through the lens of operations (Kilby, Fox and Lucas, 2004) or institutional history (Schwartz, 2003; Eadington, 1999) rather than bundling theory. This paper makes that connection. We develop a stylized conceptual framework that adapts bundling theory to spatial casino markets, formalize a “reach-extending” mechanism in which bundling expands the geographic catchment of distant tourists, and use it to motivate four empirical predictions about revenue.

We test these predictions on 186 U.S. gaming destination clusters (individual casinos or groups of nearby casinos) in the estimation sample, covering \$48.1 billion in annual gaming revenue. Separate evidence for the underlying mechanism comes from TripAdvisor reviewer-origin data, where we test whether destination clusters with hotels draw visitors from greater distances than gaming-only clusters.

These findings contribute to the tourism management literature in three ways. First, we provide a conceptual framework grounded in bundling theory for understanding the integrated resort as an economic institution, with a formally derived spatial mechanism that distinguishes the bundling story from the standard variance-reduction mechanism in Adams and Yellen (1976) and from vertical-differentiation alternatives. Second, we offer a cross-sectional empirical test of bundling theory predictions in U.S. destination clusters, using geographic variation in

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demand density and measuring revenue at the destination-cluster level. Third, we derive implications for casino-market organization, firm investment in non-gaming amenities, and, more cautiously, integrated-resort licensing policy.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literatures. Section 3 presents the conceptual framework and derives the spatial reach-extending mechanism. Section 4 describes the data and discusses the hotel-room proxy. Section 5 presents the empirical results. Section 6 discusses implications. Section 7 concludes.

2. Literature Review

2.1. Bundling Theory in Industrial Organization

The economics of bundling begins with Stigler (1963), who observed that a monopolist selling two goods can increase profits by offering them only as a bundle when consumers have negatively correlated valuations. Adams and Yellen (1976) formalized this insight and introduced the distinction between *pure bundling* (components available only as a bundle), *mixed bundling* (components available separately and as a bundle), and *pure components* (no bundle offered). They showed that mixed bundling weakly dominates both pure bundling and pure components under general conditions.

Schmalensee (1984) derived optimal bundling strategies under the assumption that consumer valuations follow a bivariate normal distribution, showing that bundling profitability depends on the correlation between valuations and the ratio of marginal cost to mean valuation. McAfee et al. (1989) extended the analysis to multiproduct settings and established conditions under which bundling is profitable even when consumer valuations are independently distributed.

More recent contributions have examined bundling as a competitive strategy. Nalebuff (2004) showed that an incumbent can use bundling as an entry barrier, and Stremersch and Tellis (2002) synthesized the marketing literature's distinction between "price bundling" (pure price discount) and "product bundling" (integration that creates new functionality). Venkatesh and Mahajan (1993) developed probabilistic pricing rules for bundles when components have heterogeneous demand.

The classical bundling literature focuses primarily on pricing strategy: how a firm can extract more surplus by selling goods together at a single price. The casino resort context differs in an important respect. Guests purchase each component separately (a hotel room, a restaurant meal, a show ticket, and gaming). The relevant concept is therefore what Stremersch and Tellis (2002) term *product bundling*, which creates value through co-location and demand spillovers, rather than bundling through pricing packages of goods and services. The key insight that carries over from the classical theory is that the returns to integration depend on the composition of consumer valuations: tourists, who value the destination experience (hotel, dining, entertainment) highly but may value gaming only moderately, versus local residents, who value gaming but have less need for lodging and hospitality services. This heterogeneity determines when investing in the integrated resort is valuable.

2.2. Tourism Bundling and Destination Packaging

The tourism literature has addressed bundling primarily through the lens of package tourism and destination marketing. Sheldon (1986) analyzed the tour operator industry as a bundling intermediary that combines transportation, accommodation, and activities into packages. Buhalis (2000) argued that destination competitiveness depends on the configuration of attractions, amenities, and access. This is effectively a destination-level bundling problem. Crouch and Ritchie (1999) introduced the original conceptual model of destination competitiveness, and Ritchie and Crouch (2003) extended it into the comprehensive determinants-and-indicators framework. Dwyer and Kim (2003) developed an integrative model of destination competitiveness in which non-gaming amenities are an essential component of the value proposition for any tourist-oriented destination, and Prideaux (2000) examined the role of transport accessibility in destination development, which is relevant to casino drive-in markets. Pine and Gilmore (1999) reframed the value proposition of integrated leisure properties from selling services to staging memorable experiences. Most recently, Calveras (2019) provides a formal economic model of when all-inclusive bundling is part of the hospitality equilibrium. Its focus on consumers' convenience value complements our analysis of the visitors converted at the participation margin by an amenity bundle.

What is missing from this literature is a formal connection to the microeconomic theory of bundling. Tourism researchers have documented that amenities matter, but have not formalized *why* bundling creates value, *when* it is optimal, or *how* returns to bundling vary with market structure. Our paper fills this gap.

2.3. Casino Economics and Spatial Competition

The economic analysis of casino markets has focused on several themes: the social costs and benefits of gambling (Walker, 2007, 2013; Philander, 2019), the spatial structure of demand (Huff, 1963; Thalheimer and Ali, 2008), competition (Economopoulos and Luxem, 2015), economies of scale (Gu, 2001), and the revenue effects of resort amenities (Lucas and Tanford, 2010). Eadington (1999) emphasizes regulatory rents, scale and scope economies, and the interaction between casino legalization and tourism, while Ahn and Back (2018) reviews the integrated-resort literature. The Asian integrated-resort literature (Henderson, 2006; McCartney, 2020) likewise emphasizes non-gaming amenities in the transition from gambling-based tourism to broader destination tourism. Philander (2019) documents that increased casino availability is associated with higher problem gambling prevalence, underscoring why regulatory frameworks treat local participation as a policy concern.

Related research reinforces the treatment of casino resorts and clusters as multidimensional tourism products. Casino service quality spans gaming, hotel, restaurant, and other service dimensions (Bradley and Wang, 2022), and non-gaming business contributes to Las Vegas tourism efficiency (Deng, Gu, Law and Lian, 2020). More broadly, hotel location responds to agglomeration economies (Woo and Mun, 2020), tourism productivity can spill across neighboring places (Kim, Park, Chen and Williams, 2021), and shared hotel resources can create benefits for nearby destination competitors (Bianco, Singal, Zach and Nicolau, 2023). These findings motivate distinguishing the property that chooses the bundle from the destination cluster over which visitor demand and revenue are observed.

The empirical foundation for our analysis is a gravity model of casino revenue described in Section 4. We note that bundling theory is not the only framework that could explain the patterns we study. Vertical differentiation (Tirole, 1988), economies of scope, and destination competitiveness models (Buhalis, 2000; Dwyer and Kim, 2003) could each generate some of the same predictions, and we return to these alternatives in the Discussion. We adopt bundling theory because it directly addresses the *composition* of the product offering and generates testable predictions about how bundling returns interact with market characteristics, which the alternatives do not.

3. Conceptual Framework

We develop a stylized model in which casinos serve two populations: locals, whose visit decision is driven by gaming alone, and distant tourists, whose visit depends on the broader amenity bundle. The aim is not to solve a full equilibrium model but to motivate empirically testable predictions and to identify the spatial mechanism that distinguishes a bundling-based explanation from alternatives such as vertical differentiation. The model produces one formally derived result (Proposition 1: a positive bundling premium for tourist-serving casinos) and three empirical conjectures (Hypotheses 1–3), which are tested directly. Section 3.3 formalizes the spatial reach-extending mechanism that motivates the central empirical prediction.

The framework separates the property's amenity decision from the traveler's destination decision. Individual properties choose their amenity bundles, but those amenities contribute to the attractiveness of the destination in which the properties are located. A traveler may choose a destination because its combined lodging, dining, entertainment, and gaming offer justifies the trip, and then allocate expenditure among several properties after arriving. In a single-property market, the property and destination coincide. In a multi-property market, destination demand may be shared across neighboring properties. This destination-level logic extends Stremersch and Tellis (2002)'s concept of product bundling: the value to the visitor arises from jointly available components, even when those components are provided by neighboring properties.

3.1. Assumptions

Consider a market with J casino properties indexed by j , each choosing a bundling intensity $b_j \in [0, 1]$, where $b_j = 0$ represents a pure gaming operation and $b_j = 1$ represents a fully integrated resort. Bundling intensity maps to observable property attributes: hotel rooms, restaurant quality, entertainment capacity, and other non-gaming amenities. We note that casino resort guests typically purchase each component separately (a hotel room, a restaurant meal, a show ticket). Higher b_j requires higher fixed and variable costs but potentially expands the addressable market.

There are two types of consumers: *locals* (L) and *tourists* (T), present in proportions α and $1 - \alpha$, respectively. Each consumer i of type $\tau \in \{L, T\}$ has valuations (v_{ig}, v_{ia}) for gaming (g) and amenities (a). We assume:

$$v_{ig} \sim F_g^\tau(\mu_g^\tau, \sigma_g^\tau) \quad (1)$$

$$v_{ia} \sim F_a^\tau(\mu_a^\tau, \sigma_a^\tau) \quad (2)$$

with $\text{Cov}(v_{ig}, v_{ia}) = \rho^\tau \sigma_g^\tau \sigma_a^\tau$.

Assumption 1 (Heterogeneous consumer segments). Tourists have higher mean amenity valuation than locals ($\mu_a^T > \mu_a^L$), while locals have weakly higher gaming valuation ($\mu_g^L \geq \mu_g^T$). Tourists exhibit positive correlation between gaming and amenity valuations ($\rho^T > 0$): those who travel farther for gaming also value the destination experience.

Assumption 2 (Bundling technology). A casino with bundling intensity b_j generates consumer utility:

$$U_{ij} = v_{ig} + b_j \cdot v_{ia} - p_j - c(d_{ij}) \quad (3)$$

where p_j is the price, $c(d_{ij})$ is the travel cost from consumer i 's location to casino j , and the amenity component v_{ia} is weighted by bundling intensity. A pure gaming operation ($b_j = 0$) provides only gaming utility. An integrated resort ($b_j = 1$) provides both.

Assumption 3 (Cost of bundling). The cost of operating casino j is:

$$C(b_j) = c_0 + c_g + c_a(b_j) \quad (4)$$

where c_0 is a fixed cost, c_g is the gaming operation cost, and $c_a(b_j)$ is the amenity cost, increasing and convex in b_j : $c'_a > 0$, $c''_a > 0$, $c_a(0) = 0$.

3.2. Bundling Value

Consider first a single casino choosing b to maximize profit. Expected demand from type τ consumers at distance d is:

$$D^\tau(b, p, d) = \Pr(v_{ig} + b \cdot v_{ia} \geq p + c(d)) \cdot N^\tau(d) \quad (5)$$

where $N^\tau(d)$ is the population density of type τ at distance d .

The key insight is that bundling affects the *distribution* of the composite valuation $v_{ig} + b \cdot v_{ia}$. For the tourist segment with $\rho^T > 0$:

$$\text{Var}(v_{ig} + b \cdot v_{ia}) = (\sigma_g^T)^2 + b^2(\sigma_a^T)^2 + 2b\rho^T \sigma_g^T \sigma_a^T \quad (6)$$

When $\rho^T > 0$, increasing b increases both the mean and variance of the composite valuation. The firm faces a classic bundling trade-off: higher b attracts more tourists (higher mean utility) but increases the dispersion of willingness to pay, making it harder to extract surplus through uniform pricing.

However, in the spatial context, bundling has an additional effect absent from the standard bundling literature: it *expands the geographic catchment area*. A tourist with $v_{ig} + v_{ia} > p + c(d)$ may be willing to travel distance d , while a tourist with only $v_{ig} > p + c(d)$ may not. This “reach-extending” property of bundling is particularly valuable when the local population is small.

Proposition 1 (Bundling Value). *A casino's optimal bundling intensity b^* is strictly positive whenever the market contains tourists ($1 - \alpha > 0$) with heterogeneous valuations ($\sigma_a^T > 0$) and the amenity cost function satisfies $c'_a(0) < (1 - \alpha) \cdot \mu_a^T \cdot \bar{N}^T$, where $\bar{N}^T$ is the expected tourist population within the catchment area. The bundling premium (the revenue gain from $b^* > 0$ relative to $b = 0$) is increasing in the share of tourists ($1 - \alpha$) and the mean tourist amenity valuation μ_a^T .*

At $b = 0$, the marginal revenue from increasing b is $(1 - \alpha) \cdot \mu_a^T \cdot \bar{N}^T > 0$ (first-order effect of adding amenity value for tourists), while the marginal cost is $c'_a(0)$. Under the stated condition, the first-order condition requires $b^* > 0$. The comparative static in $(1 - \alpha)$ follows from the envelope theorem. $\square$

3.3. The Reach-Extending Mechanism

The standard bundling literature (Adams and Yellen, 1976; Schmalensee, 1984; McAfee et al., 1989) treats bundling as a device for extracting surplus from a fixed customer base. In spatial casino markets, the bundle has a second effect: it expands the population willing to make the trip in the first place. We capture this with a stylized decomposition. Total revenue is the sum of two components,

$$\text{Rev}(b, G_{\text{local}}) = R_L(G_{\text{local}}) + R_D(b), \quad (7)$$

where R_L depends on local population scale G_{local} but not on the bundle (locals visit for gaming regardless of amenities), and R_D depends on b but not on G_{local} (the distant catchment is determined by the geography of tourist origins, not by the casino's near-population). Both invariance assumptions are stylizations: locals do patronize on-property restaurants, and denser local populations may correlate with denser distant ones, but neither qualification overturns the basic structure.

The marginal effect of bundling on log revenue and its cross-partial with local demand follow directly:

$$\frac{\partial \log \text{Rev}}{\partial b} = \frac{R'_D(b)}{R_L(G_{\text{local}}) + R_D(b)}, \quad \frac{\partial^2 \log \text{Rev}}{\partial b \partial G_{\text{local}}} = - \frac{R'_D(b) R'_L(G_{\text{local}})}{[R_L(G_{\text{local}}) + R_D(b)]^2} < 0. \quad (8)$$

The cross-partial is negative because both R'_D and R'_L are positive: bundling adds revenue from distant tourists, and that contribution is a larger percentage of the total when the local-revenue base is smaller. The substantive content of the framework is the economic argument for the decomposition. Locals do not require the bundle to justify a short trip while distant tourists do. The empirical analog is a negative interaction between resort intensity and local demand in the gravity model.

3.4. Testable Hypotheses Derived from the Conceptual Framework

The four predictions tested in Section 5 are stated below. Proposition 1 above is the only formally derived result. Hypotheses 1, 2, and 3 are conjectures motivated by the conceptual framework but not derived as theorems.

Hypothesis 1 (Low-demand gradient). *The bundling–revenue association is steeper in markets with smaller local demand:*

$$\frac{\partial^2 \log \text{Rev}}{\partial b \partial G_{\text{local}}} < 0.$$

This hypothesis is motivated by the reach-extending mechanism formalized in Section 3.3: bundling expands the addressable population by giving distant tourists a reason to travel, and the proportional revenue response is largest where the local-revenue denominator is smallest.

Intuition. Macau is a bundle not because it has a large local population, but because it must attract visitors from outside its borders. The bundle justifies the trip. By contrast, a casino in Los Angeles can rely on local gaming demand and need not invest in destination amenities. The hypothesis predicts that the $\text{RII} \times \text{demand}$ interaction should be negative.

Hypothesis 2 (Bundling and competition). *In markets with higher competitive intensity, bundling yields higher marginal returns:*

$$\frac{\partial^2 \log \text{Rev}}{\partial b \partial \text{Comp}} > 0,$$

where *Comp* is a measure of local competitive density.

Motivation. Under spatial competition with Huff-type allocation, a casino's market share is proportional to its attractiveness relative to competitors. Adding amenity dimensions to the attractiveness function creates differentiation along non-gaming axes. In a crowded gaming market, the gaming component of attractiveness is competed away, but the amenity component may be less substitutable across properties because amenity bundles are heterogeneous. This motivates the positive interaction in Hypothesis 2, although we do not derive primitive conditions under which it holds.

Hypothesis 3 (Cluster-level mixed bundling). *A casino cluster functions as a mixed-bundling market in which individual properties specialize in different bundle components while the destination as a whole offers a complete bundle to visitors. Cluster revenue is positively associated with the mean bundling intensity of member properties, conditional on cluster size and local demand.*

Motivation. On the Las Vegas Strip, the Bellagio offers high-end gaming and luxury accommodation. The LINQ offers mid-scale entertainment. The convention center provides business travel infrastructure. No single property offers everything, but the cluster as a whole does. This is analogous to the “mixed bundling” result from Adams and Yellen (1976): the market-level bundle captures more surplus than any single firm's pure bundle. The hypothesis predicts that cluster performance is positively associated with mean RII across member properties, controlling for cluster size and local demand.

4. Empirical Strategy

4.1. Data

The unit of analysis is the gaming destination cluster, indexed by m , rather than the individual casino property, indexed by j . As Section 3 explains, properties choose amenity bundles, but the participation decision concerns whether to visit the destination. Visitors to multi-casino markets such as the Las Vegas Strip, Atlantic City, or Biloxi routinely patronize multiple properties during a single trip. This treatment is consistent with tourism evidence that destination choices reflect portfolios of attractions and amenities and that agglomeration effects can spill across neighboring tourism businesses (Buhalis, 2000; Kim et al., 2021; Bianco et al., 2023). Appendix C reports the corresponding casino-level analysis.

The casino inventory comprises 1,014 operating fixed-location U.S. casino properties drawn from the World Casino Directory (2024) and regulator rosters. The primary market definition groups these properties into 595 destination clusters using single-linkage hierarchical clustering (Everitt, Landau, Leese and Stahl, 2011) at a five-mile threshold. Table E.5 reports sensitivity to 10- and 25-mile thresholds. Regulator-reported gaming revenue is available for 187 clusters. Excluding the one observed cross-state cluster leaves 186 estimation clusters containing 424 properties in 27 states and \$48.1 billion in annual gaming revenue (2026 dollars). Appendix F documents facility screening, market construction, reporting periods, and data sources. Supplementary Online Appendix S1 provides the complete property–cluster crosswalk.

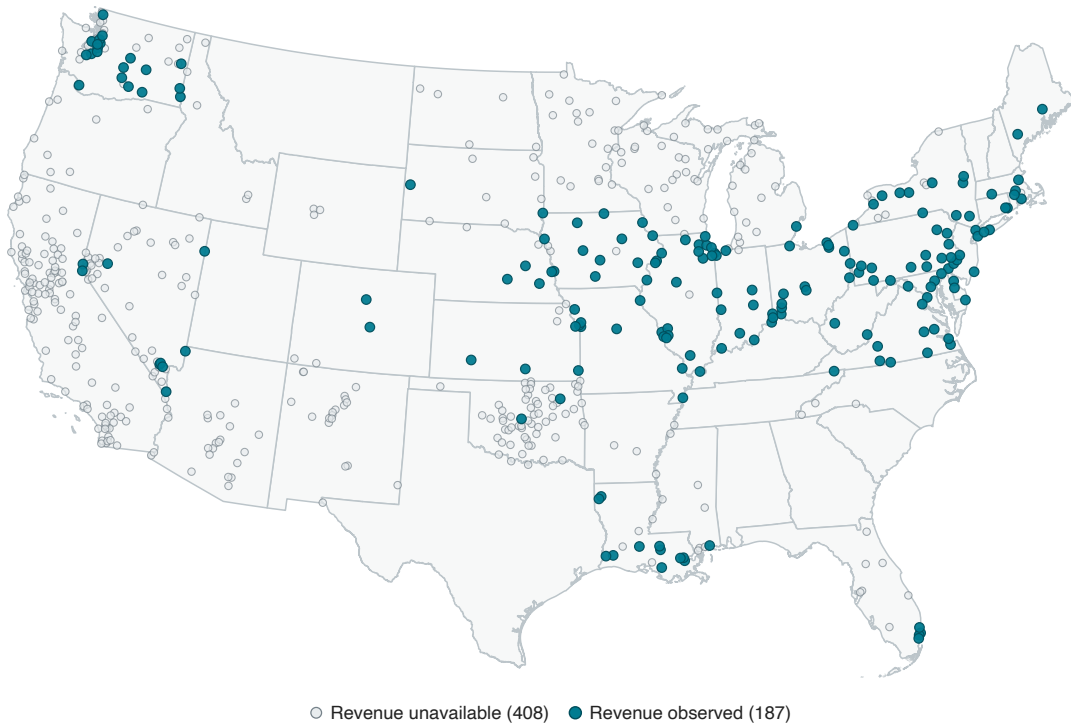


Figure 1: U.S. gaming destination clusters and gaming-revenue coverage. The map includes all 595 clusters. Of these, 187 have usable regulator-reported gaming revenue and 408 do not. The headline model excludes the observed cross-state cluster, leaving 186 estimation observations.

For each cluster we observe geographic location, the number of constituent casinos, total hotel rooms, the presence of table games, and whether the facility is a cardroom only.

We supplement the core casino data with maximum statutory gaming tax rates from the American Gaming Association’s annual State of the States reports and applicable state law (American Gaming Association, 2025; Washington State Gambling Commission, 2026).

Demand is measured by a Huff-type gravity model (Huff, 1963). For each cluster m , local demand G_m is computed as the population-income-weighted gravity sum across approximately 31,600 ZIP codes within a 125-mile catchment

radius:

$$G_m = \sum_{z: d_{zm} \leq 125} W_z \cdot (d_{zm} + 0.1)^{-1} \quad (9)$$

where $W_z = \text{AdultPop}_z \times \text{MedianIncome}_z$ is the demand weight for ZIP code z and d_{zm} is the haversine distance in miles (Sinnott, 1984). Competition is measured as the distance-weighted density of rival destination clusters within 125 miles:

$$\text{Comp}_m = \sum_{k \neq m: d_{mk} \leq 125} (d_{mk} + 0.1)^{-1} \quad (10)$$

4.2. Resort Intensity Index

Our theoretical framework takes property-level bundling intensity b_j as a latent variable. Empirically, we require a cluster-level proxy for how strongly cluster m combines gaming with non-gaming components. We adopt the Resort Intensity Index (RII), defined as the inverse hyperbolic sine of total cluster hotel-room capacity:

$$\text{RII}_m = \text{arcsinh}(\text{rooms}_m) = \ln \left(\text{rooms}_m + \sqrt{\text{rooms}_m^2 + 1} \right) \quad (11)$$

RII is a purpose-built proxy for the scale of the resort amenity bundle. Hotel rooms are both a core bundle component and the consistently observable property attribute most closely associated with the broader amenity portfolio, as examined in [Appendix B](#). The construction rests on two substantive choices: hotel rooms as the observable proxy for the multi-dimensional bundling construct b_j , and arcsinh as a concave continuous functional form.

A fully integrated resort bundles gaming with hotel rooms, full-service and casual dining, bars and lounges, entertainment venues, convention and meeting space, retail, and spa and wellness facilities. A comprehensive amenity-by-amenity inventory would be the most direct measure of bundling intensity, but no such inventory is published for the 186 clusters in our sample. Hotel rooms create an overnight customer base that supports fixed investment in dining, entertainment, and related services. Room count is thus both a bundle component and a concise proxy for resort scale.

[Appendix B](#) provides empirical support for the rooms-as-proxy argument using amenity data on a subset of properties. Hotel room counts correlate positively with every available non-room amenity: $r = 0.75$ with restaurant counts ($N = 205$), $r = 0.50$ with gaming floor area ($N = 87$), $r = 0.47$ with bars ($N = 119$), and $r = 0.45$ with entertainment venue seating ($N = 21$).

We use the inverse hyperbolic sine (arcsinh) transform, which is concave for rooms ≥ 0 , smooth at zero without the arbitrary offset of $\ln(1+x)$ ([Bellemare and Wichman, 2020](#)), and approximately logarithmic for large room counts. The headline findings are robust to five alternative functional forms tested in [Section 5](#), including ordinal bands and alternative concave transforms. Only the linear specification fails all hypothesis tests, suggesting that some concavity is essential.

Of the 186 estimation clusters, 87 have zero hotel rooms ($\text{RII} = 0$) and 99 have at least one hotel-having casino. Across the full sample, RII has mean 3.48, standard deviation 3.39, and ranges from 0 to 12.22. [Appendix A](#) reports summary statistics by hotel-room category for descriptive purposes. The headline regression uses the continuous RII directly.

4.3. Empirical Specification

The gravity model is the standard framework for analyzing spatial demand in retail, trade, and gaming contexts ([Huff, 1963](#)). A casino market's revenue increases with the size of the population within its catchment area and decreases with competition from rival markets. In log-linear form:

$$\begin{aligned} \ln(\text{GamingRev}_m) = & \beta_0 + \gamma \ln G_m + \delta_H \text{hotel}_m + \delta_R \ln(\text{rooms}_m) + \delta_T \text{tables}_m \\ & + \delta_C \text{card}_m + \delta_K \text{arcsinh}(\text{Comp}_m) + \delta_S \text{Strip}_m + \varepsilon_m \end{aligned} \quad (12)$$

where GamingRev_m is annual gaming revenue, G_m is gravity-weighted local demand, and the remaining variables are defined at cluster m . The hotel hurdle decomposes overnight capacity into an extensive margin (having any hotel) and an intensive margin (rooms conditional on having a hotel). All standard errors use the state-clustered CR1 covariance ($G = 27$) and two-sided $t(G-1)$ inference to allow errors to correlate within state regulatory and reporting environments.

The hotel terms in equation (12) represent a two-part decomposition of hotel capacity's association with revenue. Rather than retain separate extensive and intensive terms, we replace both with a single concave continuous measure.

The bundling interaction model substitutes RII for the individual hotel terms and adds the interaction and quadratic terms predicted by the conceptual framework:

$$\ln(\text{GamingRev}_m) = \alpha + \gamma \ln G_m + \delta \cdot \text{RII}_m + \phi_1 \cdot \text{RII}_m \times \ln G_m + \phi_2 \cdot \text{RII}_m \times \text{arcsinh}(\text{Comp}_m) + \phi_3 \cdot \text{RII}_m^2 + \mathbf{X}'_m \boldsymbol{\eta} + \varepsilon_m \quad (13)$$

where $\mathbf{X}_m$ includes table games, the cardroom indicator, competition, and the Las Vegas Strip indicator. Table games present is an indicator for whether the destination cluster contains table gaming, rather than a count of gaming tables. The $\text{RII} \times \ln G$ interaction tests whether the revenue premium associated with resort intensity varies with local demand density (Hypothesis 1). The $\text{RII} \times \text{arcsinh}(\text{Comp})$ interaction tests whether resort intensity is more strongly associated with revenue in competitive clusters (Hypothesis 2). The squared RII term tests for convexity.

The specifications estimate conditional associations. Local population geography is plausibly predetermined relative to an individual property's amenity choice, but resort scale may respond to expected revenue. Omitted destination appeal may affect both amenities and revenue. State statutes may jointly shape location, casino format, and reporting. Sensitivity checks add state fixed effects, county employment location quotients for restaurant, retail, and personal-care specialization, an indicator for regulator-aggregated outcomes, and a statutory casino-format indicator. The low-demand interaction remains negative in each case, supporting the stability of the spatial pattern across these observed regulatory and destination differences. Resort scale and unobserved destination appeal nevertheless remain potential sources of endogeneity.

In the full specification (Model 5), we add the maximum statutory gaming tax rate (American Gaming Association, 2025; Washington State Gambling Commission, 2026) as a control for the regulatory environment. High-tax environments reduce the margin available to finance non-gaming amenities, potentially penalizing bundling.

4.4. Testable Hypotheses

Our theoretical propositions map to the following testable hypotheses, which we frame as conditional associations rather than causal claims:

H1 $\delta > 0$. RII is positively associated with revenue.

H2 $\phi_1 < 0$. The RII–revenue association is stronger in low-demand clusters.

H3a $\phi_2 > 0$. The RII–revenue association is stronger under competitive pressure.

H3b $\phi_3 > 0$. The relationship between RII and log revenue is convex.

H4 In the cluster-level analysis, mean RII is positively associated with cluster revenue, controlling for cluster size and local demand.

We note that H1 (a positive RII coefficient) does not by itself test super-additivity. Rather, the convexity claim is reserved for H3b. We frame H1 as a baseline test that RII is correlated with revenue at all, separate from the question of whether the relationship is convex on the log scale.

5. Results

5.1. Revenue Results

Model 1 in Table 1 reports the base gravity estimates. With state-clustered standard errors ($G = 27$), the model explains 74.3% of the cross-sectional variation in log cluster revenue ($N = 186$). Local demand elasticity is approximately 0.60, so a 10% increase in gravity-weighted local demand is associated with approximately 6.0% higher revenue. The hotel hurdle has a negative extensive-margin coefficient and a positive intensive-margin coefficient, crossing at approximately 86 rooms. This threshold is descriptive, not a structural estimate of minimum viable hotel scale. Competition is negatively associated with revenue, and the cardroom indicator captures the discount for cardroom-only clusters.

These results already hint at bundling dynamics: the hotel hurdle is effectively a bundling threshold, and the Strip premium captures the world's most extreme integrated resort cluster. The question is whether a unified bundling

Table 1: Regression Models

	(M1)	(M2)	(M3)	(M4)	(M5)
Intercept	11.301*** (0.804)	10.800*** (0.792)	8.297*** (0.886)	8.980*** (1.112)	8.054*** (1.291)
$\ln(G_{\text{local}})$	0.600*** (0.059)	0.622*** (0.065)	0.835*** (0.073)	0.794*** (0.092)	0.932*** (0.121)
Has hotel	-2.302*** (0.425)				
$\ln(\text{rooms})$ intensive	0.516*** (0.071)				
Table games present	0.132 (0.231)	0.154 (0.220)	0.130 (0.221)	0.113 (0.226)	0.120 (0.252)
Cardroom	-2.522*** (0.166)	-2.535*** (0.170)	-2.339*** (0.178)	-2.387*** (0.187)	-2.612*** (0.221)
$\text{arcsinh}(\text{Competition})$	-0.432 (0.257)	-0.017 (0.254)	-0.249 (0.291)	-0.505 (0.306)	-0.697 (0.532)
LV Strip	0.924*** (0.316)	2.739*** (0.342)	3.055*** (0.321)	-0.020 (0.266)	0.486 (0.321)
RII		0.136*** (0.032)	0.737*** (0.203)	0.247 (0.196)	0.308 (0.192)
$\text{RII} \times \ln(G_{\text{local}})$			-0.050*** (0.017)	-0.043*** (0.015)	-0.041** (0.016)
$\text{RII} \times \text{arcsinh}(\text{Comp})$				-0.053 (0.061)	-0.080 (0.069)
RII^2				0.058*** (0.007)	0.047*** (0.009)
Tax rate					-1.696** (0.647)
N	186	186	186	186	184
R^2	0.743	0.698	0.710	0.760	0.771
Adj. R^2	0.731	0.686	0.697	0.746	0.757

Notes: State-clustered CR1 standard errors in parentheses. Two-sided significance tests use a $t(G - 1)$ reference distribution, where G is the number of state clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: $\ln(\text{GamingRev})$. Model 1 estimates equation (12). Models 2 and 3 sequentially introduce the terms in equation (13). Model 4 estimates equation (13). Model 5 adds the maximum statutory gaming-tax-rate control, assigns Washington the 20% maximum local rate authorized by state law, and excludes Connecticut's two tribal-compact clusters. RII (Resort Intensity Index) is the concave continuous transform $\text{arcsinh}(\text{hotel rooms})$ of the cluster's total hotel-room count, used as a proxy for the latent bundling-intensity construct.

framework captures these associations more parsimoniously and reveals additional structure. Table 1 presents the progression of RII models.

Introducing the Resort Intensity Index alone (Model 2) yields a positive coefficient ($\delta = 0.136$, $t = 4.29$). The conditional marginal associations in Model 4 are also positive across the observed demand distribution, supporting H1. The $\text{RII} \times \ln G$ interaction in Model 3 is negative, consistent with H2: higher RII is more strongly associated with revenue in low-demand clusters. Flexible demand terms below address whether this pattern is induced by the log-linear form.

Model 4 adds the competition interaction and the quadratic RII term and is our preferred specification. The headline coefficients are $\text{RII} = 0.247$ ($t = 1.26$), $\text{RII} \times \ln G = -0.043$ ($t = -2.78$), $\text{RII} \times \text{arcsinh}(\text{Comp}) = -0.053$ ($t = -0.88$), and $\text{RII}^2 = 0.058$ ($t = 8.15$). Three of the four are consistent with the theoretical predictions: the level coefficient (Proposition 1) is positive, the low-demand gradient (Hypothesis 1) is negative and significant, and the convexity term (H3b) is large and significant. The competition interaction is not statistically significant in this parametric specification, and the joint Wald test in the dummy-variable specification also fails to reject the null at the 5% level. The Las Vegas

Strip indicator is positive in Models 2 and 3 but insignificant in Model 4 (-0.020), as the convex RII^2 term absorbs the Strip's outside bundling intensity, leaving little residual Strip premium.

At the 10th, 25th, 50th, 75th, and 90th percentiles of $\ln G$, the conditional marginal associations of RII are 0.186, 0.160, 0.129, 0.093, and 0.073, respectively, and each is statistically different from zero. For hotel-having clusters, these are approximate partial elasticities of revenue with respect to rooms. Thus a 10% increase in rooms is associated with approximately 1.9% higher revenue at the 10th percentile of local demand, about 2.6 times the association at the 90th percentile. Figure 2 illustrates Model 4's quadratic and interaction terms.

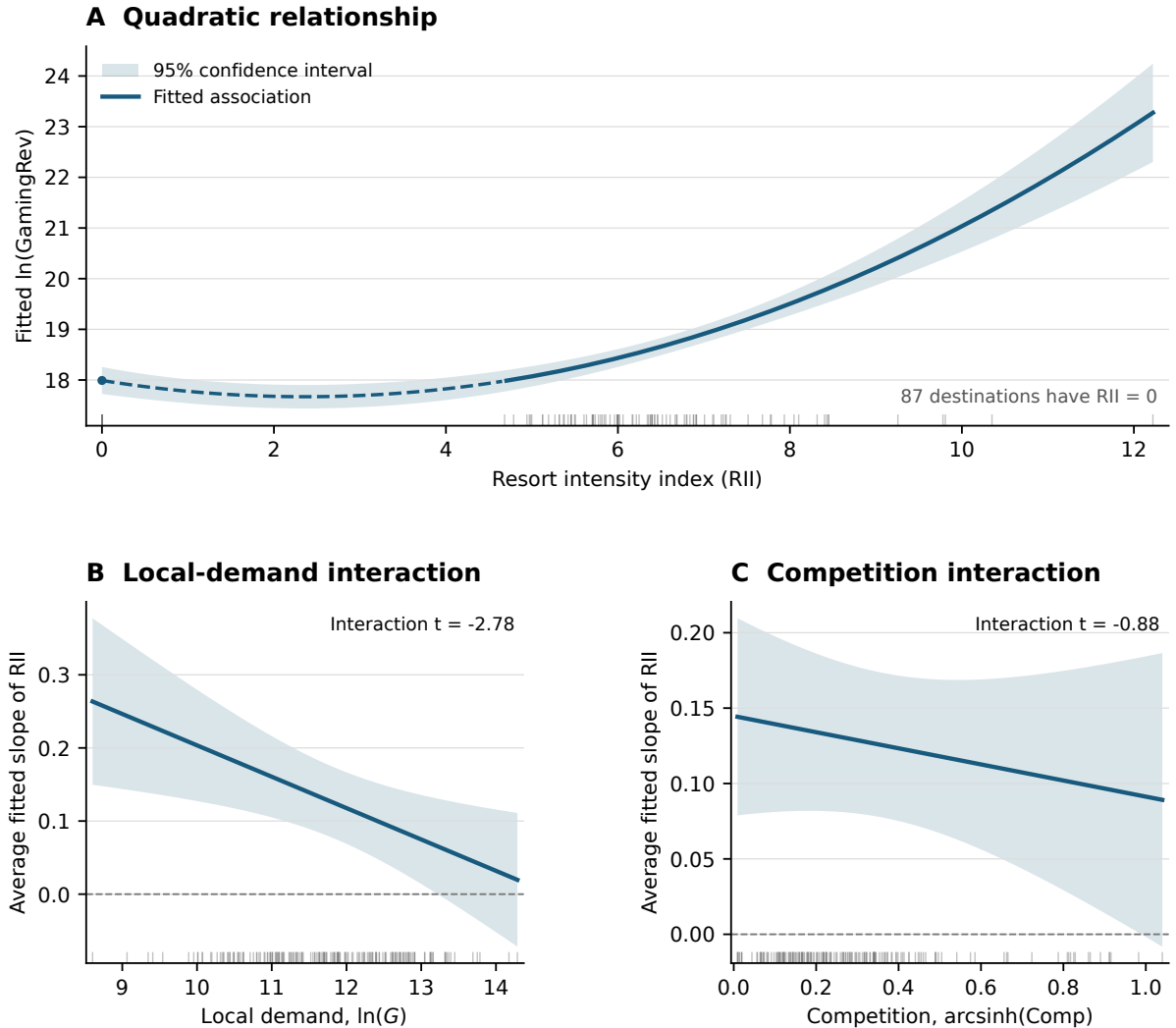


Figure 2: Model 4 associations for 186 destination clusters. Panel A shows fitted log gaming revenue across the resort intensity index. Panels B and C show the marginal association between RII and log gaming revenue across levels of local demand and competition, respectively. Other covariates are held at their sample means. Shading shows pointwise 95% confidence intervals based on state-clustered standard errors. Tick marks show observed values. Panel A's dashed segment spans the unobserved range between zero and the smallest positive RII .

Model 5 adds the maximum statutory gaming tax rate. The low-demand interaction remains negative (-0.041 , $t = -2.66$), and the convexity term remains positive (0.047 , $t = 5.46$). Re-estimating Model 4 on the 99 hotel-having clusters gives a similar interaction estimate (-0.037 versus -0.043) but a larger standard error ($t = -0.83$). Appendix D reports the two-part decomposition. The point estimate therefore survives within the hotel-having margin, but the full sample supplies substantially greater precision.

To test H4, we analyze the 40 estimation-sample clusters containing two or more casino properties. This definition includes all destinations in which cross-property bundling can occur. We regress log cluster revenue on log cluster size, log local demand density, and mean RII across member casinos. Standard errors are HC1 heteroskedasticity-robust. The regression has $R^2 = 0.696$. Cluster size (0.772, $t = 5.18$), local demand (0.538, $t = 4.40$), and mean RII (0.432, $t = 8.65$) are positively associated with cluster revenue, supporting H4. The mean-RII relationship remains when Nevada is excluded (0.462, $t = 8.03$) and when standard errors are clustered by state ($t = 4.24$). As a sensitivity test, adding total cluster rooms reduces the mean-RII estimate to 0.120 ($t = 1.50$). Because total rooms and mean RII are constructed from the same underlying room counts, that specification cannot precisely distinguish average property resort intensity from aggregate hotel capacity.

Appendix E reports robustness tests related to functional form, market definition, and sample selection. The low-demand interaction remains negative across these specifications, while the linear-room specification behaves differently and the competition interaction remains unsupported. Because disclosure is non-random, the estimates describe the disclosed segment of the industry.

5.2. Direct Evidence of Spatial Reach: Visitor Origins

The reach-extending mechanism formalized in Section 3.3 predicts that markets with higher bundling intensity draw visitors from greater distances. The main analysis tests this prediction indirectly, through the $\text{RII} \times \ln G$ interaction in a revenue regression. This subsection provides a direct test using visitor-origin data from TripAdvisor reviews.

The sample covers the non-Nevada destination clusters in the inventory. Nevada is excluded because its tourism ecosystem, in which casinos are the primary destination rather than a component of it, would confound the reach test. For each cluster we identified a flagship property (the largest hotel-having casino, or, for no-hotel clusters, the most prominent gaming-only venue), queried the TripAdvisor Content API for the corresponding location, verified the result against the casino's category metadata, and collected the available English-language reviews. After auditing the matches and dropping cardrooms, bar casinos, and newly opened venues for which no verified listing existed, we obtained reviews for 123 verified casino listings. Of the 2,783 reviews collected, 1,218 (44%) included a stated reviewer home location. Of these, 1,075 were successfully geocoded against a lookup table based on mean ZIP-code coordinates of U.S. city-state pairs constructed from the American Community Survey ZIP-code file used elsewhere in the paper. Clusters with fewer than three geocoded reviews were dropped. The final analysis sample contains 110 clusters (66 hotel-having, 44 no-hotel) and 1,062 reviewer-casino distance pairs.

Figure 3 shows the distance distributions. Hotel-cluster reviewers have a median travel distance of 143 miles, compared with 53 miles for no-hotel-cluster reviewers. The share of reviewers traveling from beyond 125 miles is 56% for hotel clusters and 33% for no-hotel clusters, and a Mann-Whitney U test rejects the null of equal distance distributions ($p < 10^{-3}$).

Table 2 reports five specifications. In Model A, the hotel indicator alone is positive and significant ($\beta = 0.651$, $t = 3.66$); hotel clusters draw TripAdvisor reviewers from farther away even without controlling for demand density. Adding $\ln G_{\text{local}}$ in Model B absorbs some of this association (the hotel coefficient falls to 0.462, $t = 2.73$), because hotel clusters and high-demand clusters are correlated. Demand density itself enters with a large negative coefficient (-0.249 , $t = -4.56$). Model D regresses the cluster-level share of reviewers from beyond 125 miles on the hotel indicator and $\ln G_{\text{local}}$:

$$\text{pct}_{>125\text{mi},m} = 1.648 + 0.171 \cdot \text{Hotel}_m - 0.113 \cdot \ln G_m + \varepsilon_m$$

with HC1 robust standard errors. Having a hotel is associated with a 17 percentage-point increase in the share of distant reviewers ($t = 4.08$, $p < 0.001$), and local demand density has a strong negative association ($t = -6.57$, $p < 0.001$). Together these two variables explain 42% of the cross-cluster variation in the share of distant visitors ($R^2 = 0.418$). Model E, which uses $\ln(\text{median distance})$ as the dependent variable, yields a consistent pattern: hotel clusters have 92% longer median reviewer travel distances ($e^{0.651} - 1 \approx 0.92$, $t = 3.32$, $p < 0.001$), and demand density is again strongly negative ($t = -5.89$). Model C substitutes continuous RII for the hotel indicator and finds a positive and statistically significant coefficient ($\beta = 0.073$, $t = 2.94$, $p < 0.01$): clusters with greater resort intensity draw reviewers from farther away. The reach pattern appears both at the threshold of having a hotel at all and across hotels of different sizes.

Three patterns emerge. First, clusters with less local demand draw visitors from farther away. Second, clusters with hotels draw a higher share of distant visitors than clusters without hotels, conditional on demand density (+0.171, $t = 4.08$). Third, continuous RII is positively associated with reviewer travel distance (0.073, $t = 2.94$). This reach

Table 2: TripAdvisor Reviewer Travel Distance Regressions

	(A)	(B)	(C)	(D)	(E)
	ln(mean distance)	ln(mean distance)	ln(mean distance)	Share > 125 mi	ln(median distance)
Has hotel	0.651*** (0.178)	0.462*** (0.169)		0.171*** (0.042)	0.651*** (0.196)
RII			0.073*** (0.025)		
ln(G_{local})		-0.249*** (0.055)	-0.262*** (0.053)	-0.113*** (0.017)	-0.400*** (0.068)
Intercept	4.914*** (0.159)	7.880*** (0.641)	8.022*** (0.605)	1.648*** (0.202)	8.733*** (0.809)
N	110	110	110	110	110
R^2	0.130	0.227	0.236	0.418	0.329

Notes: HC1 robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample: 110 non-Nevada destination clusters with ≥ 3 geocoded TripAdvisor reviews from verified casino listings (66 hotel-having, 44 no-hotel). “Has hotel” = 1 if the cluster has any hotel rooms. Models A–C and E use $\ln(\text{distance} + 1)$. Model D uses the cluster-level share of reviewers whose geocoded home location is more than 125 miles from the casino.

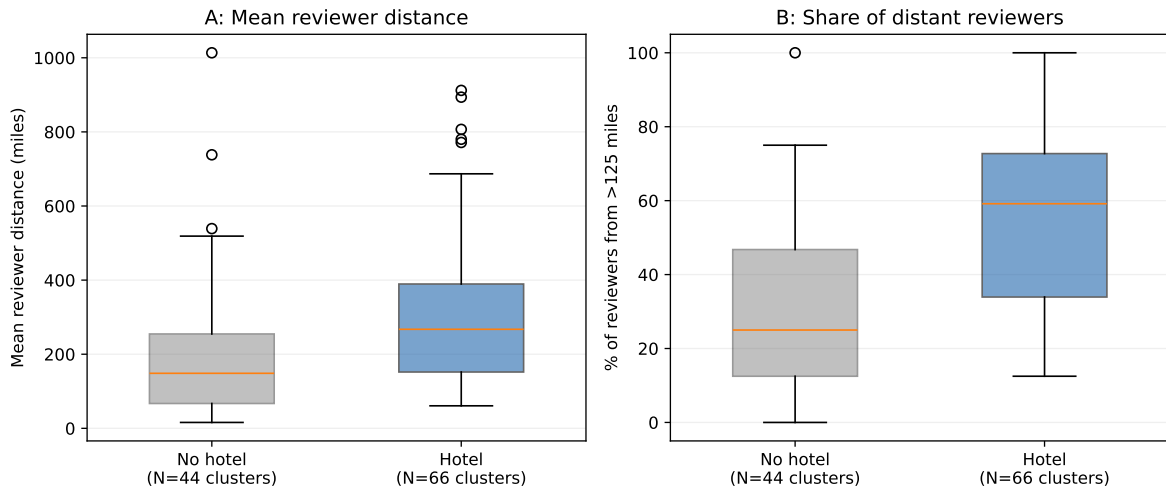
 TripAdvisor reviewer travel distances: verified casino matches, non-Nevada
(1062 geocoded reviews across 110 destination clusters)


Figure 3: TripAdvisor reviewer travel distances across 110 non-Nevada destination clusters (1,062 geocoded reviews from audited and verified casino listings, including 66 hotel-having and 44 no-hotel clusters). Panel A: box plots of cluster-level mean reviewer distance for hotel vs. no-hotel clusters. Panel B: box plots of the share of reviewers from beyond 125 miles for hotel vs. no-hotel clusters. Hotel clusters exhibit higher medians on both measures, consistent with the reach-extending mechanism: casinos with hotels draw reviewers from farther away on average and a larger fraction of distant reviewers.

evidence complements the revenue interaction, whose hotel-only estimate remains similar in magnitude (-0.037 versus -0.043) but is imprecise at $N = 99$.

Several limitations should be noted. The TripAdvisor Content API returns a maximum of 25 reviews per location, and the 44% reviewer-location disclosure rate means more than half of the collected reviews contribute no distance information. TripAdvisor reviewers are not representative of all casino visitors. They likely overrepresent leisure tourists who plan trips in advance and underrepresent local repeat visitors and business travelers, which may inflate the measured share of distant reviewers in both cluster types. The consistency of the demand-density gradient across specifications and the hotel association in Model D nevertheless suggest that the spatial reach pattern is a robust feature

of the data. Larger-scale studies using loyalty-program ZIP codes or hotel-reservation origin data would test the pattern more directly.

6. Discussion

The central argument is that an integrated casino resort is a spatial tourism product, not simply a gaming operation with amenities attached. A standalone venue relies more heavily on nearby demand. A resort bundle can give distant travelers a reason to make the trip. Three patterns are consistent with this view: resort intensity is positively associated with revenue across the demand distribution, the proportional association is largest where local demand is weakest, and bundled clusters attract visitors from greater distances.

The demand gradient alone is not decisive because any distant-visitor contribution is mechanically a larger share when local revenue is small. The visitor-origin evidence is more direct: hotel clusters draw reviewers from beyond the catchment of gaming-only clusters, and larger hotel clusters draw from farther away. This evidence helps distinguish spatial reach from a purely on-property stay-duration channel. Scope economies, marketing, and brand may also contribute to the observed relationships.

State regulation can shape the casino business models observed in the data. New Jersey tied casino development to Atlantic City tourism and substantial hotel capacity, while Pennsylvania's 2004 statute created racetrack, standalone, and resort license categories (New Jersey Casino Control Commission, 2026; Commonwealth of Pennsylvania, 2004). Such rules can jointly determine location, amenity scale, and gaming operations. State fixed effects and the statutory-format sensitivity check show that the low-demand interaction is not eliminated by coarse controls for these regimes, but the statutory categories are not instruments because they can affect revenue through several direct channels. The results therefore inform comparisons among regulated business models while recognizing that licensing categories capture several regulatory channels at once.

6.1. Theoretical implications

These results extend the theory of bundling to a spatial setting that the canonical models do not address. Adams and Yellen (1976) and Schmalensee (1984) explain why a multiproduct firm can profit by selling goods jointly rather than separately, but their mechanism concerns the extraction of additional surplus from a given set of consumers and is silent on the location of those consumers. The casino-resort bundle operates on a margin the canonical account does not consider. Rather than only capturing more surplus from a fixed clientele, it expands the clientele itself, converting a local gaming proposition into a destination worth traveling to. This reach-extending role (Section 3.3) accounts for the spatial structure of the bundling premium, in which the proportional return to bundling is largest where the local demand available for extraction is smallest, and it is a prediction the surplus-extraction account cannot generate.

Framing the resort in these terms links the industrial-organization literature on bundling to the tourism literature on destination development, competitiveness, and packaging. In the terms of the destination-competitiveness framework (Crouch and Ritchie, 1999; Ritchie and Crouch, 2003; Dwyer and Kim, 2003), the reach-extending resort is a created rather than an inherited attraction, a firm-level investment that generates the locational appeal a peripheral market lacks by nature, much as transport access and purpose-built infrastructure render remote destinations visitable (Prideaux, 2000). It is likewise consistent with the experience-economy perspective (Pine and Gilmore, 1999) and with earlier tourism research on packaged and all-inclusive offerings (Sheldon, 1986; Stremersch and Tellis, 2002; Calveras, 2019), in which the joint consumption of complementary services converts a single-purpose visit into a multi-day stay.

6.2. Managerial and policy implications

For operators, the observed association is strongest at larger resort scale. Small amenity additions, such as a restaurant or limited-service hotel at a slot parlor, are associated with smaller revenue differences, whereas fully integrated resorts exhibit larger differences, a threshold-shaped pattern that parallels the all-inclusive hotel sector (Calveras, 2019). Because the design is cross-sectional, these estimates do not provide investment-return calculations or rank intermediate strategies. They instead suggest that operators evaluating amenity expansion should consider whether a project is large enough to alter destination appeal. Project costs and returns require separate evaluation. Feasibility work can examine visitor catchments, transport access, accommodation demand, and complementary attractions. Coordination among properties may help address gaps in destination amenities.

For policymakers weighing legalization or licensing design, the spatial pattern is one relevant input rather than a decision rule. The association between resort intensity and revenue is largest in places with dispersed local demand,

consistent with a greater role for destination amenities there. Jurisdictions that restrict local participation, including the Bahamas, South Korea, and Singapore (Government of The Bahamas, 2014; Government of the Republic of Korea, 2024; Government of Singapore, 2024), likewise have a stronger practical need to attract visitors from elsewhere. The relevance of these comparisons depends on the surrounding regulation, taxation, and destination infrastructure, which jointly shape the feasible casino business model. Evaluation should track visitor origins, overnight stays, and spending across businesses, distinguishing additional destination demand from displaced spending and gaming revenue from net community benefit.

7. Conclusion

This paper reframes the integrated casino resort as an instrument for extending market reach rather than for extracting additional surplus from existing customers, and the evidence is consistent with that interpretation. Bundling is positively associated with revenue, the association strengthens with resort scale, its proportional association is largest where local demand is weakest, and bundled clusters draw visitors from substantially greater distances. The unifying interpretation is that the amenity bundle may be one mechanism through which a casino in a low-demand market constitutes itself as a destination worth traveling to. The contribution is conceptual as well as empirical. The paper offers a mechanism linking a property's amenity investment to the formation of a destination market, together with a research design that pairs a gravity-model interaction with direct visitor-origin evidence. The cross-section documents the contrast between clusters with and without a resort bundle.

7.1. Limitations and future research

Several limitations bound these conclusions. Bundling intensity is an endogenous investment choice. Table-game presence may also reflect anticipated demand. Panel data on property renovations, expansions, openings, and closures, linked to property revenue where available, would show how revenue changes following bundle investments.

A second limitation concerns measurement. The Resort Intensity Index captures the scale of resort capacity through hotel-room counts but not the quality or composition of the amenity portfolio, so that a 1,000-room budget hotel and a 1,000-room luxury resort receive identical scores. The validation exercise in Appendix B shows that room counts correlate positively with every available non-room amenity attribute (r from 0.45 to 0.75), which supports the proxy. Quality-adjusted indices constructed from star ratings, brand affiliations, and review-platform scores would distinguish high- from low-investment properties at a given room count and refine the construct.

A third concerns coverage and external validity. The regression sample spans 31% of the 595 U.S. casino clusters, while 408 clusters lack usable gaming revenue, predominantly in tribal and rural non-disclosure markets. The loss of low-demand observations reduces precision. If the omitted, especially isolated clusters have a stronger low-demand relationship, their omission would move the negative interaction toward zero. The unreported outcomes prevent the direction or size of remaining selection bias from being identified. The conclusions therefore describe the disclosed segment of the industry. The TripAdvisor visitor-origin analysis, although it provides direct evidence on the mechanism, rests on a modest and self-selected sample (1,062 geocoded reviews, a 25-review API cap, and a 44% location-disclosure rate) of leisure-oriented reviewers who are not representative of all casino patrons. Loyalty-program ZIP codes, reservation records, or license-plate surveys would test the reach-extending prediction more directly.

Finally, the analysis is confined to the United States. Whether the reach-extending mechanism generalizes to non-U.S. regulatory and cultural conditions remains open (Henderson, 2006; McCartney, 2020). The cluster analysis supports a positive association between mean property RII and cluster revenue, but it cannot separately identify average resort intensity from aggregate hotel capacity. Richer property-level amenity and patronage data are needed to distinguish the within-cluster specialization channel. This paper takes a first quantitative step within the U.S. cross-section, with explicit scoping of the available evidence.

CRedit author statement

Kahlil Simeon-Rose: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing.

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Declaration of competing interest

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Appendix A. Summary Statistics

Table A.1: Summary Statistics by Hotel Room Category (descriptive)

Hotel rooms	0 (no hotel)	1–99	100–499	500–1499	≥1500
<i>N</i> (clusters)	87	10	61	16	12
Median rooms	0	74	202	696	2336
Median RII	0.00	4.99	6.00	7.24	8.45
Mean gaming revenue (\$M)	132.9	75.3	191.0	303.5	1603.7
Median gaming revenue (\$M)	92.5	71.3	153.8	187.6	860.2
Mean G_{local} (\$ thous.)	248	62	190	162	155
Mean competition index	0.36	0.19	0.23	0.22	0.50
% with table games	76	90	87	100	100

Notes: All 186 estimation-sample casino clusters, grouped by hotel-room range for descriptive purposes only. The headline regression uses $RII = \text{arcsinh}(\text{rooms})$ as a continuous concave variable. Bands are reported here only to illustrate the distribution of properties along the room dimension and to anchor the dummy-variable robustness specification discussed in Section 4. Gaming revenue in millions of dollars (most recent reporting year). G_{local} is gravity-weighted population-income demand within 125 miles, in thousands of dollars-per-(distance unit).

Table A.1 shows that the sample spans clusters without hotels through large resort clusters. Gaming revenue rises sharply in the largest room category, while local demand does not increase consistently across the categories.

Appendix B. Hotel Room Capacity as a Proxy for Bundling Intensity: Empirical Validation

This appendix reports correlations between hotel room counts and other observable amenity attributes to validate the use of hotel rooms as a proxy for the broader resort amenity bundle (Section 4.2). Amenity data were obtained from CasinoCity.com (Casino City, Inc., 2026) and matched to the casino inventory by property name and location. The amenity attributes with sufficient coverage are: number of restaurants, number of bars, gaming floor area in square feet, and entertainment venue seating capacity. Coverage varies because CasinoCity does not report all attributes for all properties. Binary amenity indicators (spa, pool, fitness center) were not consistently populated in the source data and are excluded.

Table B.1: Correlations between hotel room counts and amenity attributes

	N	Pearson r	Spearman ρ
Restaurants	205	0.752	0.711
Bars	119	0.468	0.370
Gaming floor (sq ft)	87	0.496	0.535
Entertainment venue seats	21	0.451	0.355

Notes. Each row reports the Pearson and Spearman correlation between hotel room count and the named non-room amenity attribute. All variables are arcsinh-transformed before computing correlations to reduce the influence of outliers. Hotel rooms appear only on the left. There is no overlap with the right-hand side. Coverage varies because CasinoCity does not report all fields for all properties. Source: CasinoCity.com data matched to 472 hotel-having casinos in the inventory.

Hotel room counts correlate positively with every available non-room amenity attribute. The strongest relationship is with restaurant counts ($r = 0.75$, $N = 205$), which is also the attribute with the broadest coverage. Bars ($r = 0.47$, $N = 119$), gaming floor area ($r = 0.50$, $N = 87$), and entertainment venue seating ($r = 0.45$, $N = 21$) all show positive associations, though the entertainment result rests on a small sample. Properties with more hotel rooms tend to have more restaurants, more bars, larger gaming floors, and larger entertainment venues, supporting the use of hotel rooms as a reasonable proxy for the broader amenity portfolio.

Appendix C. Casino-Level Analysis

The main analysis uses the destination cluster as the unit of observation. We re-estimate Model 4 on 225 casinos in 23 states whose individual revenue can be attributed unambiguously: casinos with direct property reports and sole casinos in property-reported clusters. Nevada, Colorado, South Dakota, and Mississippi are excluded because their usable outcomes are reported only at the area level. The comparison cluster model is re-estimated on the same state subsample ($N = 173$).

Table C.1: Casino-Level vs. Cluster-Level Regression on the Same State Subsample

	Casino level	Cluster level
Intercept	11.838*** (1.041)	9.059*** (1.154)
$\ln(G_{\text{local}})$	0.542*** (0.087)	0.787*** (0.096)
RII	-0.066 (0.213)	0.248 (0.261)
$\text{RII} \times \ln(G)$	-0.007 (0.024)	-0.039 (0.025)
$\text{RII} \times \text{arcsinh}(\text{Comp})$	-0.000 (0.021)	-0.001 (0.133)
RII^2	0.036 (0.022)	0.048*** (0.011)
$\text{arcsinh}(\text{Comp})$	-0.088 (0.135)	-0.483 (0.321)
Table games present	0.134 (0.259)	0.122 (0.229)
Cardroom	-2.959*** (0.235)	-2.400*** (0.196)
LV Strip	-- -	-- -
N	225	173
State clusters	23	23
R^2	0.782	0.737

Notes: State-clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: $\ln(\text{GamingRev})$. The casino-level sample additionally excludes Colorado, South Dakota, and Mississippi, whose regulators report gaming revenue at the town/area-aggregate level rather than per individual property. Casino-level gaming revenue is the casino's own property-level gaming revenue when reported by the state regulator, or, in single-casino clusters, the cluster-level gaming revenue assigned trivially to the sole property. The cluster-level column re-estimates Model 4 on the same state subsample for direct comparability. Because the outcome and RII are both redefined at the property level, differences between columns are a unit-of-analysis sensitivity and do not identify cross-property spillovers.

At the cluster level, the low-demand interaction is -0.039 ($t = -1.56$) and RII^2 is 0.048 ($t = 4.25$). At the casino level, the corresponding estimates are -0.007 ($t = -0.30$) and 0.036 ($t = 1.64$). These weak casino-level estimates limit what can be concluded about how the relationship appears at an individual property. The casino-level regression combines differences across destinations with differences among properties within them. Illustratively, a visitor may choose Atlantic City because of the destination's combined lodging, dining, entertainment, and gaming offer, then divide gaming expenditure across several casinos. Cross-property spillovers are plausible in that example, but the difference between the two regressions does not estimate them.

Appendix D. Two-Part Model: Extensive and Intensive Margins

The headline specification enters hotel-room capacity as a continuous RII on the full 186-cluster sample, including 87 clusters with zero rooms. The two-part model separates the extensive margin (having any hotel) from the intensive margin (room scale among hotel-having clusters).

Part 1 is a logit for whether the cluster has a hotel. Part 2 re-estimates Model 4 on the 99 hotel-having clusters, so its interaction and convexity terms use only intensive-margin variation.

Table D.1: Two-Part Model: Extensive and Intensive Margins

	Part 1: Has any hotel (Logit, full sample)	Part 2: ln(GamingRev) (OLS, hotel-having)
Intercept	3.287 (3.824)	11.167*** (3.126)
$\ln(G_{\text{local}})$	-0.305 (0.352)	0.765** (0.309)
RII	-	-0.373 (0.686)
$\text{RII} \times \ln(G)$	-	-0.037 (0.044)
$\text{RII} \times \text{arcsinh}(\text{Comp})$	-	-0.109 (0.187)
RII^2	-	0.096** (0.045)
$\text{arcsinh}(\text{Comp})$	-1.939 (2.041)	-0.119 (1.586)
Table games present	1.189** (0.518)	0.137 (0.162)
LV Strip	-	-0.756 (0.863)
N	186	99
State clusters	27	23
R^2 / Pseudo- R^2	0.091	0.678

Notes: State-clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Part 1 is a logit model for the binary outcome “the cluster has at least one hotel-having casino,” estimated on the full 186-cluster regression sample. Part 2 re-estimates Model 4 on the hotel-having subsample only, so the interaction and convexity coefficients are identified entirely by within-hotel-cluster variation in room count. Pseudo- R^2 for Part 1 is McFadden’s.

Cardroom status perfectly predicts no hotel and is omitted from Part 1. Demand density does not predict the extensive-margin hotel decision ($z = -0.87$), while table-game presence is positively associated with it.

The intensive-margin interaction is -0.037 , close to the full-sample -0.043 , but its standard error increases to 0.044 ($t = -0.83$). RII^2 remains positive (0.096 , $t = 2.13$). The gradient is therefore similar in magnitude within hotel-having clusters but is estimated less precisely.

Appendix E. Alternative Specifications and Sample Definitions

The following tables report the functional-form, flexible-demand, influential-observation, market-definition, reporting-unit, state-regime, destination-specialization, leave-one-state-out, and selection checks discussed in Section 5. Hotel-room bands reject the joint null on their levels ($p = 0.013$). Joint tests of their interactions with $\ln G$ ($p = 0.092$) and competition ($p = 0.072$) do not reject at the 5% level. The low-demand interaction remains negative under all concave RII transforms, polynomial demand controls, the Las Vegas-area and Nevada exclusions, and alternative cluster radii. A data-driven Yeo–Johnson transformation (Yeo and Johnson, 2000) also selects a form close to the natural logarithm.

Table E.1: Functional Form Sensitivity of the RII Specification

Functional form (standardized)	RII	$\text{RII} \times \ln G$	$\text{RII} \times \text{arcsinh}(\text{Comp})$	RII^2
$\text{arcsinh}(\text{rooms})$ (headline)	0.838	−0.145***	−0.181	0.662***
$\ln(1 + \text{rooms})$	0.995	−0.144**	−0.185	0.577***
$\sqrt{\text{rooms}}$	3.813***	−0.222***	−0.334*	−0.059
$\text{rooms}^{1/3}$	2.737***	−0.193***	−0.203	0.105**
Bands/4 (ordinal)	1.199	−0.109*	−0.085	0.252***
Rooms/1,000 (linear)	6.444**	0.200	−3.131***	−3.417***

Notes: Dependent variable: $\ln(\text{GamingRev})$. Each row reports the four RII-related coefficients from Model 4 estimated under a different functional-form transform of the cluster's hotel-room count. All transforms are divided by their sample standard deviation to make magnitudes comparable across rows. The headline specification uses $\text{arcsinh}(\text{rooms})$ (top row). State-clustered CR1 standard errors. Two-sided significance tests use a $t(G - 1)$ reference distribution. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The bands/4 row corresponds to the 5-level ordinal proxy used in earlier drafts of this paper, retained here so readers can compare the continuous and ordinal specifications side by side.

Table E.1 shows that the negative $\text{RII} \times \ln G$ interaction persists across the concave room-count transformations, while the linear specification behaves differently.

Table E.2: Robustness Checks

	Headline	$+\ln(G)^2$	Excl. LV areas	Excl. NV
Intercept	8.980*** (1.112)	6.579 (5.553)	8.957*** (1.102)	8.942*** (1.132)
$\ln(G_{\text{local}})$	0.794*** (0.092)	1.201 (0.899)	0.796*** (0.091)	0.797*** (0.094)
RII	0.247 (0.196)	0.270 (0.217)	0.262 (0.191)	0.297 (0.231)
$\text{RII} \times \ln(G_{\text{local}})$	-0.043*** (0.015)	-0.045** (0.017)	-0.043*** (0.015)	-0.047** (0.021)
$\text{RII} \times \text{arcsinh}(\text{Comp})$	-0.053 (0.061)	-0.055 (0.060)	-0.085 (0.072)	-0.012 (0.122)
RII^2	0.058*** (0.007)	0.058*** (0.007)	0.056*** (0.006)	0.056*** (0.007)
Table games present	0.113 (0.226)	0.111 (0.228)	0.112 (0.226)	0.112 (0.226)
Cardroom	-2.387*** (0.187)	-2.376*** (0.189)	-2.391*** (0.187)	-2.387*** (0.195)
$\text{arcsinh}(\text{Competition})$	-0.505 (0.306)	-0.515 (0.307)	-0.487 (0.309)	-0.497 (0.326)
LV Strip	-0.020 (0.266)	-0.021 (0.262)		
$\ln(G_{\text{local}})^2$		-0.017 (0.036)		
N	186	186	183	177
R^2	0.760	0.760	0.743	0.743
Adj. R^2	0.746	0.745	0.729	0.729

Notes: State-clustered CRI standard errors in parentheses. Two-sided significance tests use a $t(G - 1)$ reference distribution, where G is the number of state clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: $\ln(\text{GamingRev})$. RII (Resort Intensity Index) is the concave continuous transform $\text{arcsinh}(\text{hotel rooms})$ of the cluster's total hotel-room count, used as a proxy for the latent bundling-intensity construct.

Table E.2 shows that the low-demand interaction is similar after adding quadratic demand or excluding the three Las Vegas-area exceptions or all Nevada observations.

Table E.3: Sample-Selection Sensitivity: OLS, Penalized Selection Diagnostic, and IPW

	OLS (Model 4)	Penalized diagnostic	IPW
$\text{RII} \times \ln G$	-0.043*** ($t = -2.78$)	-0.044*** ($t = -2.72$)	-0.044*** ($t = -3.52$)
RII^2	0.058*** ($t = 8.15$)	0.057*** ($t = 7.63$)	0.058*** ($t = 9.27$)
Inverse Mills ratio	—	0.063 ($t = 0.30$)	—
N	186	186	186

Notes: The dependent variable is $\ln(\text{GamingRev})$. All columns are the Model 4 specification with state-clustered standard errors. The selection column adds a generated inverse Mills term from a ridge-penalized probit for whether a cluster has usable gaming revenue. Tribal sector and state disclosure regime are additional first-stage predictors (details in the replication code). Because these predictors may affect gaming revenue through regulation, the specification is a sensitivity diagnostic, not an identified correction for selection bias. Its generated term and the IPW weights are treated as fixed in second-stage inference. IPW weights the Model 4 regression by the inverse first-stage selection probability. The coefficients are numerically similar across the three specifications, but the diagnostics do not identify the direction or size of remaining selection bias.

Table E.3 shows that the low-demand interaction and RII^2 estimates remain close to Model 4 under the penalized-selection and inverse-probability-weighted specifications.

Table E.4: Flexible Demand Curvature and Regional Fixed Effects

	$+\ln(G)^2 + \ln(G)^3$	+ Region FE
Intercept	54.541 (34.859)	8.868*** (1.284)
$\ln(G_{\text{local}})$	-11.454 (9.308)	0.818*** (0.109)
$\ln(G_{\text{local}})^2$	1.088 (0.824)	
$\ln(G_{\text{local}})^3$	-0.032 (0.024)	
RII	0.271 (0.217)	0.213 (0.202)
$\text{RII} \times \ln(G_{\text{local}})$	-0.044** (0.017)	-0.040** (0.017)
$\text{RII} \times \text{arcsinh}(\text{Comp})$	-0.041 (0.066)	-0.077 (0.056)
RII^2	0.056*** (0.008)	0.059*** (0.007)
Table games present	0.083 (0.239)	0.055 (0.208)
Cardroom	-2.336*** (0.202)	-2.479*** (0.300)
$\text{arcsinh}(\text{Competition})$	-0.620 (0.376)	-0.527 (0.341)
LV Strip	-0.045 (0.294)	-0.051 (0.293)
Region: Northeast		-0.219 (0.257)
Region: Midwest		-0.020 (0.209)
Region: South		-0.220 (0.288)
N	186	186
R^2	0.762	0.763
Adj. R^2	0.746	0.745

Notes: State-clustered CRI standard errors in parentheses. Two-sided significance tests use a $t(G - 1)$ reference distribution, where G is the number of state clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: $\ln(\text{GamingRev})$. RII (Resort Intensity Index) is the concave continuous transform $\text{arcsinh}(\text{hotel rooms})$ of the cluster's total hotel-room count, used as a proxy for the latent bundling-intensity construct.

Table E.4 shows that adding quadratic and cubic demand terms or census-region fixed effects leaves the negative low-demand interaction similar to the headline estimate.

Table E.5: Robustness to Cluster-Size Threshold

	5 miles (headline)	10 miles	25 miles
Intercept	8.980*** (1.112)	8.184*** (1.399)	8.112*** (1.774)
$\ln(G_{\text{local}})$	0.794*** (0.092)	0.868*** (0.116)	0.852*** (0.155)
RII	0.247 (0.196)	0.297 (0.239)	0.166 (0.280)
$\text{RII} \times \ln(G_{\text{local}})$	-0.043*** (0.015)	-0.046** (0.019)	-0.032 (0.024)
$\text{RII} \times \text{arcsinh}(\text{Comp})$	-0.053 (0.061)	-0.066 (0.118)	0.041 (0.255)
RII^2	0.058*** (0.007)	0.058*** (0.007)	0.050*** (0.008)
Table games present	0.113 (0.226)	0.132 (0.238)	0.444 (0.300)
Cardroom	-2.387*** (0.187)	-2.195*** (0.211)	-2.324*** (0.185)
$\text{arcsinh}(\text{Competition})$	-0.505 (0.306)	-1.151* (0.670)	-1.044 (1.931)
LV Strip	-0.020 (0.266)	–	–
N	186	168	128
State clusters G	27	27	26
R^2	0.760	0.744	0.753

Notes: State-clustered CRI standard errors in parentheses. Two-sided tests use a $t(G - 1)$ reference distribution. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: $\ln(\text{GamingRev})$. The 5-mile column is the headline Model 4 from Table 1. The 10-mile and 25-mile columns re-cluster the 595 5-mile clusters within state and sector at the larger thresholds via single-linkage hierarchical clustering on cluster centroids. Revenue and rooms are summed within each resulting super-cluster. Estimation requires observed revenue for every constituent cluster. All super-clusters remain in the competition calculation.

Table E.5 shows that the interaction remains negative when clusters are re-clustered at 10- and 25-mile thresholds, although precision declines as aggregation reduces the number of observations.

Table E.6: Robustness to Gaming-Revenue Reporting Units and State Regulatory Regimes

	Headline	+ Aggregate indicator	+ State FE	Direct property reports
RII	0.247 (0.196)	0.200 (0.220)	0.325 (0.281)	0.250 (0.258)
$\text{RII} \times \ln(G_{\text{local}})$	-0.043*** (0.015)	-0.036* (0.019)	-0.045* (0.022)	-0.039 (0.025)
$\text{RII} \times \text{arcsinh}(\text{Comp})$	-0.053 (0.061)	-0.074 (0.056)	0.003 (0.097)	-0.001 (0.134)
RII^2	0.058*** (0.007)	0.053*** (0.009)	0.044** (0.018)	0.048*** (0.012)
N	186	186	186	171
R^2	0.760	0.761	0.814	0.732

Notes: Dependent variable: $\ln(\text{GamingRev})$. Each column reports the four RII-related coefficients from Model 4. State-clustered CRI standard errors are in parentheses. Two-sided significance tests use a $t(G - 1)$ reference distribution. The aggregate indicator equals one for six directly mapped Nevada reporting areas, the three disclosed Las Vegas reporting-area exceptions, two Colorado destination totals, Biloxi, and Deadwood (13 of 186 observations). The state-fixed-effects specification uses Nevada as the reference and omits the cardroom indicator because it is nested in Washington. The direct-property-reporting column retains only observations classified as property_reported and therefore also excludes the two method-adjusted Connecticut observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.6 shows similar negative interaction estimates across all four reporting and regulatory specifications.

Table E.7: Robustness to Destination Specialization and Statutory Casino Formats

		+ County employment	+ Statutory category
	Headline	LQs	
RII	0.247 (0.196)	0.231 (0.195)	0.104 (0.206)
$RII \times \ln(G_{\text{local}})$	-0.043*** (0.015)	-0.040** (0.016)	-0.034** (0.016)
$RII \times \text{arcsinh}(\text{Comp})$	-0.053 (0.061)	-0.048 (0.063)	-0.085 (0.062)
RII^2	0.058*** (0.007)	0.055*** (0.007)	0.064*** (0.007)
Statutory hotel/resort category	—	—	-1.163*** (0.264)
County employment LQs included	No	Yes	No
N	186	186	186
R^2	0.760	0.765	0.768

Notes: Dependent variable: $\ln(\text{GamingRev})$. The employment-location-quotient specification adds county-level LQs for full-service restaurants (NAICS 722511), retail trade (NAICS 44), and personal-care services (NAICS 8121) from the 2022 County Business Patterns. These controls measure destination-area specialization, including off-property establishments, and do not replace the on-property room-based RII. The statutory-category indicator equals one for the New Jersey observation and Pennsylvania's two Category 3 resort-license clusters (3 observations). It is a sensitivity control, not an instrument, because statutory formats can affect gaming capacity, location, and gaming revenue directly. State-clustered CR1 standard errors appear in parentheses. Two-sided significance tests use a $t(G-1)$ reference distribution. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

An LQ of 1 denotes the national employment share. Across the 186 clusters, the mean restaurant, retail, and personal-care LQs are 1.05, 1.14, and 0.91, with interquartile ranges of 0.85–1.24, 0.96–1.29, and 0.53–1.21, respectively. Table E.7 shows that the negative interaction is similar after controlling for county destination specialization or statutory casino format.

Table E.8: Leave-One-State-Out Robustness

Omitted	N	Coef.	SE	p	Omitted	N	Coef.	SE	p
CO	184	-0.044	0.015	0.009	MS	185	-0.042	0.015	0.011
CT	184	-0.043	0.016	0.012	NE	182	-0.040	0.016	0.021
DE	183	-0.042	0.016	0.012	NJ	185	-0.041	0.016	0.020
FL	182	-0.042	0.015	0.011	NV	177	-0.047	0.021	0.031
IA	171	-0.039	0.016	0.021	NY	172	-0.049	0.017	0.009
IL	172	-0.047	0.016	0.007	OH	175	-0.039	0.015	0.014
IN	174	-0.044	0.015	0.008	OK	184	-0.048	0.017	0.008
KS	182	-0.043	0.016	0.011	PA	170	-0.044	0.018	0.021
LA	175	-0.043	0.016	0.014	RI	184	-0.044	0.016	0.010
MA	183	-0.044	0.016	0.010	SD	185	-0.040	0.016	0.019
MD	180	-0.048	0.015	0.004	VA	176	-0.039	0.016	0.021
ME	184	-0.043	0.016	0.011	WA	166	-0.032	0.013	0.024
MI	185	-0.045	0.015	0.007	WV	181	-0.047	0.015	0.005
MO	175	-0.044	0.016	0.011					

Notes: Dependent variable: $\ln(\text{GamingRev})$. Each row re-estimates Model 4 after deleting all observations from the named state. Coef. is the $RII \times \ln(G_{\text{local}})$ estimate. Standard errors use the state-clustered CR1 covariance. Two-sided p -values use a $t(G-1)$ reference distribution. Indicators that become constant after a deletion are omitted.

Table E.8 shows that the interaction remains negative and statistically significant when each state is omitted in turn.

Appendix F. Data Appendix

This appendix documents the data sources, construction procedures, and variable definitions used in the empirical analysis. Supplementary Online Appendix S1 provides the property–cluster crosswalk, state-level implementation details, screening decisions, and official source-page links. Data and replication code are available from the corresponding author upon reasonable request.

F.1. Overview

The analysis draws on six datasets: (i) an inventory of 1,014 U.S. casino properties, (ii) 595 destination clusters, of which 186 form the estimation sample, (iii) regulator-reported gaming-revenue records, (iv) ZIP-level demographic data for the gravity model, (v) an amenity database used in the RII validation, and (vi) state gaming tax rates and county employment location quotients used in sensitivity checks.

F.2. Casino-Level Inventory

For this study, a casino property is an operating fixed-location facility at which casino gaming or licensed cardroom gaming is a principal regulated activity. Table F.1 states the operational rule. The initial name-pattern audit flagged 62 records as possible route or non-traditional locations. Manual review retained eight legitimate properties: one licensed Nevada casino, four Washington cardrooms, and three tribal casinos. It excluded 54 Nevada restricted-gaming locations where gaming was incidental to a tavern, retail, airport, grocery, sportsbook, or travel-service business. The final inventory contains 1,014 properties. Supplementary Online Appendix S1 reports the implementation by state, all 69 recoverable screening decisions, every retained property, every source-backed record correction, and every cluster. The screening log is not a census of distributed-gaming outlets that never entered the candidate property file.

Table F.1: Operational definition of a casino property

Facility class	Treatment	Operational rule
Standalone and integrated-resort casinos	Include	Operating fixed-location properties for which casino gaming is a principal regulated activity, whether or not lodging is present.
Tribal casinos and gaming facilities	Include	Operating fixed-location tribal gaming properties are treated as casinos under the same activity-based rule.
Racinos and track casinos	Include	Include when the regulator recognizes a named casino gaming facility at the track. Exclude sportsbook-only locations.
Licensed cardrooms	Include	Include fixed-location licensed cardrooms in states where they constitute regulated casino-style gaming properties, including California and Washington.
Satellite, mini-casino, and temporary facilities	Include	Include when operating under a casino license during the study period. This includes Pennsylvania's York and Shippensburg satellites and operating Illinois temporary casinos.
Distributed or restricted-location gaming	Exclude	Exclude gaming incidental to ordinary taverns, bars, groceries, airports, truck stops, retail stores, and similar route locations.
Online gaming, sports wagering, and fantasy contests	Exclude	Exclude activities without a distinct physical casino property and sportsbook-only locations.
Proposed, closed, replaced, duplicate, or subsidiary venues	Exclude	Exclude facilities not operating in the study period and records that do not represent a distinct active property.

Table F.1 distinguishes fixed-location casino businesses from locations where gaming is incidental, while applying the same activity-based inclusion standard to commercial and tribal properties.

F.3. Destination Cluster Construction

Destination clusters are constructed by single-linkage hierarchical clustering (Everitt et al., 2011) on the pairwise haversine distance matrix (Sinnott, 1984), cut at 5 miles. Two casinos share a cluster if a chain of pairwise sub-5-mile distances connects them. Tribal and commercial properties are clustered separately. After facility screening and source-backed record corrections, the five-mile partition is rebuilt nationally. The three Las Vegas reporting-area exceptions described below are then retained. The final inventory yields 595 clusters. Two clusters cross state boundaries. The Arizona–California Quechan cluster lacks public revenue and does not enter estimation. The observed Casino Queen–Lumière Place cluster spans Illinois and Missouri and is excluded because it cannot be assigned one state regulatory regime.

F.4. Gaming-Revenue Data

Usable gaming revenue is available for 187 clusters in 27 states: Colorado, Connecticut, Delaware, Florida, Iowa, Illinois, Indiana, Kansas, Louisiana, Maine, Massachusetts, Maryland, Michigan, Mississippi, Missouri, Nebraska, New Jersey, Nevada, New York, Ohio, Oklahoma, Pennsylvania, Rhode Island, South Dakota, Virginia, Washington, and West Virginia. After excluding the observed cross-state cluster, 186 observations remain. The estimation sample includes official property records for Iowa, Indiana, Massachusetts, Maryland, Missouri, New York, Ohio, and Pennsylvania. The remaining states were also reconciled against archived regulator records.

Each outcome is classified as direct property-reported, direct geographic aggregate, allocated aggregate, method-adjusted, or unobserved. The estimation sample contains 171 direct property-reported clusters, 13 direct geographic aggregates, and two method-adjusted Connecticut observations. It contains no allocated outcomes. Six Nevada reporting areas (Laughlin, Churchill County, Mesquite, North Shore Lake Tahoe, South Shore Lake Tahoe, and Wendover) map directly to separate five-mile clusters, as do two Colorado destinations, Biloxi, and Deadwood. We also retain the Gaming Control Board's Las Vegas Strip, Downtown Las Vegas, and Boulder areas as transparent market-definition exceptions. These areas do not map neatly to distinct five-mile components within the continuous Las Vegas urban corridor, but have long-established destination-market identities and separately reported gaming-revenue totals. A sensitivity specification excludes all three together. Reno/Sparks, North Las Vegas, other rural county aggregates, and residual Clark and Washoe categories without usable market correspondence are left unobserved. The source archive contains 183 regulator files across 27 states, official URLs, extraction notes, hashes, and fixed-seed reconciliation checks.

Most outcomes are for calendar year 2024. Washington is retained using licensees' fiscal years ending in 2024 and labeled accordingly. West Virginia calendar-year 2024 is reconstructed from regulator weekly workbooks spanning FY2024 and FY2025. Connecticut publishes slot gaming revenue only. Its two observations apply the documented 32.2% table-share adjustment and are classified as `method_adjusted`. All other observed outcomes are ordinary sums of direct property or retained geographic reports before the common inflation conversion.

F.5. ZIP-Level Demographic Data

Household population and income data by ZIP code tabulation area come from the U.S. Census Bureau's 2016–2020 American Community Survey 5-Year Estimates (U.S. Census Bureau, 2022). After filtering missing income and coordinates, the gravity file contains 31,577 ZIP codes. Equation (9) defines G_m .

F.6. Employment Location Quotients

The alternative controls use 2022 County Business Patterns (U.S. Census Bureau, 2024). We compute county employment location quotients for full-service restaurants (NAICS 722511), retail trade (NAICS 44), and personal-care services (NAICS 8121) and attach the host-county values to each cluster. They measure destination-area specialization, including off-property establishments. They are therefore included as controls rather than substituted for the purpose-built, on-property RII.

F.7. Amenity Database

The amenity database, used only for the RII proxy validation in Appendix B, was collected from casinocity.com property pages (Casino City, Inc., 2026). A parser extracted restaurant counts, bar counts, gaming-floor square footage, and entertainment capacity for 714 properties. Coverage is non-random, and missingness is not treated as zero.

F.8. Gaming Tax Rate

The maximum statutory gaming tax rate used in Model 5 was compiled from the American Gaming Association's *State of the States 2025* report and applicable state law (American Gaming Association, 2025; Washington State Gambling Commission, 2026). For states with graduated tax structures (e.g., IL, LA, VA), the reported rate is the maximum statutory rate for the highest revenue tier. Washington cardrooms are assigned the 20% maximum local gambling tax authorized by RCW 9.46.110. Connecticut's two tribal-compact clusters are excluded from Model 5 because their compact payments are not comparable to the commercial statutory tax-rate measure.