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Spatial coopetition and peer-to-peer accommodation price

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Spatial competition and peer-to-peer accommodation price

Abstract

Peer-to-peer accommodation prices can be derived from individual accommodation and destination characteristics. This study focuses on spatially cooperative pricing among peer-to-peer accommodations at both individual and clustered levels. Applying spatial analytical techniques to 2,090 Airbnb properties across 275 census tracts in Miami-Dade County, Florida, we model peer-to-peer accommodation prices based on three cooperation antecedents: market commonality, resource similarity, and supply commonality. The results reveal the presence of three clusters of spatially cooperative pricing dynamics, namely, cooperation-dominant, competition-dominant, and balanced cooperation, across three cooperation antecedents. This study offers effective guidance for accommodation rental platforms, hosts, and policymakers regarding the development of cooperative pricing strategies that are shaped by tourism demand, supply, and resources within and across tourism destinations.

Keywords: Spatial cooperation; Peer-to-peer accommodation price; Market commonality; Resource similarity; Supply commonality

Introduction

The peer-to-peer accommodation market is a socioeconomic ecosystem built around the sharing of human and physical resources to improve efficiency, sustainability, and community economy (Mi & Coffman, 2019). Over the decades, Airbnb's astronomical growth has led to an operational risk between cooperation and competition in regard to Airbnb prices both within and across regions (Cai, Zhou, & Scott, 2019). Recent statistics show that the Airbnb market is poised to drive much higher competition among hosts due to the tremendous increase in rental supply, which has reached as high as 23 percent in the U.S. and even higher worldwide (AirDNA, 2022). Under the increased Airbnb supply, existing or new hosts might need to apply a strategic approach to actively respond to pricing decisions and maintain their market performance.

Competitive pricing is an essential practice for peer-to-peer accommodation hosts to ensure profitability in their operations (Gibbs et al., 2018; Jiang et al., 2023). Research has shown that peer-to-peer accommodations have more complex pricing considerations, such as property attributes, guest experience, and neighboring communities, than traditional hotels (Guttentag, 2015; Lee et al., 2019). When pricing accommodation services, lodging firms, including peer-to-peer accommodations, need to decide whether to cooperate, to compete, or to both cooperate and compete (i.e., coopete) with their competitors for each of their best interests (Della Corte & Aria, 2016). Although Airbnb has provided hosts with pricing algorithms to determine competitive prices, most hosts tend to set their prices by focusing more on guest insights and expectations (Chattopadhyay & Mitra, 2019). However, research suggests that hosts should build appropriate pricing strategies while considering coopetition dynamics from a macro perspective (Chim-Miki & Batista-Canino, 2017).

While research has examined the effects of destination-level coopetition strategies on cost reduction (Wang & Krakover, 2008) and financial performance (Della Corte & Aria,

2016), scholars have overlooked the importance of spatially coopetitive pricing among peer-to-peer accommodation providers within and across destinations. For instance, Airbnb organizes regional host gatherings called Airbnb Meetups. These events are designed to facilitate networking among local hosts, allowing them to exchange experiences and strategies related to hosting services, maximize profits, and contribute to their local economy (Airbnb Meetups, 2023). Coopetition researchers argue that high external competition from other regions can generate the need for unity among the players in a particular destination, leading such players to come together to design marketing strategies and share knowledge and risks (Czakoń & Czernek, 2016). The inter-firm coopetition approach is taken to establish a holistic economic structure based on the competitiveness of a particular industry and regional resources (Chim-Miki & Batista-Canino, 2017). While a coopetitive strategy can be employed to integrate economic actors into the destination market, there remains a dearth of empirical evidence regarding how peer-to-peer accommodation providers implement coopetitive relationships in accommodation pricing at the macro level (Kirillova et al., 2020).

To fill this gap, this study is aimed at assessing the coopetition dynamics in peer-to-peer accommodation pricing across both individual and clustered levels. From a theoretical study of Madhavan et al. (2004), we identify three antecedents of coopetitive pricing among peer-to-peer accommodation providers (i.e., market commonality, resource similarity, and supplier commonality) and explore the spatially varying relationships between coopetition antecedents and peer-to-peer accommodation prices across individual and clustered accommodations. In contrast to previous studies that deal with tourism coopetition at a micro- or meso-level (Chim-Miki & Batista-Canino, 2017), this study explores both micro- and macro-level coopetitive relationships in peer-to-peer accommodation pricing. Empirically, we model prices of 2,090 Airbnb properties across 257 census tracts in Miami-Dade County, Florida, and visualize the spatially coopetitive dynamics that distinguish Airbnb price

variations across three coopetition antecedents and Airbnb properties at individual and clustered levels.

This study contributes to the coopetition literature by revealing three types of coopetitive pricing dynamics in the peer-to-peer accommodation market by identifying the type of their coopetition antecedents. First, we find that hosts in some destinations tend to benefit from cooperative pricing by setting relatively higher prices and focusing on the quality of accommodation products and services (“cooperation-dominant”) (Damayanti et al., 2017; Fong et al., 2018). Second, hosts in some destinations engage in price competition by setting relatively lower prices than hosts in other destinations (“competition-dominant”) (Czakov & Czernek-Marszałek, 2021). Finally, neighboring hosts in some destinations can use both cooperation (setting high prices) and competition (setting low prices) strategies in accommodation pricing (“balanced coopetition”) (Bahar et al., 2022). Our findings offer peer-to-peer accommodation providers strategic guidance on how to price accommodation services in a coopetitive way while using (1) destination attributes, such as market commonality, supply commonality, and resource similarity, and (2) geospatial clustering perceptions across neighboring accommodations. Furthermore, this study provides policymakers with useful information on the best practices in supporting peer-to-peer accommodation markets through the effective use of tourism resources within and across destinations.

Literature Review

Coopetition in tourism

Assessing cooperation, competition, and coopetition has challenged many tourism scholars, and literature has seldom proposed effective methodologies for assessing coopetition. The extant literature on tourism coopetition focuses on the micro or meso perspective of coopetition activities either among individuals (Bahar et al., 2022; Czernek-Marszałek, 2018; Damayanti et al., 2017) or among firms (Fong et al., 2021; Köseoglu, Yick, & Okumus, 2021). Most coopetition studies have relied on qualitative data (e.g., interviews and case studies) rather than quantitative data such as real-world observational data. Furthermore, scholars have investigated coopetition-related activities as outcome variables, including coopetition tension, coopetition capacity, expansion in supply networks, and destination sustainability. However, these studies offer limited insights into the business performance implications of coopetition, such as the economic benefits or pricing strategies. This study is aimed at contributing to the coopetition literature by addressing this gap. Table 1 exhibits the exemplary literature on tourism coopetition.

[Insert Table 1 about here]

The comparatively new concept of coopetition is applied to an interrelated networking relationship among tourism firms that subsidize the growth of tourism destinations with limited tourism resource capacity (Chim-Miki & Batista-Canino, 2017). Tourism coopetition was first introduced by Brandenburger and Nalebuff (1996), who proposed a concept in which coopetition penetrates both (1) the horizontal network between competitors and complementary firms and (2) the vertical network between suppliers and customers. Extant studies have investigated one side of collaborative relationships among tourism firms, either a horizontal network (e.g., Köseoglu et al., 2021) or a vertical network (e.g., Bahar et al., 2022). Based on qualitative case studies, scholars have examined the horizontal coopetition relationships among informal economy actors (e.g., street food vendors and local transportation providers) (Damayanti et al., 2017). However, tourism firms may engage with

actors (e.g., visitors and accommodation providers) in vertical relationships. Given that interfirm relationships can occur across both horizontal and vertical networks (Bengtsson & Kock, 2014), the literature has mainly treated only with a single side of a network in tourism coopetition rather than considering simultaneous coopetition in both horizontal and vertical networks.

Research has explained that a network of coopetitive relationships adds value for competitors by allowing them to access network-embedded resources both vertically and horizontally in a network (Adler & Kwon, 2002). Tourism firms tend to be simultaneously involved in both competitive relationships due to conflicting goals and cooperative relationships due to common goals (Della Corte & Aria, 2016), which are identified as interdependent and complementary in successful tourism coopetition (Wang & Krakover, 2008). That is, competing tourism firms are likely to develop long-term cooperative efforts due to the vertical and horizontal interdependence that exists within and across destinations. Some examples of horizontal and vertical coopetition include the relationships between hotels and travel agencies (Guo et al., 2014), between hotels and online travel platforms (Bahar et al., 2022), and between tourist destinations (Beritelli & Laesser, 2011). Hence, we employ a relational network approach, both vertical and horizontal, to explore the coopetitive pricing practices embedded in peer-to-peer accommodations.

Antecedents of coopetition in peer-to-peer accommodation pricing

Scholars have investigated numerous antecedents of peer-to-peer accommodation prices from various perspectives, including property, reputation, host, and location. These insights are derived from hedonic pricing models (Jiang et al., 2023). Research from the property and reputational perspective has shown that room type significantly impacts Airbnb

prices (Wang & Nicolau, 2017). Additionally, it has been found that general product features, as well as the quantity and rating scores of online reviews, contribute to an increase in Airbnb prices (Chattopadhyay & Mitra, 2020; Gibbs et al., 2018; Huang, Coghlan, & Jin, 2020; Xie & Kwok, 2017). From the host perspective, studies have demonstrated that the “superhost” attribute is associated with an increase in Airbnb prices (Cai et al., 2019). Furthermore, Airbnb hosts’ expertise, classified as casual (i.e., with one or two properties) versus professional (i.e., more than two properties), has been shown to significantly influence pricing (Arvanitidis et al., 2020). From the locational perspective, rural, urban, and tourism-density districts have been found to differentiate Airbnb prices (Falk et al., 2019). However, these hedonic pricing models have primarily focused on identifying pricing determinants based on internal and external characteristics of peer-to-peer accommodations, without considering cooperation, competition, or coopetition among accommodations.

Economics research suggests that cooperation, competition, and spatial positioning have varying effects on pricing strategies. Some theoretical researchers argue that competition tends to lower prices in a market, whereas cooperation can maintain prices at higher levels (e.g., Chen & Riordan, 2008). Other empirical studies show that new competition can lead to increased prices (e.g., Thomadsen, 2007). Although these arguments highlight the context-dependent nature of the relationship between competition and pricing strategy, some economists emphasize the importance of understanding spatial competition models in pricing. While Hotelling (1929) laid the groundwork by arguing that firms compete for market share based on spatial positioning and pricing strategies, Kohlberg (1983) extended Hotelling’s model by introducing the idea of clustering, where firms group together in specific locations to minimize the impact of negative network externalities. Negative network effects can cause less competition, which often leads to higher prices; conversely, positive network effects can increase competition, resulting in lower prices (Navon, Shy, &

Thisse, 1995). Therefore, it is essential to identify the antecedents of spatial coopetition when modeling peer-to-peer accommodation prices.

Recent tourism studies have advanced by incorporating spatially heterogeneous factors into the modeling of peer-to-peer accommodation prices. For instance, geographical factors such as accessibility to tourist attractions, proximity, ethnicity of local residents, and spatial spillover effects significantly influence Airbnb price determination (Adamiak, 2018; Chica-Olmo et al., 2020). Additionally, Airbnb prices are spatially associated with demographic and socioeconomic factors such as population density, crime rates, unemployment, and household income (Tang et al., 2019). While these studies have considered spatial heterogeneity in modeling Airbnb prices, there remains a gap in investigating spatially cooperative peer-to-peer accommodation pricing.

Applying a network-based view (Madhavan et al., 2004), we delineate three types of coopetition antecedents in the peer-to-peer accommodation market: market commonality, resource similarity, and supply commonality. From a vertical perspective, market commonality (a downstream element) is defined as the degree to which hosts compete for access to the same customers with their products and services, while resource similarity (an upstream element) refers to the extent to which competitors have access to similar resources (Chen, 1996). From a horizontal perspective, we define supplier commonality as the degree to which accommodation providers offer similar products or services in the same destination area (Brandenburger & Nalebuff, 1996). In this paper, we consider inbound visitors to a particular destination as market commonality, tourism resources as resource similarity, and Airbnb properties and hotels as supply commonality.

Coopetition dynamics and peer-to-peer accommodation prices

Research suggests that coopetition studies not only focus on the sources and antecedents of coopetition but also on the dynamics of cooperative relationships that drive firms' performance and competitive strategies (Gnyawali & Park, 2011). Coopetition dynamics occur when the concept of coopetition balance does not equally weigh the levels of cooperation and competition (Gnyawali & Ryan Charleton, 2018). Because of the paradoxical nature of coopetition (i.e., cooperation versus competition), which offers a competitive advantage to relevant economy entities, business management often employs two-sided strategies such as sharing and protecting information, creating and appropriating value, attracting and retaining customers, and trusting and distrusting business partners (Bahar et al., 2022; Chiambaretto et al., 2020). Importantly, coopetition dynamics are likely to establish a hybrid level of interfirm relationship between competition and cooperation, aiding firms in strengthening their competitive capabilities through usable resources (Gnyawali & Madhavan, 2001). However, prior studies lack empirical evidence on how coopetition dynamics shape both organization- and network-level strategic behaviors (e.g., pricing).

In this study, we propose that the degree of interaccommodation coopetition creates three networks of competition dynamics in peer-to-peer accommodation pricing: (1) cooperation-dominant, (2) competition-dominant, or (3) balanced coopetition (Bahar et al., 2022). In *cooperation-dominant* networks, firms aim to maintain high prices while focusing on offering higher quality goods and services, greater variety, and fostering innovation. For instance, hotels can collaborate with online booking platforms to attract more guests, rather than aggressively promoting their official website for direct bookings or engaging in price competition (Bahar et al., 2022). On the other hand, in *competition-dominant* networks, firms tend to set lower prices as they prioritize maximizing self-interest without considering common goals (Khanna et al., 1998). For example, hotels in a competition-dominant network

may opt to generate more direct bookings by offering lower prices through their official website instead of using online booking platforms. Finally, *balanced coopetition* occurs when cooperation and competition coexist across firms. Networks characterized by balanced coopetition apply moderate levels of both cooperation and competition, leading tourism managers to make productive decisions (Chen, 2008). As such, we expect that peer-to-peer accommodations may adopt different coopetitive pricing strategies across three networks of interaccommodation coopetition (i.e., cooperation-dominant, competition-dominant, and balanced) to maximize profits.

As coopetitive activities exhibit geographical associations, such as through knowledge sharing and relationship building, we propose modeling peer-to-peer accommodation prices from the spatially clustered perspective of coopetitive dynamics. A cluster is defined as a density of interconnected firms and institutions in a specific area, characterized by commonalities and complementarities (Porter, 1998). Furthermore, spatial coopetition can be understood as a mutual attraction among competing firms aiming to maximize their market share in a specific geographic area, where demand and supply are either shared or equal (Kohlberg, 1983). Spatial coopetition among tourism firms contributes to the establishment of a long-term business network by enhancing destination and brand image, ultimately fostering sustainable tourism destinations (Della Corte & Aria, 2016). Building on the concept of spatial coopetition, this study aims to assess the potential for developing spatial coopetitive dynamics within and across destinations where peer-to-peer accommodations set their prices.

Based on the arguments presented above, we intend to incorporate multiple factors – coopetition antecedents, coopetitive dynamics, and spatial heterogeneity – when modeling peer-to-peer accommodation prices. The multifaceted nature of destination characteristics (Cutter et al., 2016) necessitates integrating various coopetitive elements (i.e., market

commonality, resource similarity, and supplier commonality) by leveraging their embeddedness within the focal destination. Fig. 1 illustrates our research model, which we will utilize to investigate the spatial heterogeneity of cooperation-dominant, competition-dominant, and balanced coopetition in peer-to-peer accommodation prices across individual and clustered accommodations.

[Insert Fig. 1 about here]

Methods

Data and variables

We selected Miami-Dade County as our study area due to its prominence in the Airbnb market. In 2019, Miami-Dade ranked as the top revenue-generating county for Airbnb businesses, generating \$261 million in combined income and welcoming 1.2 million Airbnb guests in 2019 (Alvarado, 2020). Specifically, the City of Miami stands as the second-most visited city in the U.S. after New York City, attracting over five million visitors as of 2019. With a population of 2.7 million people, Miami-Dade County encompasses a wide range of areas, including cities, villages, towns, and communities, spanning from coastal to urban, rural to suburban, and downtown to industrial. These diverse characteristics can significantly influence various coopetitive Airbnb pricing behaviors, providing unique strategic implications for both individual and clustered Airbnb properties. Our study focuses on Airbnb property-level pricing, which will be impacted by coopetition antecedents existing within the census tract-level marketplace.

Empirical data were gathered from multiple sources. Initially, price and location information for 2,090 Airbnb properties and 272 economy and medium-scale hotels located

in Miami-Dade County were collected from AirDNA and STR, respectively. Subsequently, census tract-level visitor information from the Florida Department of Transformation, specifically from mobile phone users who traveled to Miami-Dade County in 2019, was obtained. This visitor information was supplemented by data from AirSage, an American telecommunications company specializing in collecting and analyzing call records of anonymized cellphone users. The mobile phone calls originated from Verizon Wireless networks in Miami-Dade County. Finally, data on census tract-level tourism resources were collected from the Florida Department of Transportation. Both visitor and tourism resource data were acquired by one of the study authors who participated in a project funded by the Florida Department of Transportation and had access to the related data for this study. Consequently, our final sample consisted of coopetition antecedents and 2,090 Airbnb property prices across 275 census tracts. Fig. 2 illustrates (a) the spatial distribution of 2,090 Airbnb properties' prices and (b) the classification of urban and non-urban areas across Miami-Dade County. Most Airbnb properties are densely located in the east and northeastern areas, with fewer properties in the rest of the areas.

[Insert Fig. 2 about here]

As the dependent variable of peer-to-peer accommodation price, we measured the mean value of the average daily rates of Airbnb properties from January 1, 2019, to December 31, 2019. Regarding the independent variables, we identified market commonality, resource similarity, and supply commonality as coopetition antecedents of peer-to-peer accommodation prices. Table 2 reports the detailed operationalization of variables and data sources.

[Insert Table 2 about here]

To operationalize market commonality, we focused on the downstream element in the accommodation-sharing economy, where the number of visitors traveling to a given census

tract represents the addressable customers for Airbnb properties (Chen, 1996). To estimate visitor flows for each census tract, we initially accessed data comprising approximately 8 billion mobile phone call records in 2019. We assumed that travel movements spanning at least a 50-mile distance were for tourism purposes (Connell & Page, 2008; Pearce, 1979). A filtering process was then applied to retain traveler visits, defined by the minimum 50-mile distance, and each travel movement was aggregated based on the call origination census tract and the destination census tract. As a result, we could summate trip counts in each census tract, enabling us to measure the number of inbound visitors traveling to a particular census tract (*Number of visitors*).

Regarding resource similarity, we assessed the level of resource similarity based on the tourism resources accessible to Airbnb properties in each census tract (*Tourism resources*). Since tourism industry-related location quotients are only available at the county level (Lee et al., 2020), we computed census tract-level tourism resource indices using a database containing 92 types of geo-referenced tourism resources (e.g., beaches, lakes, and theme parks) provided by the Florida Department of Transportation. Following suggestions from previous studies (Formica & Uysal, 2006; Lovingood & Mitchell, 1989; Spotts, 1997), we employed factor analysis to consolidate several related measures into a single measure. Adhering to Smith's (1987) regional analysis approach, we generated factor scores for tourism resource indices. This was accomplished by multiplying the loading of each tourism resource on a specific factor by the original score of that resource in each census tract. This procedure was iterated for every tourism resource category on a factor, and the products were then aggregated. Subsequently, we standardized the factor scores for the identified 12 tourism resource categories and further aggregated them into a single factor representing tourism resources.

For supply commonality, which refers to the extent to which firms compete for supply over similar accommodation services, we considered two types of accommodation providers: peer-to-peer accommodation (i.e., Airbnb) and traditional lodging (i.e., hotels). Due to the difference in the size of their operations, with Airbnb properties typically having fewer rooms compared to hotels, we opted to count the number of rooms rather than the number of accommodation providers. Thus, we measured the number of Airbnb rooms (*Airbnb rooms*), collected from AirDNA, and the number of hotel rooms (*Hotel rooms*), collected from STR, in each census tract.

Following the methodology of previous studies on hedonic pricing models (e.g., Gyódi & Nawaro, 2021; Wang & Nicolau, 2017), we controlled for seven variables representing accommodation, competition, and location characteristics that may influence peer-to-peer accommodation prices. First, we included three accommodation factors: *number of bookings*, *review volume*, and *property age*. These factors have been shown to influence the price levels of each property (Tong & Gunter, 2022). Second, considering that hotel room prices affect Airbnb supply (Dogru et al., 2020), we included *hotel price* as a competitive factor. This was measured as the mean value of the average daily rates of hotels in a given census tract from January 1, 2019, to December 31, 2019. Finally, we incorporated three locational factors in the model (Deboosere et al., 2019; Jiang et al., 2023): (1) the distance between a property and the nearest airport (*Airport proximity*), (2) the total distance of main roads within the census tract where an Airbnb property is located (*Road distance*), and (3) the size of census tract to which a property belongs to (*Census tract size*).

Data analysis

We conducted four types of data analysis to demonstrate both the aspatial and spatial effects of coopetition antecedents on individual Airbnb property prices. First, we ran an ordinary least squares (OLS) regression to measure the aspatial model, as shown in Equation (1):

$$y_i = \alpha_0 + \sum_{j=1}^k \alpha_j x_j + \varepsilon \quad (1)$$

where y_i is the price of Airbnb property $i \in \{1, 2, \dots, n\}$; x_j is the j th independent variable of the coopetition antecedent, where $j \in \{1, 2, \dots, k\}$; α_j is the j th coefficient; and ε is the error term.

Second, we implemented a spatial Durbin model (SDM) to consider the spatial lag effect on both the independent and dependent variables (Gyódi & Nawaro, 2021; Jang & Kim, 2022), as demonstrated in Equation (2):

$$y_i = \sum_{j=1}^k (\rho_i W y_j + \beta_{ij} x_{ij} + W x_{ii} \theta_{ij}) + u_i + \varepsilon_i \quad (2)$$

where, for Airbnb property i , W represents the spatial weight matrix, which captures the spatial arrangement for k Airbnb properties, ρ_i and θ_{ij} denote the spatial parameters, u_i represents spatial-specific effects, and ε_i is the error term. In SDM, defining the neighborhood and constructing the spatial weights matrix are crucial for capturing the spatial relationships among observations and addressing spatial autocorrelation. We employed a distance weight matrix using kernel weights because distance-based weights are appropriate for point data in SDM (LeSage & Pace, 2009). Specifically, to define the neighborhood property, we applied a one-mile distance band, consistent with previous studies (e.g., Xie,

Kwok, & Heo, 2020). In our study, Airbnb properties within this bandwidth were considered neighborhoods and contributed to the spatial weight calculations.

Third, we conducted a spatial analysis using geographically weighted regression (GWR) to explore the spatially heterogeneous effects of coopetition antecedents on Airbnb property prices (Fotheringham et al., 2000). Unlike OLS and SDM, which assumes homogeneity of relationships between variables across the entire study area, GWR provides insights into local variations in those relationships and further allows for the visualization of spatially varying relationships through maps of parameter estimates, aiding in the identification of spatial patterns and localized effects in coopetitive dynamics. The GWR is depicted in Equation (3):

$$y_i = \gamma_0(u_i, v_i) + \sum_{j=1}^k \gamma_{ij}(u_i, v_i)x_{ij} + \varepsilon_i \quad (3)$$

where (u_i, v_i) refers to the coordinate at property i . As researchers have commonly used the Gaussian kernel with a fixed bandwidth and a bisquare kernel with adaptive bandwidth in GWR, we employed a bisquare kernel function due to the geographically heterogeneous size of census tract units across the geography (Kim et al., 2020). The Gaussian kernel with a fixed (adaptive) bandwidth is suitable when the sample points are regularly (irregularly) distributed in the study area. Furthermore, the employment of the bisquare kernel function could maximize the model of fit of GWR, compared with the Gaussian kernel function (Lee, Kim, & Jang, 2021). Hence, we determined the optimal kernel size using an iterative optimization approach to minimize the corrected Akaike information criterion (Fotheringham, Charlton, & Brunsdon, 1998).

Subsequently, we visualized the local GWR coefficients across the 1,279 Airbnb properties both individually and in subclusters. The subclustered maps illustrate the spatial

configuration of the relationships between coopetition antecedents and Airbnb prices across Miami-Dade County. For conducting the spatial analysis, we utilized various software programs, including Stata (version 16.1), GWR (version 4.09), and ArcGIS Pro.

Results

Descriptive statistics

Table 3 presents the descriptive statistics and correlation coefficients for the dependent and independent variables. In the Airbnb sample of Miami-Dade County, the average nightly Airbnb property price was \$180.016 in 2019, ranging from \$22.770 to \$492.520, thereby showing a large variation in Airbnb prices across Miami-Dade County. Concerning market commonality, the average number of visitors per census tract in 2019 was 1,763, with a range of between 0 and 41,310. Regarding resource similarity, the average factor score of tourism resources per census tract was 0.143, ranging from -0.216 to 2.579, indicating that tourism resources varied across Miami-Dade census tracts. Regarding supply commonality, the average number of Airbnb rooms per census tract was 547.580, ranging from 2 to 1,771, while the average number of hotel rooms was 547,560, ranging from 0 to 3,991. Due to the absence of hotels in specific census tracts, one control variable (i.e., hotel price) had 38% missing values. To address this, we empirically handled missing values by either replacing them with mean values or omitting their cases in the model. Finally, we found the highest variance inflation factor (VIF) was 3.570, confirming that multicollinearity is not a serious concern in the model.

[Insert Table 3 about here]

Global model estimations

Table 4 presents the results of two types of global models (i.e., OLS regression and SDM). To address missing values, we conducted two OLS regression models: (1) replacing missing values with mean values and (2) omitting cases with missing values. We chose the second model (i.e., omitting cases with missing values) due to better model performance based on R-squared values (0.116 versus 0.097). The results of Model 1 reveal that while the number of visitors (market commonality) had no significant effect on Airbnb prices, other coopetition antecedents had significant effects. Specifically, tourism resources decreased Airbnb prices ($\beta = -54.708, p < 0.05$), whereas Airbnb rooms and hotel rooms increased Airbnb prices ($\beta = 0.028, p < 0.05$; $\beta = 0.019, p < 0.05$). These findings imply that peer-to-peer accommodation prices are influenced by tourism resources and accommodation supply rather than tourism demand.

Furthermore, Model 1 provides insights into the effects of control variables on Airbnb prices. The number of bookings, Airbnb age, and hotel price were found to have a positive relationship with Airbnb prices, while review volume and distance to the nearest airport were negatively related to Airbnb prices. These results suggest that, on average, experienced properties tend to set higher prices, hotel prices do not negatively impact Airbnb pricing, and proximity to airports leads to higher prices due to convenience. Interestingly, Airbnb popularity, indicated by the number of bookings and review volume, has contrasting effects. This finding is partially in line with prior studies (Tong & Gunter, 2022; Wang & Nocolau, 2017), which suggests that cheaper Airbnb listings are booked more frequently than expensive ones.

The SDM results (Model 2 in Table 4) confirmed the findings of the OLS regression model: tourism resources directly decreased Airbnb prices ($\beta = -60.831, p < 0.05$), while both

Airbnb rooms and hotel rooms directly increased Airbnb prices ($\beta = 0.135, p < 0.05$; $\beta = 0.101, p < 0.05$). Furthermore, the SDM results revealed significant spatial spillover effects of $W \times$ variables (e.g., tourism resources, Airbnb rooms, hotel rooms, number of bookings, and hotel price). These spatial spillover effects, captured by the SDM, represent the average impact of independent variables on an Airbnb property's price compared to its neighboring properties, and vice versa (Gyódi & Nawaro, 2021; Jang & Kim, 2022). For example, the coefficient of the spatial spillover of tourism resources is 19.579, indicating that tourism resources had an indirectly positive spillover effect on Airbnb prices of neighboring properties. Detailed information about the direct, indirect, and total effects for each variable on Airbnb property price can be provided upon request. However, both OLS regression and SDM do not fully capture the complex cooperative dynamics occurring in Airbnb pricing strategies across properties in Miami-Dade County. Therefore, to explore location-specific cooperative pricing dynamics further, we conducted a local model estimation (i.e., GWR).

[Insert Table 4 about here]

Local model estimations

Model 3 (GWR model) in Table 4 reports the spatially heterogeneous effects of each variable on Airbnb prices across 1,279 properties after omitting cases with missing values, as suggested by prior research (Su et al., 2017). The number of visitors, on average, had a positive impact on Airbnb prices ($\beta_{\text{Mean}} = 1.954$); however, this effect varied across properties, ranging from negative ($\beta_{\text{Min}} = -127.251$) to more positive ($\beta_{\text{Max}} = 28.278$). Similar spatial variations were observed for the variables of tourism resources, the number of Airbnb rooms, and the number of hotel rooms; the local coefficients ranged from -650.981 to 816.710, from -2.634 to 2.638, and from -0.688 to 0.365, respectively. Fig. 3 illustrates the

spatially varying coefficients for four coopetition antecedent variables (Model 3). For example, the number of visitors had a more positive effect on Airbnb prices in certain northeast and western Miami-Dade areas (indicated by red coloring), while exerting a negative effect in other mid and southern areas (indicated by blue coloring) (Fig. 3-a). Similarly, the number of Airbnb rooms increased Airbnb prices in northwest and southern (rural) regions (Fig. 3-c), whereas the number of hotel rooms increased Airbnb prices in eastern and mid (urban) regions (Fig. 3-d). These findings suggest that the relationship between coopetition antecedents and Airbnb pricing varies across specific antecedents and locations.

[Insert Fig. 3 about here]

Visualizing spatial coopetition dynamics

To identify spatial coopetition dynamics in the Airbnb pricing model, we conducted an application study by clustering the high or low local coefficients obtained from Model 3 into four clusters (Jang & Kim, 2018; Lee et al., 2020). Hot spots (high-high coefficients) represent the cooperation-dominant areas where Airbnb hosts use coopetition antecedents to set relatively higher prices. Spatial outliers (high-low coefficients and low-high coefficients) represent the balanced coopetition areas where Airbnb hosts set their prices either higher or lower based on coopetition antecedents. Cold spots (low-low coefficients) represent the competition-dominant areas where Airbnb hosts use coopetition antecedents to set relatively lower prices. The clustering method relies on the global Moran's I statistic, which measures the existence of spatial dependence between the coefficient of a particular Airbnb property and coefficients of other neighboring properties, along with local indicators of spatial association (LISA) using the local Moran's I statistic (Li et al., 2007).

Fig. 4 illustrates spatial coopetition dynamics across coopetition antecedents at the clustered level. In the case of numerous visitors (Fig. 4-a), Airbnb properties in the cluster of red-colored eastern and western regions tend to set high prices (“price cooperation-dominated”) when more inbound visitors travel to these destinations. This indicates that in areas with high market commonality (i.e., number of visitors), Airbnb properties in hotspot regions engage in cooperation-dominant pricing strategies by collaborating to provide superior quality products and services (Bahar et al., 2022). Conversely, Airbnb properties in the cluster of the blue-colored southern regions tend to set lower prices (“price competition-dominated”) when more visitors travel to these rural destinations. That suggests that clusters of persistent low accommodation prices are located throughout rural destinations due to a lack of demand, leading to price competition and lower prices for home rentals. Lastly, Airbnb properties in the cluster of the light blue- and red-colored mid regions set either higher or lower prices (“price balanced coopetition”). These areas exhibit a mix of cooperation and competition in pricing strategies, resulting in varied pricing dynamics across different types of properties.

[Insert Fig. 4 about here]

The same phenomenon of spatially heterogeneous cooperative dynamics is also observed in the context of resource commonality and supply similarity. Regarding resource commonality (Fig. 4-b), our observations reveal distinct pricing patterns across different regions. In the mid areas (e.g., Miami city), characterized by a significant presence of Airbnb properties, tourism resources lead to lower prices. Conversely, in the west and northern areas, which exhibit a moderate presence of Airbnb properties, hosts leverage tourism resources to set higher prices. Interestingly, tourism resources in southern rural areas, characterized by low Airbnb density, also lead to lower prices. Regarding supply similarity, Airbnb rooms (Fig. 4-c) and hotel rooms (Fig. 4-d) play distinct roles in shaping cooperative Airbnb prices across

Miami-Dade County. In northwestern Miami-Dade, the large Airbnb supply leads Airbnb hosts to prioritize price cooperation (i.e., setting higher prices), while the large hotel supply leads hosts to engage in price competition (i.e., setting lower prices). Conversely, in eastern Miami-Dade, the large hotel supply leads to price cooperation, whereas the large Airbnb and hotel supply in southern areas results in a mix of price competition (lower prices), price cooperation (higher prices), and price co-occurrence (either higher or lower).

Discussion and Implications

This study investigates the dynamics of coopetition in pricing among peer-to-peer accommodations, considering both individual and clustered properties. We specifically investigate how market commonality, resource similarity, and supply commonality influence pricing strategies in coopetitive environments. Furthermore, we explore the spatial relationship between these factors and peer-to-peer accommodation prices, utilizing advanced spatial analytic methods. Our analysis covers 1,279 properties in Miami-Dade County, Florida, revealing spatially heterogeneous coopetitive dynamics in Airbnb room prices. We find that certain regional clusters of Airbnb hosts set higher prices, indicating a cooperation-dominant scenario, while others set lower prices, reflecting a competition-dominant situation. Additionally, some regions exhibit balanced coopetition, where both higher and lower prices are observed. These insights offer valuable guidance for researchers and practitioners aiming to understand and model peer-to-peer accommodation prices from a spatially coopetitive perspective.

Theoretical implications

Our study makes several significant contributions to the literature on coopetition and peer-to-peer accommodation pricing. First, it enriches the literature on tourism coopetition by furnishing empirical evidence on the dynamics of coopetition in the pricing strategies of peer-to-peer accommodations. While previous studies have explored various factors impacting the prices of peer-to-peer accommodations (e.g., Jiang et al., 2023) and underscored the spatial correlations and location attributes' significance on Airbnb prices (e.g., Gyódi & Nawaro, 2021), they often overlook the nuanced interplay of competitive, cooperative, or coopetitive strategic decisions within the accommodation sharing economy. Moreover, while existing research in tourism has predominantly examined tourism coopetition from either intrafirm (micro) or interfirm (meso) perspectives (Fong et al., 2018), there remains a dearth of studies applying the interfirm coopetition framework to understand how tourism firms determine their pricing strategies within and across diverse destinations. Our study bridges this gap by empirically unveiling the phenomenon of spatially coopetitive pricing both at the micro and macro levels. By shedding light on how peer-to-peer accommodations strategically set their prices through cooperation, competition, or coopetition, at both individual and clustered levels, our research advances the discourse within the hedonic pricing literature.

Second, this study represents a significant inquiry into whether the three antecedents of coopetition – market similarity, supply commonality, and resource similarity – coexist in shaping peer-to-peer accommodation pricing strategies. While prior research has extensively explored various property-, host-, or location-level attributes as determinants of peer-to-peer accommodation prices, the simultaneous impact of multiple shared resources within and across destinations has been largely overlooked (Jiang et al., 2023). This study extends the empirical understanding of coopetition antecedents, encompassing both vertical and horizontal dimensions, which can influence cooperative and competitive pricing strategies across locations (Damayanti et al., 2017). The findings shed light on how spatial coopetition

plays a crucial role in the tourism industry, where context-aware competitive pricing strategies are shaped by location-specific tourism demand, supply, and resources in each destination. Understanding coopetitive pricing strategies is paramount for both traditional and peer-to-peer accommodation providers because this nuanced understanding enables accommodations to adeptly respond to market environments, thereby optimizing their revenues and profits effectively.

Finally, our visualized findings shed light on spatially coopetitive dynamics, enriching the spatial competition model in pricing. While economists have proposed frameworks detailing how cooperation, competition, and spatial positioning shape pricing strategies (Chen & Riordan, 2008; Kohlberg, 1983; Thomadsen, 2007), empirical integration of these components has been limited. Our study addresses this gap by demonstrating spatially diverse, context-dependent pricing strategies. We identify negative network effects, driving higher prices with reduced competition, and positive network effects, associated with lower prices due to increased competition. For instance, tourism resources generate positive network effects in high-level Airbnb density areas (City of Miami), but negative network effects in mid-level Airbnb density areas. Furthermore, the presence of Airbnb supply generates negative network effects in Airbnb pricing, whereas the presence of hotel supply generates positive network effects. Thus, our study enhances understanding of the intricate dynamics of coopetitive Airbnb pricing, spanning cooperation-dominant, competition-dominant, and balanced coopetition scenarios across diverse contexts and destinations.

Managerial implications

Our empirical findings carry strategic implications for accommodation sharing platforms, hosts, and destination policymakers. First, our study informs home rental

platforms about the tendency of hosts to price their accommodations competitively across different destinations. Home rental platforms should consider fostering regional host groups, such as Airbnb Meetups, to facilitate competitive pricing strategies within and across destinations. For instance, Airbnb could develop a real-time visual monitoring system to illustrate which properties and destinations (e.g., census tracts) are engaged in cooperation-dominant (setting higher prices), competition-dominant (setting lower prices), or balanced competition (setting either higher or lower) pricing practices. This information could benefit not only existing hosts, helping them align their pricing strategies with those of neighboring hosts, but also new hosts, assisting them in setting competitive prices when entering a new market.

Second, our findings advocate for peer-to-peer accommodation hosts to engage in cooperation or competition with other hosts regarding their pricing strategies, while considering the shared attributes (e.g., visiting demand, tourism resources, and accommodation supply) within their destinations. Specifically, hosts in urban areas with high visiting demand can cooperate with other hosts by setting relatively higher prices or compete by setting either higher or lower prices at will, while hosts in rural areas with high visiting demand might need to cooperate (set higher prices) or compete (set lower prices) depending on the specific region they belong to (Fig. 4-a). However, the demand-driven competitive pricing practices may change depending on other destination attributes, such as the density of accommodation supply (e.g., Airbnb and hotels) and the level of tourism resources. The complex and dynamic nature of competitive pricing suggests that hosts should (1) consider local attributes when developing pricing strategies and (2) focus on either strategic pricing or nonpricing activities (e.g., service differentiation) to maximize their performance. Hence, Airbnb hosts who belong to a particular segment in Miami-Dade can monitor and utilize the

combined role of visiting demand, tourism resources, and accommodation supply in shaping Airbnb prices in a coopetitive manner.

Finally, our findings offer extensive benefits to destination policymakers in managing tourism supply, demand, and resources. While Airbnb properties in urban areas may benefit from a high density of visitors, attractions, and hotels (Lee et al., 2020), rural destinations often lack tourism infrastructure and attractions, leading to lower Airbnb prices. However, our study suggests that an increase in inbound visitors (Fig. 4-a) and other Airbnb properties (Fig. 4-c) can foster a more cooperation-driven Airbnb business environment, prompting improvements in service quality and the setting of higher prices. From a long-term perspective, the development of tourism infrastructure and attractions is essential to mitigate continuous pricing competition among tourism firms, including peer-to-peer accommodations. However, infrastructure development requires financial support and development time. Policymakers can incentivize peer-to-peer accommodation platforms and hosts to promote destination-level travel experiences, enhancing the brand image of specific destinations among visitors and accommodation consumers. For example, the Airbnb Experiences platform has facilitated cultural exchange between local residents and travelers. Given that Airbnb online cultural experiences have generated more than \$2 million for hosts worldwide (Airbnb Newsroom, 2023), cultural experiences can serve as a strategic source of profit for hosts who set higher accommodation prices.

Limitations and Future Research Directions

This study has some limitations that provide opportunities for future research on coopetition. First, the findings on spatial coopetition are derived from a specific geographic area (i.e., Miami-Dade County) that predominantly consists of urban areas. Given that Airbnb

properties tend to cluster around tourist attractions (Xu et al., 2020), it is possible that Airbnb prices in regions with more rural areas may exhibit different spatial coopetition patterns. Therefore, future research could explore various tourism destinations to examine the coopetitive dynamics in peer-to-peer accommodation pricing across different geographic contexts.

Second, our study operationalized variables of three coopetition antecedents based on one item (market commonality and resource similarity) or two items (supply commonality). Although the nature of secondary data collection did not allow us to operationalize multiple items for each variable, these variables might raise validity concerns regarding the constructs (Jang, Kim, & Kitchen, 2018). Hence, we propose that future research obtain a wider range of measures to mitigate dependence on single-item measures.

Finally, the current study relies on cross-sectional data of Airbnb prices and coopetition antecedents from 2019, lacking contemporary observations and users' experiential and behavioral responses to coopetitive prices after the pandemic. A clear acknowledgment of this aspect will serve as a necessary caveat for stakeholders attempting to generalize the study's findings to the current post-pandemic market conditions. Therefore, we recommend that future studies collect up-to-date and behavioral data to capture coopetition antecedents and Airbnb pricing practices from a post-pandemic perspective.

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Table 1. Summary of exemplary literature relating to tourism coopetition.

Author(s)	Level	Unit of analysis	Data source	Antecedent	Outcome	Key findings
Bahar et al. (2022)	Micro	Between hotels and booking platforms	Interview	Optimization; temporal disintermediation, integration, spatial separation	Coopetition tension	Coopetition patterns are detected between cooperation- and competition-dominant approaches.
Chim-Miki and Batista-Canino (2018)	Micro	Among tourism stakeholders	Literature review	Co-location, associationism, competition, cooperation, strategic management, co-entrepreneurship, co-production	Coopetition capacity	Six antecedents of tourism coopetition optimize stakeholders' relationships to increase competitiveness.
Czernek-Marszałek (2018)	Micro	Tourist partnerships in destination marketing	Interview	Trust, information, transfer, joint problem-solving	Cooperation	Assessing tourist collaboration was based on business cooperation, mutual understanding, benefit from cooperation, and perceived fulfilled expectations.
Damayanti et al. (2017)	Micro	Within the informal tourism economy	Case study	Shared resources, rules in use, attributes of the informal actors, time	Coopetition activities	Coopetition occurs when the actors share multiple resources; a single shared resource creates sequential coopetition.
Della Corte and Aria (2016)	Meso	Among small and medium tourism firms	Interview	Typology, intensity, impact	Competitive advantage	Coopetition improves performance; trust between partners is the key determinant.
Fong et al. (2021)	Micro	Among tour operators	Case study, interview	Involvement, dyadic relations, horizontal competition	Expansion in supply network	Coopetitive relationships are formed between horizontal suppliers; the impact was found on vertical and diagonal suppliers in the supply chain.
Kallmuenzer et al. (2021)	Meso	Among small and medium tourism firms	Survey	Economic benefits, destination networks, social relationships	Firms' decision-making	Economic benefits and destination networks directly and positively influence firms' decisions.
Köseoglu, Yick, and Okumus (2021)	Meso	Among hotels	Case study, interview	Business intelligence including competitor, external and internal customer, technical	Competitive intelligence practices	Hotels can collaborate and compete in CI at an inter-organizational level by sharing open-source information and knowledge.
Nguyen et al. (2022)	Micro	Among individual stakeholders	Field observation, interview	Networking relationships in competition and cooperation	Destination sustainability	Intra-relationship between stakeholders reveals the influence of networking on coopetition sustainability.
This research	Micro & macro	Among 2,090 peer-to-peer accommodations across 275 census tracts	Real data	Market commonality, supplier commonality, resource similarity	Price	Airbnb prices are determined by three coopetition antecedents with three types of spatially coopetitive dynamics (cooperation-dominated, competition-dominated, and balanced coopetition).

Table 2. Operationalization of variables and data sources

Variable	Operational definition	Data source
Peer-to-peer accommodation price	Average daily rate per Airbnb property from January 1, 2019 to December 31, 2019	AirDNA
Number of visitors	Number of total trips (more than 50 miles) per census tract	Florida Department of Transportation (Provided by AirSage)
Tourism resources	A composite index of tourism resources across 12 categories per census tract, including park tourism, theme park tourism, urban tourism, beach tourism, and others	Florida Department of Transportation
Airbnb rooms	Total number of Airbnb rooms per census tract	AirDNA
Hotel rooms	Total number of hotel rooms per census tract	STR
Number of bookings	Total number of bookings per Airbnb property from January 1, 2019, to December 31, 2019	AirDNA
Review volume	Total number of online reviews from January 1, 2019, to December 31, 2019	AirDNA
Airbnb age	Days since a property is registered on the Airbnb platform	AirDNA
Hotel price	The mean value of the average daily rates of hotels in a given census tract from January 1, 2019, to December 31, 2019	STR
Airport proximity	The distance (in thousand miles) between an Airbnb property and the nearest airport	Florida Geographic Data Library
Road distance	Total distance (in miles) of main roads within the census tract where an Airbnb property is located	Florida Department of Transportation
Census tract size	The size of the census tract where an Airbnb property is located (in 1,000 acres)	Florida Geographic Data Library

Table 3. Descriptive statistics and correlation coefficients.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Airbnb price	1.000											
(2) Visitors (unit: 1,000)	0.029	1.000										
(3) Airbnb rooms	0.174**	-0.038	1.000									
(4) Hotel rooms	0.152**	0.496**	0.015	1.000								
(5) Tourism resources	0.048*	0.413**	0.146**	0.599**	1.000							
(6) Number of bookings	-0.007	0.040	-0.040	0.018	0.094**	1.000						
(7) Review volume	-0.171**	0.039	-0.041	-0.029	0.096**	0.223**	1.000					
(8) Airbnb age	0.049*	0.071**	-0.038	0.064**	0.038	-0.129**	0.395**	1.000				
(9) Hotel price	0.139**	0.000	-0.020	0.167**	0.095**	-0.002	-0.057*	-0.007	1.000			
(10) Airport proximity (unit: 1,000 miles)	-0.031	-0.149**	-0.182**	-0.074**	0.051*	-0.001	0.052*	0.059**	0.053	1.000		
(11) Road distance	-0.055*	-0.083**	0.260**	-0.119**	0.533**	0.063**	0.062**	-0.023	-0.183**	0.243**	1.000	
(12) Census tract size (unit: 1,000 acres)	-0.036	-0.098**	0.051*	-0.049*	0.555**	0.079**	0.089**	0.001	-0.074**	0.356**	0.812**	1.000
<i>Number of observations</i>	2,090	2,090	2,085	2,085	2,085	2,090	2,090	2,090	1,279	2,090	2,085	2,090
<i>Mean</i>	180.016	1.763	547.580	547.560	0.143	13.090	30.240	946.220	219.868	18.399	1.568	4.283
<i>Minimum</i>	22.770	0.000	2.000	0.000	-0.216	1.000	1.000	274.000	36.000	3.639	0.000	0.000
<i>Maximum</i>	492.520	41.310	1771.000	3991.000	2.579	126.000	430.000	3628.000	725.000	52.301	30.939	607.453
<i>Standard deviation</i>	96.171	3.095	427.190	882.703	0.351	14.801	44.892	607.694	112.090	7.166	2.914	47.820

** $p < 0.01$, * $p < 0.05$.

Table 4. Estimates of OLS, SDM, and GWR models.

Variable	Model 1 (OLS)	Model 2 (SDM)	Model 3 (GWR)			VIF
			Min	Mean	Max	
Number of visitors (unit: 1,000)	-0.099	-0.167	-127.251	1.954	28.278	1.605
Tourism resources	-54.708**	-60.831**	-650.981	-6.525	816.710	3.570
Airbnb rooms	0.028**	0.135**	-2.634	0.023	2.638	1.399
Hotel rooms	0.019**	0.101**	-0.688	0.005	0.365	3.037
Number of bookings	0.425*	0.539**	0.094	0.242	2.011	1.120
Review volume	-0.514**	-1.262**	-0.635	-0.574	-0.251	1.322
Airbnb age	0.023**	0.798**	-0.097	0.026	0.029	1.253
Hotel price	0.099**	0.113**	-0.106	0.121	0.171	1.076
Airport proximity (unit: 1,000 miles)	-0.919*	-1.014**	-2.558	-1.025	0.586	1.233
Road distance	1.372	1.699	-38.004	0.272	9.198	2.006
Census tract size (unit: 1,000 acres)	-0.196	-0.316	-11.957	-1.499	18.383	1.392
W × Number of visitors		0.082				
W × Tourism resources		19.579*				
W × Airbnb rooms		0.195**				
W × Hotel rooms		0.082*				
W × Number of bookings		0.375**				
W × Review volume		-0.892				
W × Airbnb age		0.632				
W × Hotel price		0.241**				
W × Airport proximity		-0.732				
W × Road distance		-0.937				
W × Census tract size		-0.266				
Intercept	145.042	150.124	138.776	171.139	346.027	
R ²	0.116	0.195	0.270	0.297	0.571	
ρ		0.002*				
σ ²		0.021				

Note: For spatial weight, distance weight matrix (using kernel) and adaptive bi-square kernel are applied for Model 2 (SDM) and Model 3 (GWR), respectively. W denotes spatial weighting matrix, ρ denotes spatial lag effect, and σ² denotes maximum likelihood residual variance.

** $p < 0.05$, * $p < 0.1$.

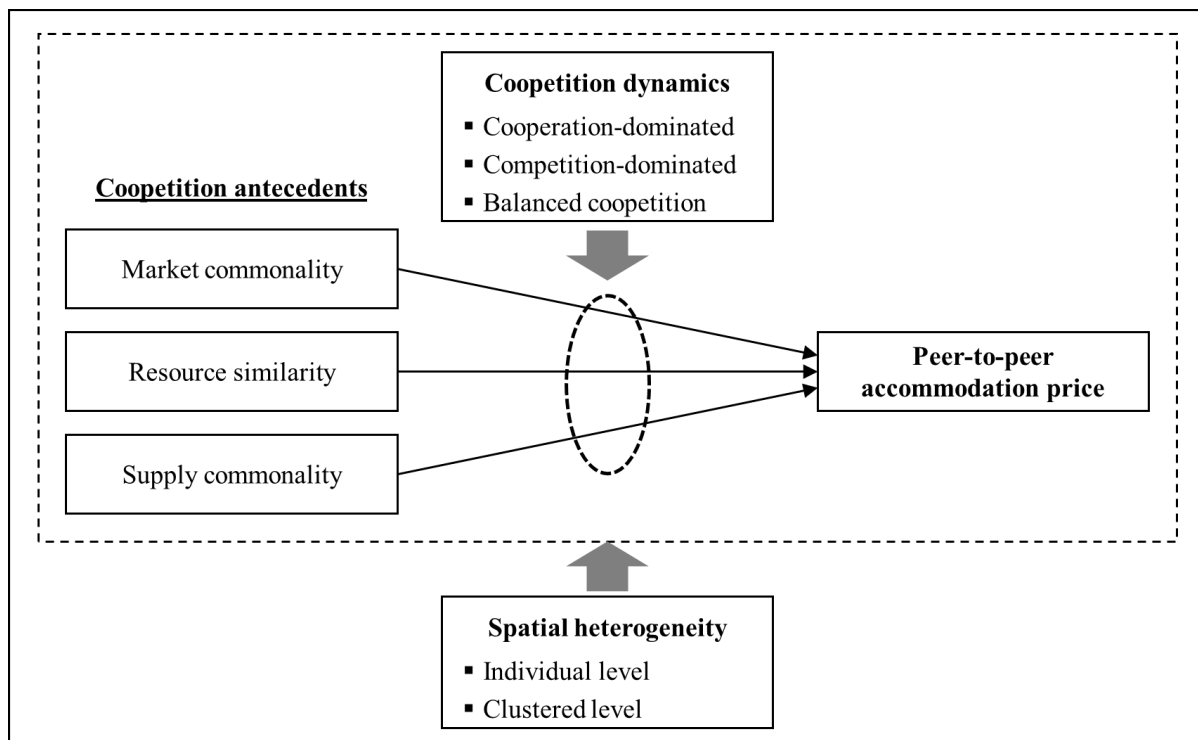


Fig. 1. Research model.

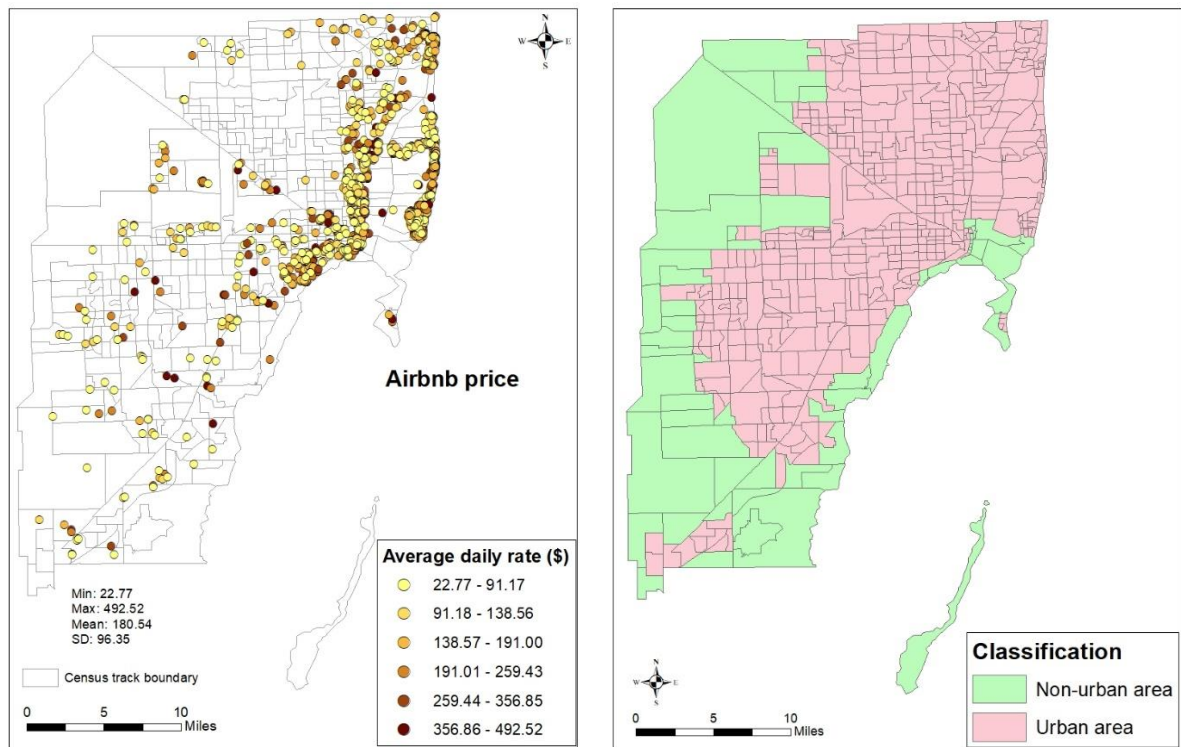
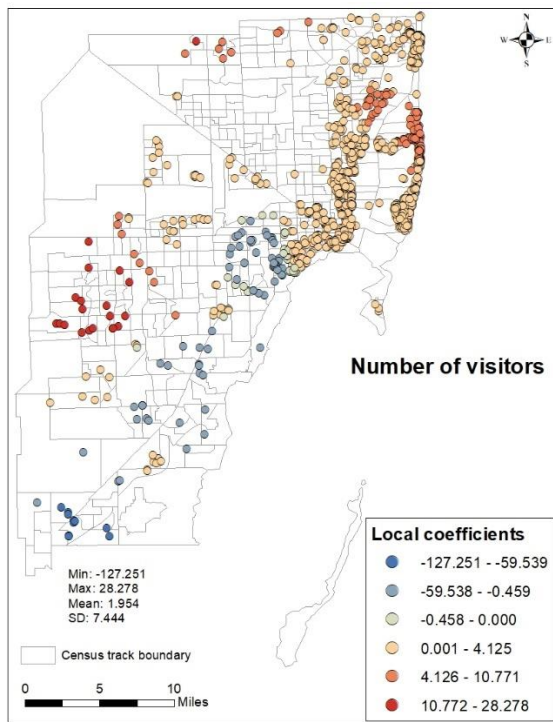
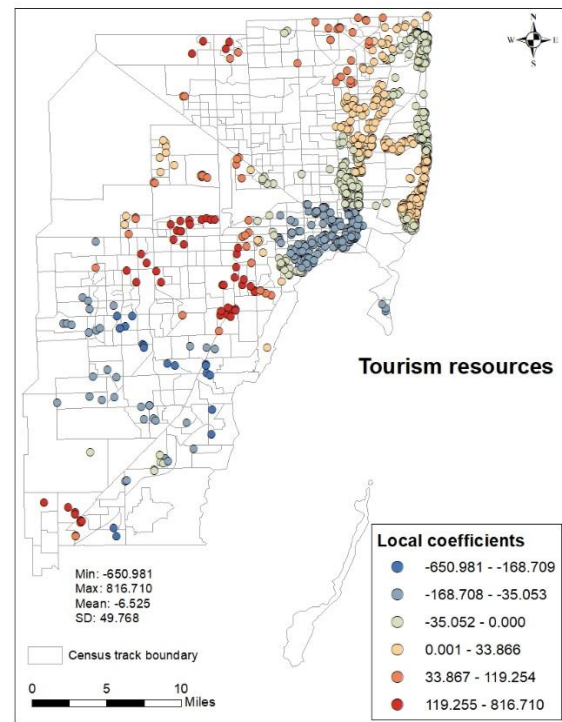


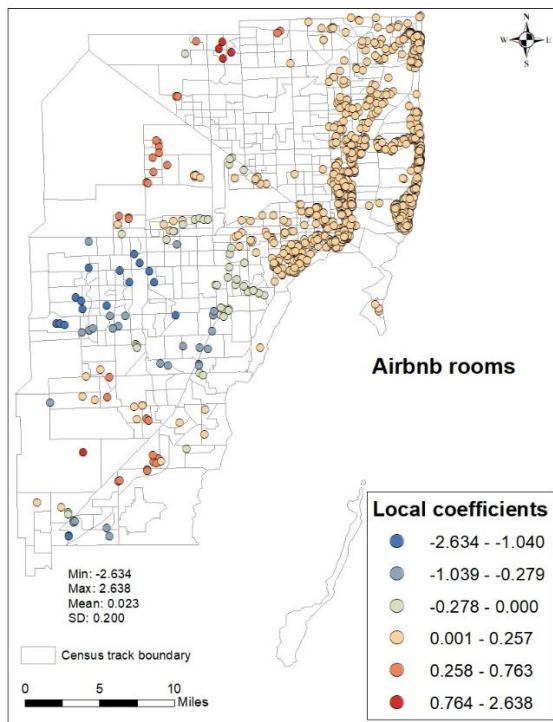
Fig. 2. Study area.



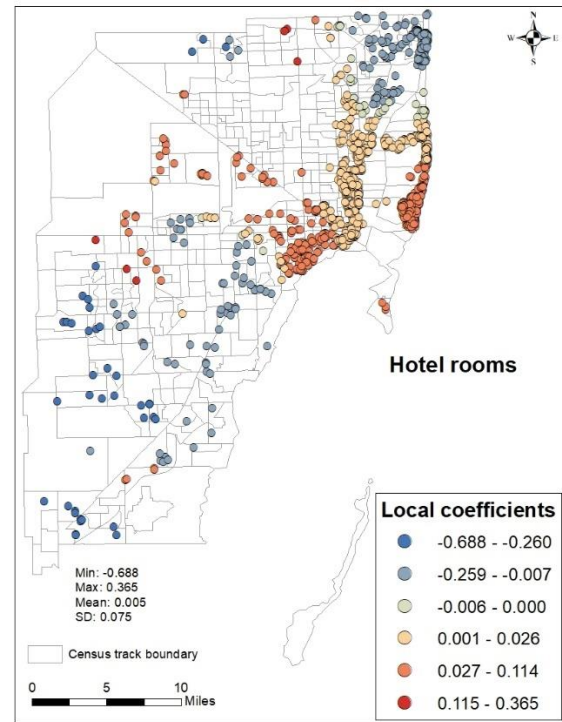
a. Number of visitors



b. Tourism resources

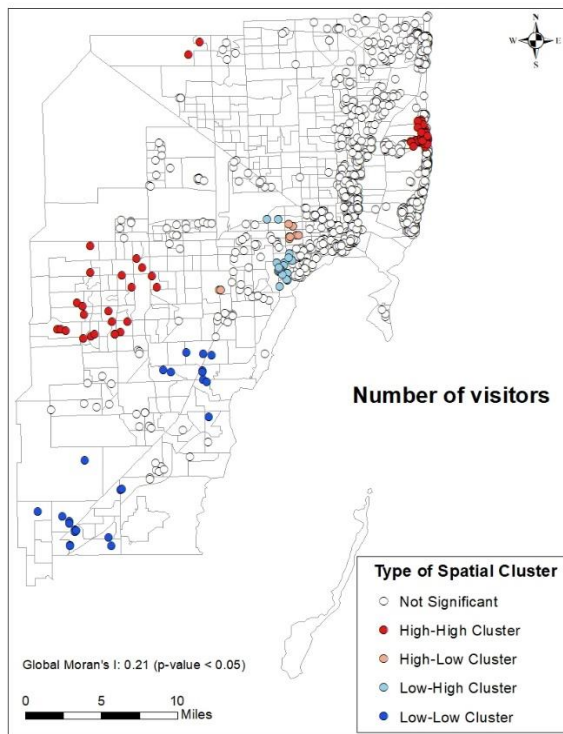


c. Airbnb rooms

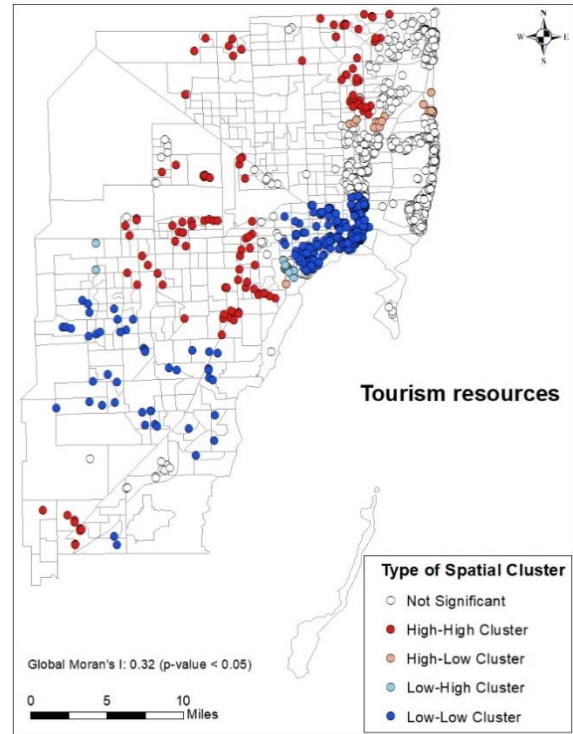


d. Hotel rooms

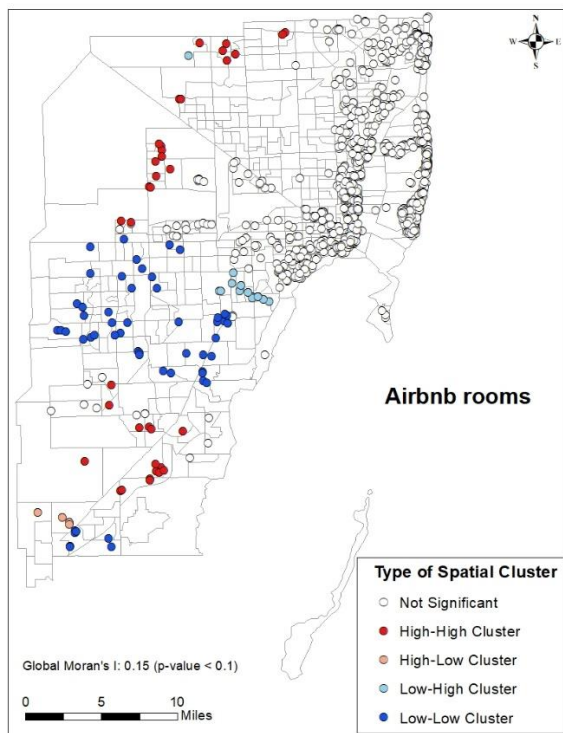
Fig. 3. Spatial distribution of local GWR coefficients (Variables of coopetition antecedents).



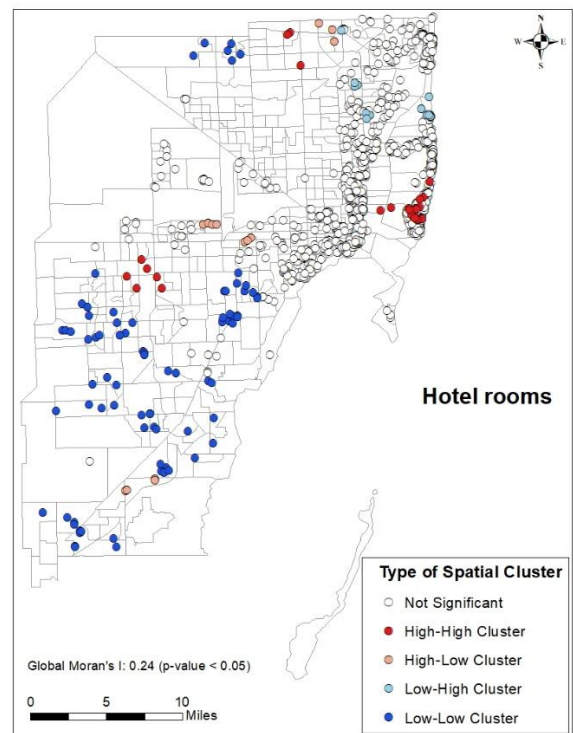
a. Number of visitors



b. Tourism resources



c. Airbnb rooms



d. Hotel rooms

Fig. 4. Spatial distribution of clustered local coefficients (Variables of coopetition antecedents).