Multi-Level Differentiation of Short-Term Rental Properties: A Deep Learning-Based Analysis of Aesthetic Design

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Abstract

This study aims to test the effects of differentiation on short-term rental performance along the dimension of aesthetic design. Online platforms display listing cover photos as search results, thus making aesthetic design a key element of differentiation. We hypothesize opposite impacts in two geographical scopes, local- and city-level, which answers an important question in differentiation literature of whom to compare to. Based on the assumption that localized competition has asymmetric influences, we introduce competition intensity as moderator. Hypotheses are tested with 96,196 listings from April 2021 to March 2022 in the Texas Airbnb market. We quantify aesthetic design by probability distribution scores over four design styles predicted by a pre-trained machine learning model. This study identifies differentiation benefits at local-level but discounts at city-level. Furthermore, it shows market intensity strengthens benefits and mitigates discounts regardless of the geographic scope. Finally, implications for aesthetic design as a strategic tool are discussed.

Keywords

Short-term rental; Aesthetic design; Deep learning; Differentiation; Conformity; Localized Competition

Highlights

- Local- and city-level aesthetic design differentiation have asymmetric effects.
- Differentiating from local rivals is beneficial due to localized competition.
- Conforming to city-level design norms dominants when competing with broader rivals.
- Competition intensity adds to differentiation gains regardless of comparison scope.

1. Introduction

Differentiation has been a pervasive topic in many areas, including marketing, strategic management, and tourism (Deephouse, 1999; M. Kim, Roehl, & Lee, 2020; Levitt, 1980). It refers to the introduction of unique products which have distinctive features. There is an ongoing debate about the effects of differentiation because of the competing demands for uniqueness and legitimacy (e.g., Baum & Haveman, 1997). Being different from competitors enables products to stand out, attract specific customer segments, and avoid direct rivalry. Firms, including lodging service providers, gain competitive advantages and revenue premiums through differentiation (Sánchez-Pérez, Illescas-Manzano, & Martínez-Puertas, 2020). However, differentiated products are vulnerable to skepticism from a diverse audience because they go against the most common forms (Deephouse, 1996). The skepticism can result in a decrease in legitimacy, thus discounting the benefits of differentiation. Such discounts are penalties that push firms to conform to their competitors (M. Kim et al., 2020). Hence, the ultimate impacts of differentiation are decided by whether differentiation benefits are offset by legitimacy penalties. We investigate short-term rental data during the COVID-19 pandemic when competition intensified due to a sharp decline in demand.

Previous differentiation studies mainly address the question of "differentiate or not" but pay little attention to the question "to whom does a firm need to compare to?" (e.g., M. Kim et al., 2020). When setting the benchmarks for positioning, previous studies utilize geographical scopes, such as rivals at the local- versus the city- level (Baum & Mezias, 1992; Yeung & Lau, 2005), whereby local is a sub-region of city. Because the strength of localized competition is contingent on geographical distances, there are significant differences between local- and city-level markets in terms of competitive pressures and market norms that decide differentiation effectiveness. This study aims to examine how city- and local-level differentiation asymmetrically affects lodging product performance. To further illustrate how competitive pressure shapes differentiation-performance relationships, we also test the moderating effects of two competition intensity indicators: number of competitors and market concentration.

In the hospitality and tourism literature, previous studies focusing on lodging products have investigated differentiation strategy in many dimensions, such as quality, size, service, amenity, and aesthetics (Baum & Haveman, 1997; Fleischer & Tchetchik, 2005; M. Kim et al., 2020). This study focuses on aesthetic design primarily for two reasons. First, our focus on visual cues is inspired by the customers' decision-making process in purchasing Airbnb stays. On the Airbnb platform, after travelers choose a destination and travel dates, they are shown a gallery of listing cover photos rather than more specific information, such as listing descriptions or amenities. As such, visual cues reflected by photos of short-term rental properties are critical for customer decision-making and host strategizing (H. Zhang, Zach, & Xiang, 2023; S. Zhang, Lee, Singh, & Srinivasan, 2022). Second, there are great differences in aesthetic designs across different levels of regions, including cities and sub-regions (X. Liu, Andris, Huang, & Rahimi, 2019). These differences across geographic levels provide a quantitative basis to further measure and distinguish differentiation degrees of aesthetic design.

The critical role of aesthetic design in strategizing lodging products has been validated for communicating product identity (Strannegård & Strannegård, 2012), differentiating product position (Lim & Endean, 2009), and boosting firm profitability (Zemke, Raab, & Wu, 2018) (Bitner, 1992; Farmaki, Spanou, & Christou, 2021; Lim & Endean, 2009; Strannegård & Strannegård, 2012). However, while qualitative studies (e.g., Farmaki et al., 2021) argue that product positioning through aesthetic design is theoretically possible, there is a lack of adequate empirical evidence to support these arguments. Hence, this study aims to quantify and verify the effects of aesthetic design differentiation in the short-term rental context using a deep-learning approach to classify aesthetic design styles.

The multi-level differentiation effects under two contextual factors, number of competitors and market concentration, are tested on the longitudinal data of 96,196 Texas Airbnb listings from April 2021 to March 2022. There are several reasons why we base this empirical study on the short-term rental sector. First, short-term rental businesses provided by micro-entrepreneurs who lack sufficient resources and knowledge to compete are highly sensitive to competitive advantages and legitimacy benefits originating from either differentiation or conformity. Second, compared with traditional lodging products, short-term rentals are facing greater market dynamics. As such, this study examines how competition intensity moderates the relationship between differentiation and performance. Given such a unique context, we first quantify listing aesthetic design using photos from the Airbnb platform with a probability distribution of interior design styles obtained from a pre-trained machine learning model. Then, the impacts of aesthetic design differentiation and moderating roles of market competition intensity are examined using time-fixed effect models.

The theoretical contribution of this study is threefold. First, it contributes to hospitality literature by introducing multi-level thinking to the differentiation stream, which matters to sectors such as short-term rentals that are highly sensitive to localized competition. At the local level where there is intense localized competition, short-term rentals can benefit from differentiation because of competition avoidance. On the other hand, as localized competition fades at the city level, discounts of differentiation overwhelm. Second, this study adds knowledge to tourism literature by identifying an urgent demand for conformity at the city level, which emphasizes the importance of collaborations between destinations and service providers. Third, the moderating effects of competition intensity in shaping strategic outcomes of differentiation adds nuances that extend our understanding of the impacts of differentiation under different contingencies.

In terms of practical contributions, this study provides guidance for practitioners and destination managers. The empirical findings assist short-term rental hosts in identifying product positions using aesthetic design under different market conditions. From the perspective of destination managers, this study highlights the importance of promoting a consistent destination aesthetic identity, which serves as a source of legitimacy for short-term rental businesses within the destination.

2. Literature Review

2.1 Differentiation and conformity

Differentiation and conformity are two sides of the same coin. Differentiation is defined as the introduction of unique products which have distinctive features, while conformity refers to providing products or services similar to those supplied by other providers. The importance and effectiveness of differentiation/conformity have been widely investigated in the hospitality literature (e.g., Sánchez-Pérez et al., 2020).

A firm gains competitive advantages by differentiating from its rivals (Porter, 1980; Sánchez-Pérez et al., 2020) in order to capture a unique position that enables it to win the favor of specific customers and stave off fierce competition (Chung & Kalnins, 2001). Previous studies empirically validate that customers with different individual characteristics, such as gender, age, and past consumption experience, have different preferences and requirements for product design such as aesthetics (Bogicevic, Bujisic, Cobanoglu, & Feinstein, 2018; Ryu & Han, 2011). Therefore, it is easier for accommodation products with features favored by a specific group of guests to capture the target market. For example, in the lodging context, home-like lodging design aesthetics help construct a "feeling at home", thus attracting particular traveler segments with high demands for a sense of control and security (Suess, Kang, Dogru, & Mody, 2020).

But, at the same time, there are contradicting findings that differentiation is sometimes useless or even harmful to lodging property performance (M. Kim et al., 2020; Yeung & Lau, 2005). It means conformity is more beneficial in some conditions. Conforming to the competitors bestows legitimacy, making the property more acceptable for target customers. Conformity also helps a firm avoid penalties associated with deviance from existing norms and achieve better performance (Abrahamson & Hegeman, 1994). K. L. Xie and Young (2021) show the improvements in short-term rental performance as a result of mimicking its substitute competitors, i.e., hotels.

One possible reason for the inconsistency in the findings related to the impacts of differentiation/conformity might be a lack of consensus on competitive set formation in prior literature. In other words, the selection of competitors to whom a focal product is compared is not clear. The competitive set scope used in previous studies of the lodging industry ranges from local-level to city-level (Baum & Mezias, 1992; Yeung & Lau, 2005). Zip code and city-level are two dominant approaches to define competition scope in hospitality literature (Kalnins & Chung, 2004; K. L. Xie & Kwok, 2017). Other studies related to competition and demand focus on local markets within the same city, such as tracts and commercial areas (Canina, Enz, & Harrison, 2005; Sánchez-Pérez et al., 2020). Among multiple ways to define competitors, there are differences in competitive dynamics and destination identities which are highly associated with how differentiation creates competitive advantages and how conformity boosts legitimacy benefits.

The importance of answering the question of "comparing to whom" is heightened within the context of our current study, particularly given our data collection period during with the COVID-19 pandemic. This scenario escalates due to the dramatic reduction in demand, leading to intensified competition among short-term rentals located in neighboring areas (Dolnicar & Zare, 2020; Milone, Gunter, & Zekan, 2023). Consequently, the urgency for these rental properties to mitigate local competition intensity while controlling legitimacy devaluation has surged. They are compelled to seek differentiation strategies, which emerge as critical survival tactics in these challenging times. We will further discuss in Section 3 how competition and legitimacy function differently at city- and local- levels and ultimately affect listing performance.

Differentiation/conformity strategy of the lodging product can be implemented in many aspects, such as quality, size, service, location, and narratives (Silva, 2015; Sonuç, 2020; Tchetchik, Fleischer, & Finkelshtain, 2008). This study focuses on differentiation in the aesthetic design dimension because aesthetic design is a crucial differentiation tool within the short-term rental market (Bitner, 1992; Candi & Saemundsson, 2011; Reimann & Schilke, 2011), while the relationship between differentiation and performance remains unclear.

2.2 Aesthetic design

Aesthetic design is an extensively studied topic in many disciplines, including architecture, psychology, management, as well as tourism and hospitality (Cross, 1982; Ravasi & Stigliani, 2012). It refers to the visual elements of products, which often constitute style, color, theme, layout, and symbols (H. Zhang et al., 2023). Previous studies concerning lodging property aesthetic design mainly focus on the impacts of specific aesthetic elements or perceived aesthetic quality on customer satisfaction and behavioral intention. For example, hotel guestroom color and design styles influence customer purchase intent and desire to stay (Bogicevic et al., 2018). Other works assess design holistically, for example, the relationship between perceived aesthetic design quality and behavioral intention (Heung & Gu, 2012; Ren, Qiu, Wang, & Lin, 2016).

Even though aesthetic design has been acknowledged as an effective differentiation tool (Bitner, 1992; Candi & Saemundsson, 2011; Reimann & Schilke, 2011), there are few studies validating the impacts of aesthetic design differentiation in the hospitality literature (Fleischer & Tchetchik, 2005). The theoretical underpinnings for differentiation effectiveness of aesthetic design stem from both the firm and the customer perspective, typically assessed in qualitative studies (e.g., Farmaki et al., 2021; Lim & Endean, 2009; Strannegård & Strannegård, 2012). In an interview study with hotel managers, Lim and Endean (2009) find that hotels try to compete by offering different aesthetic features. These are indispensable components in creating their unique brand personality, such as historical, traditional, modern, or contemporary. A similar conclusion is drawn from interviews with Airbnb hosts, revealing that unique aesthetic features, such as prestigious décor and architectural design, are critical to luxury-meaning construction (Farmaki et al., 2021). Strannegård and Strannegård (2012) investigate the communicational role of aesthetic design with an ethnographic approach. They argue that aesthetic distinctiveness is a crucial identity building block that distinguishes a hotel from its competitors.

Studies using customer interviews also revealed that differentiated design and art in hotels is an emergent mechanism to strengthen customer loyalty (Alfakhri, Harness, Nicholson, & Harness, 2018). Given the vital role of aesthetic design in developing lodging properties, conveying the properties' unique identity, distinguishing property from competitors, and creating differentiation externalities, short-term rental property performance can benefit from aesthetic design differentiation. However, a differentiation perspective that emphasizes a relative position of aesthetic design and corresponding effects remains less understood.

3. Conceptual framework and hypotheses development

We propose the following conceptual framework to examine the impacts of differentiation with aesthetic design on listing performance at both local and city levels (see Figure 1). The model also includes two factors of competition intensity – number of competitors and market concentration – to examine how the effects of aesthetic differentiation vary with market conditions.

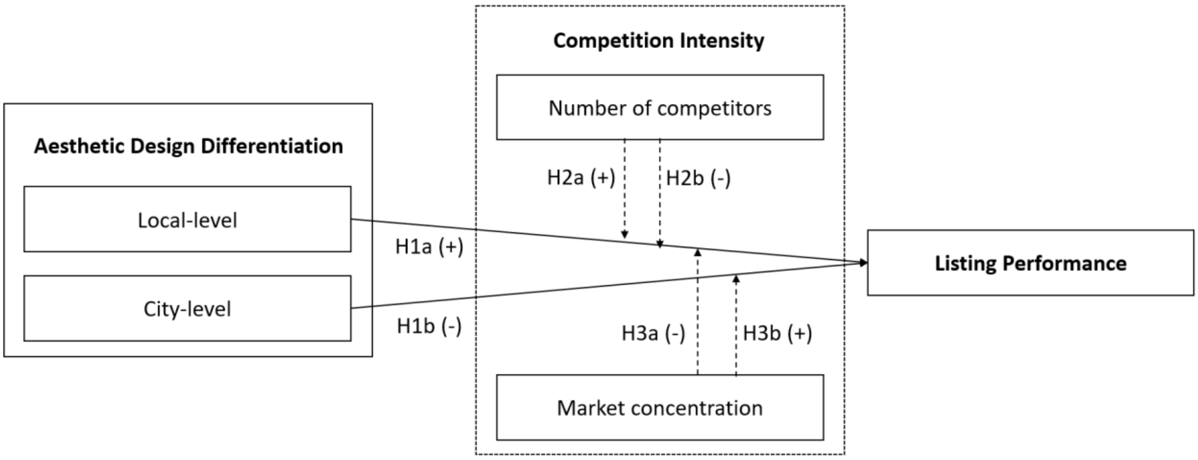


Figure 1: Conceptual framework of multi-level aesthetic design differentiation

Given the tension between legitimacy (i.e., by conforming to the market norm) and uniqueness (i.e., by differentiating from the market norm), the net benefit of differentiation is decided by two factors: first, whether, and second, to which extent, the competitive advantages of uniqueness are offset by legitimacy devaluation due to norm violation. We argue that the dynamic relationships between competitive advantages and legitimacy penalties are contingent on the geographic scope of the competitive set because of the accommodation industry's high sensitivity to location (Yang, Luo, & Law, 2014). In the hospitality and tourism context, competition intensity among competitors heavily depends on geographical distances (Bianco, Singal, Zach, & Nicolau, 2023). Also, market identities or images are normally shaped and promoted at different levels of regions.

3.1 Local-level aesthetic design differentiation

The phrase "localized competition" is conceptualized by Baum and Mezias (1992) based on spatial dependence theory, which argues that nearby competitors have stronger impacts than distant rivals (e.g., Silva, 2016). Localized competition suggests that firms with high geographic proximity pose greater threats. Therefore, lodging properties differentiating from their neighbors can avoid intense rivalry.

The benefits of differentiation from local competitors have been extensively validated in previous studies. Baum and Mezias (1992) measure size and price differentiation by comparing to competitors within a window of 50 streets, equivalent to a radius of two miles. The empirical results validate the local-level differentiation benefits with lower failure rates. Canina et al. (2005) identify tract-level differentiation benefits in size and strategic orientation dimensions for low-cost hotels in Texas. At the same time, Becerra, Santaló, and Silva (2013) found that hotels are less likely to charge a higher price when there are more similar competitors in the local market.

In this study, local-level aesthetic design differentiation refers to providing products that have aesthetic design styles different from nearby competitors. We argue that local-level aesthetic design differentiation improves listing performance because localized competition amplifies the benefits stemming from avoiding direct rivalry.

The benefits of differentiating from local competitors are also applicable to aesthetic design because lodging products compete heavily with neighbors in the aesthetic dimension. For example, hotels with more pleasing visuals are likely to charge a higher price than competitors located in the same area (Latinopoulos, 2018). Differentiated aesthetic designs thus allow lodging products to stand out from their nearby rivals. For instance, S. K. Lee and Jang (2017) argue that late movers can enjoy competitive advantages by offering newer aesthetics different from existing neighboring competitors. Hence, we hypothesize that:

H1a: Local-level aesthetic design differentiation has a positive impact on listing performance in the short-term rental context.

3.2 City-level aesthetic design differentiation

Differentiation benefits stem from competition avoidance at a city level is much lower than at a local level (i.e., a subregion of city-level) because city-level competition has weaker intensity. As such, the benefits of city-level differentiation decline accordingly. In addition, differentiation to a broader scope of competitors may result in performance discounts because of penalties for norm violation. For example, Blal and Graf (2013) measure the size and amenity differentiation by comparing all hotels in the same category across the United States, and their findings reveal a negative impact of differentiation on hotel prices.

City-level aesthetic design differentiation is defined as providing products that have aesthetic design different from competitors in the same city. Conforming to competitors from the same city in the aesthetic dimension can create legitimacy benefits. City is a popular type of destination studied in the tourism literature (Pike, 2002). Also, many marketing and branding activities, especially those related to accommodation, are conducted and analyzed at the city level (Choi, Lehto, & Oleary, 2007). Aesthetic components, including lodging property design, play an important role in building "projected" and "organic" destination identities (J. Lee, 2011; Xiao, Fang, Lin, & Chen, 2022). An identity is defined as a shared set of features representing a group of members, such as lodging suppliers in the same destination (Hardy, Lawrence, & Grant, 2005). Destination identities, including aesthetic identities, can be perceived by travelers through evaluating corresponding stakeholders and deriving their common features (Kurdoglu, Seyhan, & Bayramoglu, 2021). An example of destination aesthetic identity is that baroque is a typical style for real estate properties, including hotels, in a tourist destination (Smith, 2010).

Previous studies identified great differences in accommodation design styles from city to city and across different levels of destinations (X. Liu et al., 2019; Rahimi, Liu, & Andris, 2016). A contextual fit to the city's aesthetic identity creates a consistent tourist experience, boosts recommendation intention, and adds to accommodation products' competitiveness (J. Lee, 2011; Skogland & Siguaw, 2004). Zemke et al. (2018) also conclude that a higher social and urban integration with the environment in aesthetic elements leads to higher hotel performance. Given legitimacy benefits that are equivalent to differentiation discounts, we hypothesize that:

H1b: City-level aesthetic design differentiation has a negative impact on listing performance in the short-term rental context.

3.3 Moderating role of competition intensity

Previous studies suggest that the impact of differentiation is contingent on competition intensity (e.g., Miller & Eden, 2006). High competition pressure drives hospitality establishments to leverage different business strategies, including differentiation, to excel above their rivals (Becerra et al., 2013; Porter & Kramer, 2006; Xu, Gong, & Law, 2022). Under strong competition intensity, a pressing task for service providers is to ease the pressure coming with competition. Hence, the benefits stemming from avoiding direct competition will expand accordingly. There is ample evidence to support the reinforcement of differentiation benefits with competition intensity (e.g., Becerra et al., 2013; Hernandez, 2011). Two dominant indicators of competition intensity are identified in these studies: the number of competitors and market concentration (Kwieciński, 2017).

The number of competitors is widely utilized to measure competition intensity in the short-term rental context (e.g., Gao, Li, Liang, Yang, & Law, 2022). An increasing number of competitors means more firms are sharing customer resources in the market, which devalues property supply (Voltes-Dorta & Inchausti-Sintes, 2021). With more neighboring competitors, firms that can stand out are more likely to gain customer attention and maximize profitability. On the contrary, the mediocre ones are probably overlooked without eye-catching features.

Previous empirical studies verify that the number of competitors strengthens differentiation benefits and mitigates differentiation discounts. Becerra et al. (2013) and Sánchez-Pérez et al. (2020) find that given high local supplies, hotels that pursue differentiation strategies can charge higher room rates in the Spanish hotel market. Kankam-Kwarteng, Osman, and

Acheampong (2020) validate that competition intensity strengthens the positive impacts of differentiation strategy on restaurant performance. M. Kim et al. (2020) identify a differentiation discount on hotel performance. Their results also suggest that if there are high differentiation degrees in quality and capacity, a high location proximity of nearest neighbors, which means a higher density of competitors, can increase hotel performance. In other words, high density counteracts differentiation discounts. We thus argue that, in the short-term rental context, competition intensity amplifies differentiation benefits and mitigates differentiation discounts. Hence, we hypothesize that:

H2a: The number of competitors amplifies the local-level differentiation benefits of aesthetic design in the short-term rental context.
H2b: The number of competitors diminishes the city-level differentiation discounts of aesthetic design in the short-term rental context.

The number of competitors is, however, not sufficient to fully capture competition intensity because it ignores the distribution of market share, which largely shapes competitive behaviors in the market (Indounas, 2018). The extent to which market shares are concentrated among a small number of firms is defined as "market concentration" (Pan, 2005). In a highly concentrated market where the resources are taken by only a few firms, there will be less rivalry because of corporations and collusion among the dominant players (Menezes & Quiggin, 2012). These dominant players' performance relies less on product differentiation. On the contrary, when the market is more fragmented, service providers have more chances to leverage differentiation advantages by exploiting niche markets that offer higher profitability.

How differentiation outcomes are contingent on market concentration has been extensively tested (e.g., Li & Li, 2008). A hospitality study of US urban hotel segments conducted by Graf (2011) concludes that differentiation benefits lessen when the market is highly concentrated. Given the professionalization trend of the short-term rental market, more and more big players are entering the market. Consequently, host strategies and market competition patterns are converging with traditional lodging properties (Dogru, Mody, Suess, Line, & Bonn, 2020). Therefore, we hypothesize that:

H3a: Market concentration diminishes the local-level aesthetic design differentiation benefits in the short-term rental context**.**
H3b: Market concentration amplifies the city-level aesthetic design differentiation discounts in the short-term rental context.

4. Method

4.1 Data

To explore the impacts of aesthetic design differentiation in the short-term rental industry, we obtained data from AirDNA.com, a credible data source for short-term rental listing performance analysis (e.g., Kwok & Xie, 2019). Our sample includes monthly data from April 2021 to March 2022 in Texas, comprising listing-level information, such as cover photos, host profiles, and performance indicators. We base this study on Texas data because many previous lodging studies concerning differentiation and competition have been conducted in the Texas market. These studies provide a basis for comparison and help identify similarities and differences in the findings across time periods (Canina et al., 2005; S. K. Lee, 2015; K. Xie & Mao, 2017; Zervas, Proserpio, & Byers, 2017).

In this study, we only include Airbnb properties from urban areas to avoid distractions for lodging products caused by agglomeration effects because nearby competitors create agglomeration externalities in rural but not urban areas (Chung & Kalnins, 2001). There are four types of listings available on the Airbnb platform, i.e., entire home/apartment, private room, shared room, and hotel room. We collect monthly observations on entire home/apartment listings because they are operated for business purposes rather than unstable sharing desires. After excluding listings with missing values, a sample of 853,735 listing-month observations associated with 96,196 listings is used for the following regression analysis.

4.2 Variables

Following previous studies concerning Airbnb performance (e.g., Sainaghi, Abrate, & Mauri, 2021), we use *Revenue Per Available Room (RevPAR)* as the dependent variable. It is a typical performance measure used in the hospitality industry.

Aesthetic design differentiation is measured by the absolute difference between a focal listing's aesthetic design style relative to the market norm, which is the central design tendency of all listings in the corresponding market. For each listing, the aesthetic design is quantified by a probability distribution of interior design styles. The probabilistic scores of four interior design styles, casual, classic, modern, and natural, are generated by a pre-trained deep learning model after feeding the listing's cover photo. The model prediction accuracy reaches 0.94 – 0.98, which is close to human performance (J. Kim & Lee, 2020). Figure 2 displays examples of predicted listing style scores.

Figure 2. Examples of predicted listing style scores

This study compares the impacts of aesthetic design differentiation between city-level and local-level. To generate city-level aesthetic design differentiation, we compare the design scores of a listing l with the average design scores of all the listings from the same city. The differentiation degree is calculated by the following equation where $\theta_{l,s,t}$ denotes listing l's weight for style s at time t, $\bar{\theta}_{C,s,t}$ represents the average score for style s at time t among all the listings in the same city C, and abs means the absolute value.

$$CityDiff_{l,t} = \sum_{s=1}^{4} abs\left(\theta_{l,s,t} - \bar{\theta}_{C,s,t}\right)/4 \quad (1)$$

There are multiple ways to define a local market, like zip code, tract, and Airbnb neighbourhood (Coles, Egesdal, Ellen, Li, & Sundararajan, 2017; J.-Y. Kim & Canina, 2013; K. L. Xie, Kwok, & Heo, 2020; K. L. Xie & Young, 2021). Here, we use census tract, which is defined by the US Census Bureau to represent local markets for the following reasons: First, the boundary of a tract is well-defined and stable over a long time, while the boundaries for zip codes are vague, and some changes in zip codes may occur monthly (UCF, 2022). Second, census tracts are applicable to all cities, while Airbnb neighbourhood information is only available in a few cities. To obtain local-level aesthetic design differentiation, we compare a listing l to the census tract averages. The equation applied here is

$$LocalDiff_{l,t} = \sum_{s=1}^{4} abs(\theta_{l,s,t} - \bar{\theta}_{T,s,t})/4 \quad (2)$$

Here $\bar{\theta}_{T,s,t}$ refers to the average weight for style s at time t among all the listings in the same tract T.

Competition intensity is operationalized by two indicators, the number of competitors and market concentration. We measure *CityComp* and *LocalComp* by the number of Airbnb listings in the same city/local market (Sánchez-Pérez et al., 2020; Voltes-Dorta & Inchausti-Sintes, 2021). Herfindahl-Hirschman index (HHI) is a common measure of market concentration, which is the sum of the squared market shares of all competing firms in the market. We adjust room-based HHI measures used in previous hospitality studies to fit the Airbnb context (Duverger, 2013; Yang, Jiang, & Schwartz, 2019). The market share of each host is represented by the number of properties managed divided by the total number of properties in the same city/local market. *CityHHI* and *LocalHHI* are used to represent city- and local-level market concentration degrees, respectively.

We also control for host and listing features and location attributes, which have been identified to have significant impacts on Airbnb performance (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Kwok & Xie, 2019; Leoni, 2020). Host characteristics include superhost, host listing count, response time, and response rate. In terms of property characteristics, we consider instant bookability, maximum guests, minimum stay, listing age, cancellation, reviews per month, and number of photos. To identify the effects caused by differentiation strategy instead of regional features, we control for kilometre distance to the nearest airport, city centre, transit stop, and beach. They are measured by Euclidean distances from the specific locations, whose geographic information is available on the Texas Department of Transportation website (Chica-Olmo, González-Morales, & Zafra-Gómez, 2020). Detailed information on the variable description is displayed in Table 1. Table 2 displays descriptive statistics for the observations used in the following regression analysis.

Table 1. Variable description

Category	Variable	Description
Dependent Variables	RevPAR	Revenue per available room (USD)
Independent variables	LocalDiff	The degree to tract-level aesthetic design differentiation
	CityDiff	The degree of city-level aesthetic design differentiation
Moderators	LocalComp	Number of Airbnb listings in the same census tract
	CityComp	Number of Airbnb listings in the same city
	LocalHHI	Census tract market concentration degree
	CityHHI	City market concentration degree
Control variables	Superhost	Whether a host has a Superhost badge (superhost = 1, otherwise 0)
	Host listing count	Number of listings managed by the same host
	Response rate	The rate of new inquiries and reservation requests a host responded to
	Response time	Speed of response to guests' inquiries (within an hour, within a few hours, within a day, a few days or more)
	Instant bookablility	Whether the listings can be booked instantly (Instant bookable =1, otherwise 0)
	Maximum guests	The maximum number of guests a listing can accommodate
	Minimum stay	Minimum night stay required by the host (number of days)
	Listing age	Days since the listing was created
	Cancelation	Cancellation policy for the listing (flexible, moderate, strict, firm strict, super strict)
	Reviews per month	Number of guest reviews per month received by a listing
	Number of photos	Number of photos displayed on a listing homepage
	Transit hub	Distance from the listing to the nearest transit hub (km)
	City center	Distance from the listing to the nearest city center (km)
	Airport	Distance from the listing to the nearest airport (km)
	Beach	Distance from the listing to the nearest beach (km)

Table 2. Summary statistics

	Mean	Std. Dev.	Min	Max
RevPAR	696.72	1193.76	0	33283.33
LocalDiff	0.20	0.11	0	0.48
CityDiff	0.25	0.08	0	0.47
LocalComp	190.13	328.26	2	2856
CityComp	6698.11	6135.69	4	16610
LocalHHI	0.22	0.26	0.005	1
CityHHI	0.05	0.08	0.003	1
Superhost	0.16	0.37	0	1
Host listing count	496.87	1105.54	1	4155
Host response rate	0.95	0.18	0	1
Host response time – within an hour	0.82	0.39	0	1
Host response time – within a few hours	0.09	0.29	0	1
Host response time – within a day	0.06	0.23	0	1
Host response time – a few days or more	0.03	0.18	0	1
Instant bookability	0.64	0.48	0	1
Maximum guests	5.67	3.13	1	16
Minimum stay	11.81	26.75	1	1124
Listing age	649.17	630.07	1	4990
Cancelation – super strict	0.04	0.20	0	1
Cancelation – firm strict	0.04	0.19	0	1
Cancelation – strict	0.47	0.50	0	1
Cancelation – moderate	0.23	0.42	0	1
Cancelation – flexible	0.22	0.41	0	1
Reviews per month	1.18	1.87	0	204
Number of photos	22.67	15.21	0	507
Transit hub	29.91	52.65	0	338.63
City center	5.51	3.84	0.02	46.96
Airport	23.34	19.63	0.68	195.03
Beach	226.33	217.87	0.01	1128.95

4.3 Model specification

With the panel data, we apply the time-fixed effect model, which allows us to control the unobserved individual-specific factors that are constant over time. In the hospitality context, the time-fixed effects are often included for seasonality considerations (S. Liu, Wang, Gao, & Gallivan, 2021; Lopez Mateos, Cohen, & Pyron, 2022).

A series of models are estimated, starting with a baseline model of control variables. We then gradually include aesthetic design differentiation variables and their interaction with moderators. Accordingly, the following time-fixed effects regression tests are conducted, where μ denotes time-fixed effects and ε represents the error term.

Model 1 (Baseline):

$$\text{RevPAR} = \beta_{11}\text{Controls} + \mu + \varepsilon \tag{3}$$

Model 2 (Local-level Differentiation Effect):

$$\text{RevPAR} = \beta_{21}\text{LocalDiff} + \beta_{22}\text{Controls} + \mu + \varepsilon \tag{4}$$

Models 3&4 (Local-level Competition Intensity Moderation Effects):

$$\text{RevPAR} = \beta_{31}\text{LocalDiff} + \beta_{32}\text{LocalDiff} * \text{LocalComp} + \beta_{33}\text{Controls} + \mu + \varepsilon \quad (5)$$

$$\text{RevPAR} = \beta_{41}\text{LocalDiff} + \beta_{42}\text{LocalDiff} * \text{LocalHHI} + \beta_{43}\text{Controls} + \mu + \varepsilon \quad (6)$$

Model 5 (City-level Differentiation Effect):

$$\text{RevPAR} = \beta_{51}\text{CityDiff} + \beta_{52}\text{Controls} + \mu + \varepsilon \quad (7)$$

Models 6&7 (City-level Differentiation Effect):

$$\text{RevPAR} = \beta_{61}\text{CityDiff} + \beta_{62}\text{CityDiff} * \text{CityComp} + \beta_{63}\text{Controls} + \mu + \varepsilon \quad (8)$$

$$\text{RevPAR} = \beta_{71}\text{CityDiff} + \beta_{72}\text{CityDiff} * \text{CityComp} + \beta_{73}\text{Controls} + \mu + \varepsilon \quad (9)$$

5. Results and Discussion

This study aims to test the effects of two key variables, namely local- and city-level aesthetic design differentiation, on short-rental property performance. An assumption for the effects of city-level differentiation is that each city has a distinct aesthetic identity that can be perceived by the guests. The perceptions then further affect guests' expectations for and evaluations of a single listing during the purchase stage. If every city in Texas were identical in Airbnb's interior design style, the comparison to city norms would be meaningless. To offer a straightforward overview of Texas city aesthetic design norms, we display the design tendency of 10 cities with the most Airbnb listings (Figure 3). Large cities such as Austin, Dallas, and Houston tend to offer Airbnb properties with modern design styles. However, properties located in destinations known for their natural landscape, for example, Galveston and South Padre Island, tend to include more nature-oriented elements in aesthetic design. Given the distinct aesthetic design patterns for cities with different destination images, whether a listing meets the city norm will affect guests' choices and further influence listing performance. Similar to cities, we also observe heterogeneity in aesthetic design tendency among tracts.

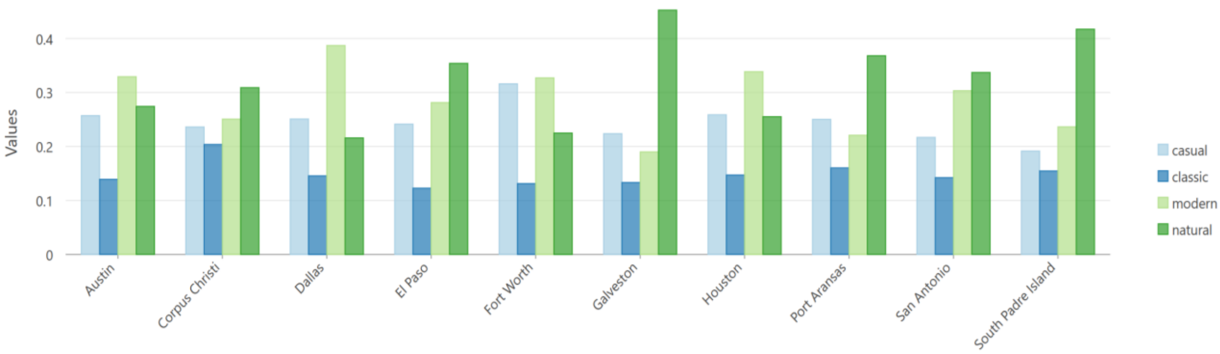


Figure 3. Short-term rental aesthetic design tendency of top 10 Texas cities

The next step is to test hypotheses with panel regression analysis. Following previous studies, a log transformation is applied to RevPAR to avoid regression assumption violation caused by skewness (Dogru, Mody, Line, et al., 2020). To avoid multicollinearity in estimating interaction effects, we standardize all continuous variables for further regression analysis (H. Zhang et al., 2023). The interpretation of coefficients for these variables will be that, when a predicting factor varies by one standard deviation, the RevPAR changes by corresponding percentages. Regression results are displayed in Table 3. Model 1 constitutes the baseline model, where we find the anticipated results for most control variables. The R^2 values for all models exceed 0.331, reflecting a good model fit.

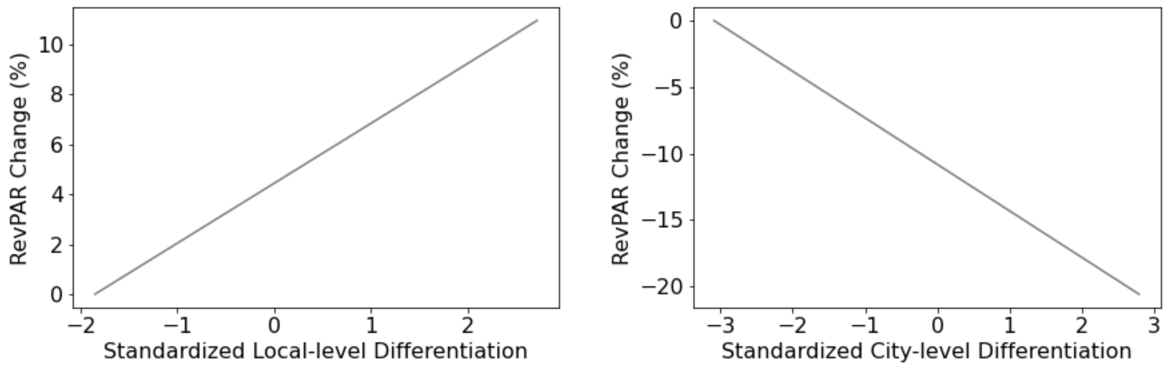
Table 3. Estimation results

	DV: RevPAR						
	Baseline	**Local-level differentiation**			**City-level differentiation**		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Main Effects							
LocalDiff		0.024***	0.025***	0.028***			
CityDiff					-0.035***	-0.035***	-0.034***
Moderation Effects							
LocalDiff*LocalComp			0.009*				
CityDiff*CityComp						0.019***	
LocalDiff*LocalHHI				-0.049***			
CityDiff*CityHHI							-0.018***
LocalComp	0.097***	0.095***	0.091***	0.094***	0.098***	0.099***	0.099***
CityComp	-0.203***	-0.205***	-0.205***	-0.204***	-0.200***	-0.201***	-0.200***
LocalHHI	-0.162***	-0.154***	-0.155***	-0.184***	-0.161***	-0.161***	-0.161***
CityHHI	-0.112***	-0.114***	-0.113***	-0.107***	-0.113***	-0.114***	-0.116***
Superhost	0.145***	0.146***	0.146***	0.151***	0.148***	0.148***	0.149***
Host listing count	-0.669***	-0.665***	-0.665***	-0.673***	-0.672***	-0.673***	-0.674***
Host response rate	0.146***	0.146***	0.146***	0.146***	0.145***	0.145***	0.145***
Host response time							
- within an hour	0.919***	0.919***	0.919***	0.917***	0.918***	0.919***	0.918***
- within a few hours	0.385***	0.384***	0.384***	0.380***	0.384***	0.386***	0.384***
- within a day	-0.185***	-0.185***	-0.185***	-0.188***	-0.185***	-0.184***	-0.186***
Instant booking	-0.083***	-0.083***	-0.082***	-0.080***	-0.085***	-0.085***	-0.085***
Maximum guests	0.203***	0.203***	0.203***	0.203***	0.203***	0.203***	0.203***
Minimum stay	-0.287***	-0.287***	-0.287***	-0.286***	-0.288***	-0.287***	-0.287***
Listing age	-0.261***	-0.261***	-0.261***	-0.264***	-0.260***	-0.261***	-0.260***
Cancelation							
- flexible	-1.274***	-1.274***	-1.274***	-1.272***	-1.274***	-1.274***	-1.274***
- moderate	-1.028***	-1.028***	-1.027***	-1.026***	-1.029***	-1.028***	-1.028***
- strict	-0.982***	-0.981***	-0.981***	-0.980***	-0.984***	-0.984***	-0.983***
- super strict	-0.331***	-0.330***	-0.330***	-0.331***	-0.334***	-0.335***	-0.334***
Reviews per month	1.117***	1.117***	1.117***	1.115***	1.117***	1.117***	1.116***
Number of photos	0.296***	0.296***	0.296***	0.296***	0.296***	0.296***	0.296***
Transit stop	0.041***	0.041***	0.041***	0.043***	0.042***	0.042***	0.042***
City center	-0.008*	-0.008*	-0.007*	-0.009**	-0.007*	-0.007*	-0.007*
Airport	0.187***	0.187***	0.187***	0.188***	0.185***	0.184***	0.185***
Beach	-0.105***	-0.105***	-0.105***	-0.101***	-0.105***	-0.104***	-0.105***
R^2	0.331	0.331	0.331	0.332	0.332	0.332	0.332
F test	707.74***	706.66***	706.64***	709***	707.87***	707.93***	709.39***
Hausman test	28,522***	28,538***	28,555***	28,486***	28,525***	28,538***	28,656***
LM Test	2,330,865 ***	2,323,540 ***	2,323,389 ***	2,332,175 ***	2,331,716 ***	2,332,175 ***	2,339,856 ***

Note: * p < 0.05, ** p < 0.01, *** p< 0.001. F test is included to test time effects; Hausman test is used to compare fixed effects model with random effects model; LM Test is applied to validate the necessity of time-fixed effects.

To test the effects of local-level aesthetic differentiation, we add LocalDiff to model 2 and obtain a positive and significant coefficient (b = 0.024, $p < 0.001$), supporting H1a. A listing with local-level aesthetically differentiated designs is predicted to generate higher revenues. An increase of one standard deviation in local differentiation degree will result in a 2.4% growth of RevPAR. Figure 4a visualizes the impacts of local-level aesthetic design differentiation on listing performance. The performance of a listing with the highest local-level aesthetic differentiation degree is over 10% higher than that with the lowest degree. Differentiation benefits identified at the local level align with previous studies (e.g., Baum & Mezias, 1992), which suggests that competition avoidance externalities overwhelm legitimacy penalties. This finding verifies the dominance of localized competition over legitimacy in shaping the impacts of differentiating from neighboring competitors.

On the contrary, we observe a negative impact of city-level aesthetic differentiation, providing empirical support for H1b. Model 5 shows a significant coefficient of CityDiff (b = -0.035, $p< 0.001$). This result suggests that RevPAR is predicted to decrease by 3.5% when the city-level aesthetic differentiation degree increases by one standard deviation. The hypothesized differentiation discount is verified. In Figure 4b, we can see that the performance of a listing with the highest local-level aesthetic differentiation degree is around 20% lower than that with the lowest degree. These negative impacts of differentiation, consistent with previous studies, suggest that, at the city level, legitimacy devaluation overtakes competition avoidance externalities (e.g., Blal & Graf, 2013). The benefits of conforming to city norms also validate that city-level aesthetic identity can be a source of legitimacy for individual service providers, including short-term rental listings. A more powerful influence of city-level conformity than local-level conformity might be because destination image is mainly promoted in cities. At the same time, it’s rare to see tract-level destination promotion organizations.

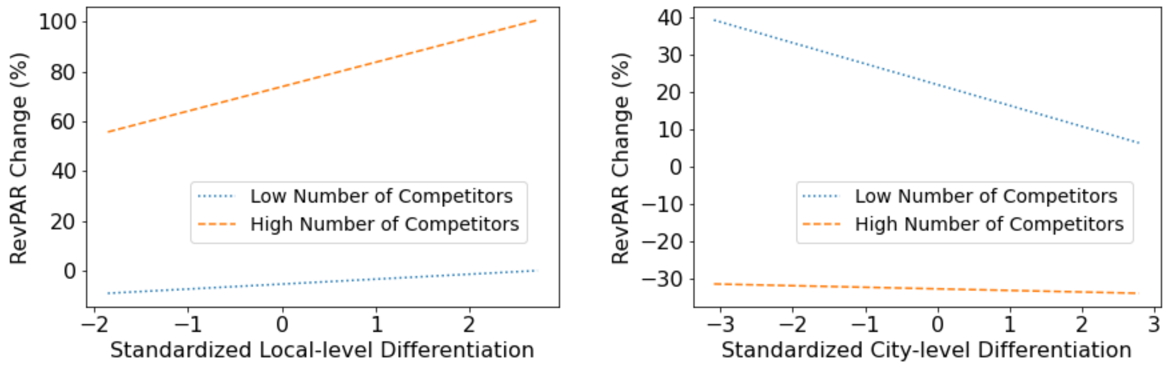


(a) (b)

Figure 4. Impacts of aesthetic design differentiation

In models 3 and 6, we find that for both local- and city-level differentiation effects, the number of competitors has a positive and significant impact. These results support H2a and H2b. Model 4 predicts that the positive impact of local-level differentiation is strengthened by the number of local-level competitors (b = 0.009, p = 0.032). As is shown in Figure 5a, the positive effect is stronger under a high number of competitors. For a listing located in the market with the lowest number of competitors, the performance increase caused by differentiation is around 5%, but this number reaches over 40% under the condition of the highest number of competitors.

Model 6 shows that the interaction term between city-level differentiation and the number of competitors has a positive and significant coefficient (b = 0.019, p < 0.001). Thus, an increase in the number of competitors reduces the negative effects of city-level differentiation. Figure 5b depicts this moderation effect, where listings with the fewest competitors witness a drop of RevPAR at 30% resulting from differentiation, while listings with the most competitors only have a slight decrease.



(a) (b)

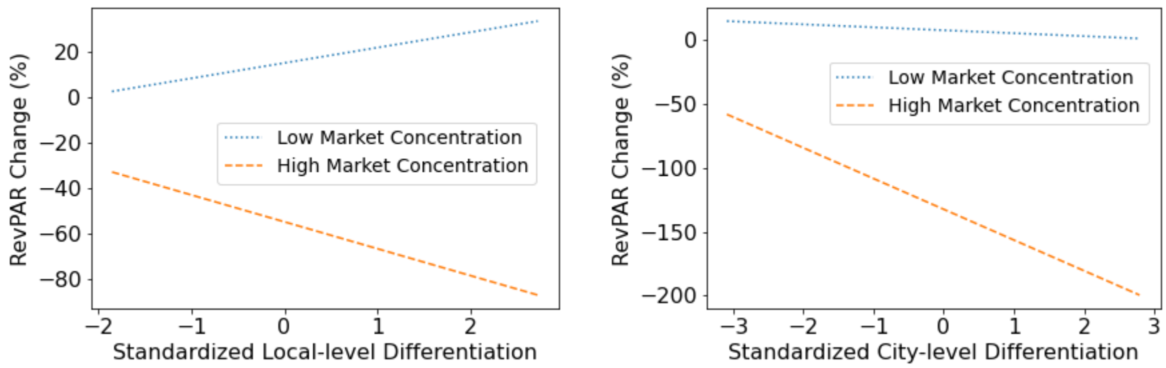
Figure 5. Moderation by the number of competitors

Strengthened differentiation benefits and mitigated differentiation discounts revealed in models 3 and 6 first imply that the gains stemming from avoiding intense competition increase with the number of competitors. This confirms that the effectiveness of the competitor density in moderating the effects of differentiation drawn from the hotel context is also applicable to short-term rental businesses (e.g., Sánchez-Pérez et al., 2020). Second, the results show that listings are more likely to benefit from conformity with fewer competitors. A possible explanation is that it is important for listings located in sparse destinations to shape a collective identity that can serve as a clear signal to attract target customers (Bianco, 2023; Dobrev, Ozdemir, & Teo, 2006).

At the local level, we also observe that the performance of listings located in dense tracts is generally higher than that in sparse tracts. A possible reason is that there might be tourist attractions associated with massive lodging demands, which attract a great amount of Airbnb businesses (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017). An alternative explanation is that there are agglomeration externalities created by tract neighbors in urban areas in the short-term rental context (K. L. Xie et al., 2020). If so, this counters the findings of Chung and Kalnins (2001) based on a zip-code setting in the Texas hotel market before the internet was widely adopted, which concludes no agglomeration externalities were detected in urban areas. At the city level, this study yields opposite empirical findings. Listings from cities with a lower number of rivals tend to generate more profits, implying trivial agglomeration externalities. It might be because agglomeration advantages decay rapidly with distances, and agglomerative forces typically operate well at a geographic scale smaller than a city (Picone, Ridley, & Zandbergen, 2009; Van Soest, Gerking, & Van Oort, 2006).

Model 4 and Model 7 provide evidence for H3a and H3b. The interaction between LocalDiff and LocalHHI is negative and significant ($b = -0.049$, $p < 0.001$), supporting H3a. When a listing competes in a more concentrated market, the benefits it gains from differentiation are lower and even turn negative. Figure 6a reflects this flipped effect. For listings operated under the highest market concentration degree, RevPAR decreases with differentiation by at most 50%. Conversely, there is a growth in listing performance when the differentiation degree increases in a less concentrated market (over 20%).

We also observe a negative coefficient of the interaction between CityDiff and CityHHI ($b=-0.018$, $p < 0.001$). It suggests that market concentration intensifies city-level differentiation discounts and thus supports H3b. Figure 6b depicts this moderation effect. For a listing with low market concentration, the impact of differentiation on its performance decreases only slightly. However, when it is in a highly concentrated market, there is a sharp drop in performance by nearly 150% from the lowest differentiation level to the highest one.



(a) (b)

Figure 6. Moderation by market concentration

Regardless of geographical scope, market concentration weakens differentiation benefits and amplifies differentiation discounts, which aligns with previous hotel studies (Graf, 2011). This finding implies that the short-term rental hosts cooperate to avoid direct competition, thus relying less on design differentiation. In a highly concentrated market, we also find that conformity is more profitable. Thus, if several big players dominate a market, an aesthetic design consistency among listings of the same host enhances operation efficiency (H. Zhang et al., 2023). Last, by comparing high versus low market concentration, we draw the opposite conclusion to the hotel industry: the overall short-term rental listing performance excels in a less concentrated market (Pan, 2005). The professionalism gap between short-term rental hosts and hotel management teams, which decides strategy effectiveness in leveraging market conditions, may explain this.

We carry on a series of robustness checks to validate the validity of empirical test results. We first compare the fixed effects model with pooling models, and the F test results confirm the necessity of applying fixed effects model. Then, the results of the Hausman test suggest that fixed effects model is more suitable than random effects model in this study. Third, Lagrange Multiplier tests are applied to validate the necessity of including time-fixed effects.

6. Implications and Limitations

Through the lens of aesthetic design, this study empirically compares the differentiation-performance relationship between two geographical competition scopes, i.e., local census tract versus city. It shows the impacts of these two geographical scopes on the effectiveness of differentiation strategy are asymmetric. Local-level aesthetic differentiation generates benefits, while city-level differentiation leads to performance discounts, decided by the alternate dominating role between competition and legitimacy within the geographic scope. The results also suggest that under high competition intensity caused by either the number of competitors or market concentration, listings can benefit more from differentiation.

This study provides several theoretical contributions. First, it contributes to the strategic management literature in hospitality and tourism by introducing multi-level thinking to the strategy of differentiation and conformity. The differences between local- and city-level reveal how localized competition influences the impacts of differentiation. The local-level differentiation gains verify the importance of spatial dependence for lodging products. The benefits of city-level conformity contribute to the destination literature by identifying the overwhelming dominance of communicating a destination aesthetic identity over rivalry, while localized competition fades with distance. We recommend subsequent studies to explore the sweet spot where the accommodation products can both benefit from city-level conformity and local competition avoidance at the same time.

Second, the findings demonstrate nuances of how differentiation-performance relationships vary with competition contingencies. The results suggest that competition intensity enhances benefits at the local level but mitigates discounts at the city level in influencing the strategic outcomes of differentiation. The opposite directions of moderation effects also emphasize the importance of competitive conditions when pursuing lodging strategies because the same strategy shows divergent patterns under different contingencies.

Third, the empirical evidence of differentiation effects adds knowledge to the hospitality literature by verifying the effectiveness of aesthetic design as a differentiating tool. The findings complement previous qualitative studies by empirically verifying the effects of aesthetic designs as differentiation tools in the hospitality industry. It may inspire future studies to explore the effects of aesthetic differentiation in more diverse visual aspects beyond interior design styles, such as color and layout.

The methodological contribution lies in quantifying lodging property aesthetics with a deep learning algorithm that offers more objectivity and interpretability than past methods, which primarily relied on qualitative assessments. As such, our approach complements extant literature based on customer perceptions to overcome bias caused by subjectivity. The design style scores can be applied to broader topics beyond differentiation, such as destination lodging image analysis, customer cognitive and affective response evaluation, and hotel aesthetic design positioning.

Several tourism stakeholders can benefit from the findings of this study. For short-term rental hosts, it is beneficial to differentiate their listings from nearby competitors by providing properties with different interior design styles. The findings of this study also suggest that hosts should not only focus on nearby competitors but also take citywide properties as references and try to align with the general design style of the city. It is also recommended to start new listings in a dense tract, a city with few listings, or a less concentrated market. Hosts are more likely to benefit from aesthetic differentiation when operating existing listings in dense regions. Following the market norm is a more profitable strategy in highly concentrated markets. Furthermore, for destination management organizations, promoting destination aesthetic images and identities and encouraging hosts to leverage related elements is an effective way to boost local short-term rental business prosperity because it can create legitimacy externalities and may help strengthen destination identity.

This study has several limitations. First, it only tests the effects of aesthetic design differentiation in Texas urban markets. We believe that the insights obtained are applicable to a wider context due to the extensive diversity across the sampled cities and tracts, thereby allowing us to capture performance variance due to differentiation. Nevertheless, the unique features of Texas markets may introduce certain biases, and we encourage further research in various geographical contexts to build upon our findings.

Second, the sample is collected during the Covid period, between April 2021 and March 2022. Although competition intensified by pandemic is a background condition in which we tested our hypotheses, how the pandemic moderates the effects of multi-level differentiation is not involved in the current study. Thus, extending the current study by testing the moderation effects of Covid on differentiation-performance relationship is recommended. We believe such studies will complement the current study in understating competitive dynamics and strategies in the hospitality context. Third, we used tract and city levels; however, other studies define competitive sets in different ways, for example, by zip code. Finally, this study only includes market competition conditions as moderators, while there are more conditional factors altering the relationship between aesthetic design differentiation and listing performance, such as host professionalism and guest demographic features.

8. References

Abrahamson, E., & Hegeman, R. (1994). *Strategic conformity: An institutional theory explanation.* Paper presented at the annual meeting of the Academy of Management, Dallas, TX.

Alfakhri, D., Harness, D., Nicholson, J., & Harness, T. (2018). The role of aesthetics and design in hotelscape: A phenomenological investigation of cosmopolitan consumers. *Journal of Business Research, 85*, 523-531.

Baum, J. A., & Haveman, H. A. (1997). Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, 304-338.

Baum, J. A., & Mezias, S. J. (1992). Localized competition and organizational failure in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, 580-604.

Becerra, M., Santaló, J., & Silva, R. (2013). Being better vs. being different: Differentiation, competition, and pricing strategies in the Spanish hotel industry. *Tourism Management, 34*, 71-79.

Bianco, S. (2023). *A Study of Resource-Based Market Entry Strategies in the Hotel Industry.* Virginia Tech,

Bianco, S., Singal, M., Zach, F. J., & Nicolau, J. L. (2023). Dual-branded hotels: Resource-based entry strategies in agglomerated markets. *Tourism Management, 95*, 104663.

Bitner, M. J. (1992). Servicescapes: The impact of physical surroundings on customers and employees. *Journal of marketing, 56*(2), 57-71.

Blal, I., & Graf, N. S. (2013). The discount effect of non-normative physical characteristics on the price of lodging properties. *International Journal of Hospitality Management, 34*, 413-422.

Bogicevic, V., Bujisic, M., Cobanoglu, C., & Feinstein, A. H. (2018). Gender and age preferences of hotel room design. *International Journal of Contemporary Hospitality Management*.

Candi, M., & Saemundsson, R. J. (2011). Exploring the relationship between aesthetic design as an element of new service development and performance. *Journal of Product Innovation Management, 28*(4), 536-557.

Canina, L., Enz, C. A., & Harrison, J. S. (2005). Agglomeration efects and strategic orientations: Evidence from the US lodging industry. *Academy of management journal, 48*(4), 565-581.

Choi, S., Lehto, X. Y., & Oleary, J. T. (2007). What does the consumer want from a DMO website? A study of US and Canadian tourists' perspectives. *International Journal of Tourism Research, 9*(2), 59-72.

Chung, W., & Kalnins, A. (2001). Agglomeration effects and performance: A test of the Texas lodging industry. *Strategic Management Journal, 22*(10), 969-988.

Coles, P. A., Egesdal, M., Ellen, I. G., Li, X., & Sundararajan, A. (2017). Airbnb usage across New York City neighborhoods: Geographic patterns and regulatory implications. *Forthcoming, Cambridge Handbook on the Law of the Sharing Economy*.

Cross, N. (1982). Designerly ways of knowing. *Design studies, 3*(4), 221-227.

Deboosere, R., Kerrigan, D. J., Wachsmuth, D., & El-Geneidy, A. (2019). Location, location and professionalization: a multilevel hedonic analysis of Airbnb listing prices and revenue. *Regional Studies, Regional Science, 6*(1), 143-156.

Deephouse, D. L. (1996). Does isomorphism legitimate? *Academy of Management journal, 39*(4), 1024-1039.

Deephouse, D. L. (1999). To be different, or to be the same? It'sa question (and theory) of strategic balance. *Strategic management journal, 20*(2), 147-166.

Dobrev, S. D., Ozdemir, S. Z., & Teo, A. C. (2006). The ecological interdependence of emergent and established organizational populations: Legitimacy transfer, violation by comparison, and unstable identities. *Organization science, 17*(5), 577-597.

Dogru, T., Mody, M., Line, N., Suess, C., Hanks, L., & Bonn, M. (2020). Investigating the whole picture: Comparing the effects of Airbnb supply and hotel supply on hotel performance across the United States. *Tourism Management, 79*, 104094.

Dogru, T., Mody, M., Suess, C., Line, N., & Bonn, M. (2020). Airbnb 2.0: Is it a sharing economy platform or a lodging corporation? *Tourism Management, 78*, 104049.

Dolnicar, S., & Zare, S. (2020). COVID19 and Airbnb–Disrupting the disruptor. *Annals of Tourism Research, 83*, 102961.

Duverger, P. (2013). Curvilinear effects of user-generated content on hotels' market share: a dynamic panel-data analysis. *Journal of Travel Research, 52*(4), 465-478.

Farmaki, A., Spanou, E., & Christou, P. (2021). Constructing meanings of luxury in Airbnb. *International Journal of Contemporary Hospitality Management*.

Fleischer, A., & Tchetchik, A. (2005). Does rural tourism benefit from agriculture? *Tourism Management, 26*(4), 493-501.

Gao, L., Li, H., Liang, S., Yang, J., & Law, R. (2022). How does constraining description affect guest booking decisions and satisfaction? *Tourism Management, 93*, 104607.

Graf, N. S. (2011). Market structure and demand-side substitutability of chained urban hotel segments. *International Journal of Hospitality Management, 30*(1), 82-90.

Gutiérrez, J., García-Palomares, J. C., Romanillos, G., & Salas-Olmedo, M. H. (2017). The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management, 62*, 278-291.

Hardy, C., Lawrence, T. B., & Grant, D. (2005). Discourse and collaboration: The role of conversations and collective identity. *Academy of management Review, 30*(1), 58-77.

Hernandez, M. A. (2011). Nonlinear pricing and competition intensity in a Hotelling-type model with discrete product and consumer types. *Economics letters, 110*(3), 174-177.

Heung, V. C., & Gu, T. (2012). Influence of restaurant atmospherics on patron satisfaction and behavioral intentions. *International Journal of Hospitality Management, 31*(4), 1167-1177.

Indounas, K. (2018). Market structure and pricing objectives in the services sector. *Journal of Services Marketing*.

Kalnins, A., & Chung, W. (2004). Resource‐seeking agglomeration: a study of market entry in the lodging industry. *Strategic Management Journal, 25*(7), 689-699.

Kankam-Kwarteng, C., Osman, B., & Acheampong, S. (2020). Performance of restaurants: Recognizing competitive intensity and differentiation strategies. *Journal of Tourism, Heritage & Services Marketing (JTHSM), 6*(3), 25-34.

Kim, J.-Y., & Canina, L. (2013). Acquisition premiums and performance improvements for acquirers and targets in the lodging industry. *Cornell hospitality quarterly, 54*(4), 416-425.

Kim, J., & Lee, J.-K. (2020). Stochastic detection of interior design styles using a deep-learning model for reference images. *Applied Sciences, 10*(20), 7299.

Kim, M., Roehl, W., & Lee, S. K. (2020). Different from or similar to neighbors? An investigation of hotels' strategic distances. *Tourism Management, 76*, 103960.

Kurdoglu, B. Ç., Seyhan, S., & Bayramoglu, E. (2021). Scrutinizing the Gestalt Principles in Natural Landscape Perception. *Online Journal of Art and Design, 9*(1).

Kwieciński, D. (2017). Measures of competitive intensity–analysis based on literature review. *Central European Management Journal, 25*(1), 53-77.

Kwok, L., & Xie, K. L. (2019). Pricing strategies on Airbnb: Are multi-unit hosts revenue pros? *International Journal of Hospitality Management, 82*, 252-259.

Latinopoulos, D. (2018). Using a spatial hedonic analysis to evaluate the effect of sea view on hotel prices. *Tourism Management, 65*, 87-99.

Lee, J. (2011). Role of hotel design in enhancing destination branding. *Annals of Tourism Research, 38*(2), 708-711.

Lee, S. K. (2015). Quality differentiation and conditional spatial price competition among hotels. *Tourism Management, 46*, 114-122.

Lee, S. K., & Jang, S. (2017). Early mover or late mover advantage for hotels? *Journal of Hospitality & Tourism Research, 41*(1), 23-40.

Leoni, V. (2020). Stars vs lemons. Survival analysis of peer-to peer marketplaces: The case of Airbnb. *Tourism Management, 79*, 104091.

Levitt, T. (1980). *Marketing success through differentiation-of anything*: Graduate School of Business Administration, Harvard University Boston.

Li, C. B., & Li, J. J. (2008). Achieving superior financial performance in China: differentiation, cost leadership, or both? *Journal of International Marketing, 16*(3), 1-22.

Lim, W. M., & Endean, M. (2009). Elucidating the aesthetic and operational characteristics of UK boutique hotels. *International Journal of Contemporary Hospitality Management*.

Liu, S., Wang, N., Gao, B., & Gallivan, M. (2021). To be similar or to be different? The effect of hotel managers' rote response on subsequent reviews. *Tourism Management, 86*, 104346.

Liu, X., Andris, C., Huang, Z., & Rahimi, S. (2019). Inside 50,000 living rooms: an assessment of global residential ornamentation using transfer learning. *EPJ Data Science, 8*(1), 4.

Lopez Mateos, D., Cohen, M. C., & Pyron, N. (2022). Field Experiments for Testing Revenue Strategies in the Hospitality Industry. *Cornell Hospitality Quarterly, 63*(2), 247-256.

Menezes, F. M., & Quiggin, J. (2012). More competitors or more competition? Market concentration and the intensity of competition. *Economics letters, 117*(3), 712-714.

Miller, S. R., & Eden, L. (2006). Local density and foreign subsidiary performance. *Academy of Management Journal, 49*(2), 341-355.

Milone, F. L., Gunter, U., & Zekan, B. (2023). The pricing of European airbnb listings during the pandemic: A difference-in-differences approach employing COVID-19 response strategies as a continuous treatment. *Tourism Management, 97*, 104738.

Pan, C.-M. (2005). Market structure and profitability in the international tourist hotel industry. *Tourism Management, 26*(6), 845-850.

Picone, G. A., Ridley, D. B., & Zandbergen, P. A. (2009). Distance decreases with differentiation: Strategic agglomeration by retailers. *International Journal of Industrial Organization, 27*(3), 463-473.

Pike, S. (2002). Destination image analysis—a review of 142 papers from 1973 to 2000. *Tourism Management, 23*(5), 541-549.

Porter, M. E. (1980). Competitive strategy: techniques for analyzing industries and competitors: with a new introduction. In *Competitive strategy: techniques for analyzing industries and competitors: with a new introduction* (pp. xxviii, 396-xxviii, 396).

Porter, M. E., & Kramer, M. R. (2006). The link between competitive advantage and corporate social responsibility. *Harvard business review, 84*(12), 78-92.

Rahimi, S., Liu, X., & Andris, C. (2016). *Hidden style in the city: an analysis of geolocated airbnb rental images in ten major cities.* Paper presented at the Proceedings of the 2nd ACM SIGSPATIAL workshop on smart cities and urban analytics.

Ravasi, D., & Stigliani, I. (2012). Product design: a review and research agenda for management studies. *International Journal of Management Reviews, 14*(4), 464-488.

Reimann, M., & Schilke, O. (2011). Product differentiation by aesthetic and creative design: A psychological and neural framework of design thinking. *Design thinking: Understand–improve–apply*, 45-57.

Ren, L., Qiu, H., Wang, P., & Lin, P. M. (2016). Exploring customer experience with budget hotels: Dimensionality and satisfaction. *International Journal of Hospitality*

Management, 52, 13-23.

Ryu, K., & Han, H. (2011). New or repeat customers: How does physical environment influence their restaurant experience? *International Journal of Hospitality Management, 30*(3), 599-611.

Sainaghi, R., Abrate, G., & Mauri, A. (2021). Price and RevPAR determinants of Airbnb listings: Convergent and divergent evidence. *International Journal of Hospitality Management, 92*, 102709.

Sánchez-Pérez, M., Illescas-Manzano, M. D., & Martínez-Puertas, S. (2020). You're the only One, or Simply the Best. Hotels differentiation, competition, agglomeration, and pricing. *International Journal of Hospitality Management, 85*, 102362.

Silva, R. (2015). Multimarket contact, differentiation, and prices of chain hotels. *Tourism Management, 48*, 305-315.

Silva, R. (2016). Competition and demand effects of geographic distance to rivals. *The Service Industries Journal, 36*(1-2), 37-57.

Skogland, I., & Siguaw, J. A. (2004). Are your satisfied customers loyal? *Cornell hotel and restaurant administration quarterly, 45*(3), 221-234.

Smith, A. (2010). The role of national identity and tourism in city planning: the case of Valletta. *Urban Research & Practice, 3*(1), 63-84.

Sonuç, N. (2020). Conformity of Hospitality Services to SDGs Related to Accessibility and Technology. In *Sustainable Hospitality Management* (Vol. 24, pp. 119-136): Emerald Publishing Limited.

Strannegård, L., & Strannegård, M. (2012). Works of art: Aesthetic ambitions in design hotels. *Annals of Tourism Research, 39*(4), 1995-2012.

Suess, C., Kang, S., Dogru, T., & Mody, M. (2020). Understanding the influence of "feeling at home" on healthcare travelers' well-being: a comparison of Airbnb and hotel homescapes. *Journal of Travel & Tourism Marketing, 37*(4), 479-494.

Tchetchik, A., Fleischer, A., & Finkelshtain, I. (2008). Differentiation and synergies in rural tourism: Estimation and simulation of the Israeli market. *American journal of agricultural economics, 90*(2), 553-570.

UCF, l. (2022). Reasons to use Census Tracts instead of ZIP Codes in your analysis. Retrieved from https://guides.ucf.edu/statistics/zip

Van Soest, D. P., Gerking, S., & Van Oort, F. G. (2006). Spatial impacts of agglomeration externalities. *Journal of Regional Science, 46*(5), 881-899.

Voltes-Dorta, A., & Inchausti-Sintes, F. (2021). The spatial and quality dimensions of Airbnb markets. *Tourism Economics, 27*(4), 688-702.

Xiao, X., Fang, C., Lin, H., & Chen, J. (2022). A framework for quantitative analysis and differentiated marketing of tourism destination image based on visual content of photos. *Tourism Management, 93*, 104585.

Xie, K., & Mao, Z. (2017). The impacts of quality and quantity attributes of Airbnb hosts on listing performance. *International Journal of Contemporary Hospitality Management*.

Xie, K. L., & Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. *International Journal of Hospitality Management, 67*, 174-184.

Xie, K. L., Kwok, L., & Heo, C. Y. (2020). Are neighbors friends or foes? Assessing Airbnb listings' agglomeration effect in New York City. *Cornell hospitality quarterly, 61*(2), 128-141.

Xie, K. L., & Young, C. A. (2021). The Copycat Effect: Do Hotel-Like Features Drive Airbnb Performance? *Journal of Hospitality & Tourism Research*, 10963480211035551.

Xu, Y., Gong, C., & Law, R. (2022). Face the competition and take proactive actions: How does neighborhood competition affect hotel online effort? *International Journal of Hospitality Management, 100*, 103092.

Yang, Y., Jiang, L., & Schwartz, Z. (2019). Who's hiding? Room rate discounts in opaque distribution channels. *International Journal of Hospitality Management, 80*, 113-122.

Yang, Y., Luo, H., & Law, R. (2014). Theoretical, empirical, and operational models in hotel location research. *International Journal of Hospitality Management, 36*, 209-220.

Yeung, P.-K., & Lau, C.-M. (2005). Competitive actions and firm performance of hotels in Hong Kong. *International Journal of Hospitality Management, 24*(4), 611-633.

Zemke, D. M. V., Raab, C., & Wu, K. (2018). How does hotel design contribute to property performance? *International Journal of Contemporary Hospitality Management*.

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of marketing research, 54*(5), 687-705.

Zhang, H., Zach, F. J., & Xiang, Z. (2023). Design standardization by Airbnb multi-unit hosts: Professionalization in the sharing economy. *Annals of Tourism Research, 98*, 103523.

Zhang, S., Lee, D., Singh, P. V., & Srinivasan, K. (2022). What makes a good image? Airbnb demand analytics leveraging interpretable image features. *Management Science, 68*(8), 5644-5666.