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RESEARCH ARTICLE

COMPETING WITH THE SHARING ECONOMY: INCUMBENTS' REACTION ON REVIEW MANIPULATION[1]

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The emergence of the sharing economy has provided the market with an untapped wealth of supplies, posing a threat to incumbents. In response to competition from the sharing economy, incumbents must adjust their competitive strategies. In this paper, we focus our investigation on a nascent competitive strategy—consumer opinion manipulation—in the lodging sector of the hospitality industry. We examine two types of opinion manipulations through online reviews: promoting oneself and demoting one's competitors. Combining data from Airbnb, Expedia, TripAdvisor, AirDNA, the Texas Comptroller's Office, and Smith Travel Research, we estimate the impact of a new sharing economy entrant, Airbnb, on conventional hotels' manipulation strategies by exploring the supply variation of the competing Airbnb listings around each hotel. We find that, intriguingly, hotels tend to reduce mutual demotion when facing the common "enemy" of Airbnb competition. However, there is considerable heterogeneity among hotels in response to Airbnb competition. Low-end hotels tend to not increase their review manipulation activities for purposes of either self-promotion or demotion, while high-end hotels tend to demote competing hotels less and promote themselves more in the presence of higher levels of Airbnb competition.

Keywords: Sharing economy, online review manipulation, strategic groups

Introduction

The sharing economy presents a new economic system that uses technology-mediated platforms to match customers with service providers for fee-based exchanges such as short-term apartment rentals, car rides, or household tasks (Slee, 2016, p. 9). These platforms provide a convenient and inexpensive way for owners to make (potentially underutilized) goods or services available to consumers. Recent years have witnessed rapid growth in sharing economy companies. Prominent examples include Uber and Lyft in the transportation industry and Airbnb in the hospitality industry.

The emergence of such companies has the potential to significantly disrupt incumbents in traditional markets. Such companies represent a different type of competitor compared to traditional firms, requiring firms to revisit models of competition to account for the novelty of this expanded competitive landscape (Eckhardt et al., 2019). Ways in which traditional firms may need to adjust include pricing decisions (Li & Srinivasan, 2019; Zervas et al., 2017), branding (Bardhi & Eckhardt, 2012), product variety (Hughes, 2017), capacity management (Cramer & Krueger, 2016), regulatory reforms (Kemp, 2017), distribution channels (Tian & Jiang, 2018), and even creating their own sharing platforms (Wallenstein & Shelat, 2017). Given the plethora of possible responses, Eckhardt et al. (2019, p. 16) observe that "further research is needed to more fully assess the impact of sharing platform entry." They go on to note that the "response by traditional firms may vary across different types of product or service categories as well as by a firm's standing in an industry."

In our work, we investigate a nascent competition strategy—consumer opinion manipulation via online review

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platforms—in the lodging sector of the hospitality industry. This represents an ideal sector for examining the impact of the sharing economy because of the advent of Airbnb. Airbnb's platform allows hosts to list their properties for rent to guests at a price set by the hosts and accrues revenues by charging service fees from both hosts and guests. Airbnb has experienced rapid growth since its launch in 2008. As of June 2021, Airbnb hosts over 5.6 million listings in more than 100,000 cities.[2] As of October 2021, Airbnb has a market cap of more than $100 billion, exceeding several major hotel chains such as Marriott and Hilton.[3]

Online reviews have become an influential source of information for helping customers make purchase decisions (e.g., Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Zhu & Zhang, 2010), especially in the hospitality industry (Ye et al., 2011). In fact, customer reviews are generally considered to be more credible than promotional campaigns (Bickart & Schindler, 2001; X. Lu et al., 2013). Online reviews are especially critical when competing with the sharing economy; such technology-mediated platforms enable strangers to transact with each other, adding importance for online reviews as a means to establish trust between customers and service providers.

Recognizing the importance of online reviews in competing for potential customers, many firms have resorted to manipulating reviews (e.g., He et al., in press; Tibken, 2013). In the context of the conventional lodging business, Mayzlin et al. (2014) have demonstrated that hotels with neighboring competing hotels tend to demote each other more. It has also been established that firms are more likely to engage in manipulation when competition intensifies (Luca & Zervas, 2016; Mayzlin et al., 2014). The success of Airbnb is taking a toll on the incumbents in the disrupted lodging business, who are forced to constantly respond to the competition. For example, Zervas et al. (2017) document that hotels have responded to the entrance of Airbnb by reducing prices.

Since Airbnb continues to intensify the competition in the lodging business, and research has shown that competition motivates hotels to engage in review manipulation, we ask whether hotels change their review manipulation strategies in response to the emergence of Airbnb in their market and question whether this is exacerbated in response to Airbnb growth. We draw on *strategic group theory* (e.g., Cool & Schendel, 1987; Fiegenbaum & Thomas, 1995; Mas-Ruiz et al., 2014) to frame our questions. The theory helps explain how the nature of competition between Airbnb properties and hotels differs from that among hotels themselves, e.g., in terms of product or service types, promotional channels, locations, and review channels. These differences have important implications for the review manipulation strategies used by incumbent hotels. Does the different nature of competition posed by the sharing economy lead incumbents to change their review manipulation activities? Specifically, the research question we address is whether and how conventional hotels change their review manipulation behaviors in response to the emergence and growth of Airbnb in their market. We examine two types of manipulation strategies, *self-promotion* and *demotion*. We further investigate whether changes in manipulation behaviors are heterogeneous across different categories of hotels (i.e., high-end and low-end hotels).

We empirically examine the review manipulation level that a hotel engages in as a function of the supply of its nearby Airbnb listings. We do this by analyzing a unique panel data of 2,188 hotels extracted from six different sources—Airbnb, TripAdvisor, Expedia, AirDNA, the Texas Comptroller's Office, and Smith Travel Research (STR).[4] We find that the supply of nearby Airbnb listings indeed exerts a significant impact on hotels' review manipulation strategies and that such impacts are not homogeneous across different types of hotels. Our main results reveal that high-end hotels promote themselves more after Airbnb penetrates their market; surprisingly, they demote each other less following the entry of Airbnb. Low-end hotels do not increase their self-promotion or demotion behaviors as Airbnb becomes more popular. Our findings suggest that the disruptive innovations from sharing economy companies change the dynamics of competition among the incumbents in unexpected ways. These findings are aligned with predictions from strategic group theory.

Our work contributes to the growing literature on the impact of the sharing economy on traditional incumbents by demonstrating how the emergence of Airbnb changes hotels' review manipulation strategies. Our findings have interesting implications both for review-hosting platforms like TripAdvisor as well as their end-users. With the understanding that increased Airbnb supply drives high-end hotels to self-promote more while reducing their demotion activities, review platforms could potentially adjust their fake-review filtering algorithms to account for both Airbnb supply near a hotel and the type of the hotel. Our results suggest that customers frequenting high-end hotels should take extra care when using reviews to help them decide where to stay, e.g., by discounting overly positive reviews for these hotels.

[2] https://www.airbnb.com/about/about-us (accessed December 11, 2021).
[3] https://companiesmarketcap.com/hotels/largest-hotel-companies-by-market-cap/ (accessed December 11, 2021)

[4] We thank AirDNA, Smith Travel Research (STR) and the Texas Comptroller's Office for graciously sharing their data with us.

Theoretical Framework

We outline the main empirical questions addressed in the paper and discuss the theoretical rationale underpinning each question.

Incentives to Manipulate Reviews

Customer reviews have been found to be important drivers of consumers' purchase decisions (e.g., Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Ye et al., 2011; Zhu & Zhang, 2010). As a result, reviews play an important role in shaping customer opinions, and firms routinely monitor and manage them as an integral part of their marketing strategy (Dellarocas, 2006; Yang et al., 2019). Because of the importance of online reviews for businesses, firms may even attempt to manipulate customer opinions by disguising self-promotion as customer recommendations (Mayzlin, 2006).[5] Research has shown that many firms resort to manipulating reviews (e.g., He et al., in press; Tibken, 2013). Consequently, it is not uncommon to encounter fake (manipulated) reviews on review websites like TripAdvisor and Yelp (Lappas et al., 2016). For example, more than 50,000 Chinese retailing accounts were suspended from Amazon in 2021 because of review manipulations, costing these third-party merchants an estimated $15.4 billion (Einhorn et al., 2021). Despite the commitment to combating fraud using filtering algorithms and legal actions (Marinova, 2016), a significant portion of online reviews have been found to be fake. The percentage of fake reviews is estimated at around 15% to 30% despite the best efforts of review platforms to combat fake reviews (Belton, 2015; Lappas et al., 2016; Luca & Zervas, 2016).

Review manipulation occurs in two different ways: self-promotion and demotion. Firms promote themselves by posting fake positive reviews, a phenomenon that has been scrutinized in the popular press. For example, in February 2004, due to a software error, Amazon.com's Canadian site mistakenly revealed the identities of book reviewers and a number of these reviews were found to be written by the books' own publishers and authors. For example, it was found that Dave Eggers, the author of *A Heartbreaking Work of Staggering Genius*, posted positive reviews for his own book to inflate its rating (Harmon, 2004). Similarly, Luca and Zervas (2016) found that a restaurant is more likely to self-promote after receiving negative reviews. Mayzlin et al. (2014) observe that independent hotels tend to promote themselves more than chain-affiliated hotels.

Besides promoting themselves, firms may demote their competitors by posting negative reviews. Consumers are found to respond more to negative reviews than to positive reviews (Chevalier & Mayzlin, 2006). Therefore, firms may be inclined to post disingenuous negative reviews for its competitors, especially when their products are strong substitutes. For example, Luca and Zervas (2016) found that a restaurant is more likely to demote other restaurants when facing increased competition. In the lodging business, before Airbnb became popular, Mayzlin et al. (2014) documented that hotels with nearby competitors are more likely to receive fake unfavorable reviews than those without competitors in the neighborhood.

The incentives to manipulate reviews may also depend on the firm's own quality as demonstrated in two analytical modeling papers. Mayzlin (2006) argued that producers with lower quality will expend more resources on manipulating reviews. On the other hand, Dellarocas (2006) showed that an equilibrium exists where the high-quality producer will invest more resources in review manipulation. Both papers assume that posting negative reviews about one's competitor is qualitatively equivalent to posting positive reviews about oneself, without differentiating self-promotion from demotion.

However, self-promotion and demotion may impact consumers in different ways. Leading review platforms such as Yelp and TripAdvisor consider both the quality and quantity of reviews when ranking search results. Lappas et al. (2016) use simulations to show that the relative effectiveness of self-promotion and demotion in influencing a hotel's visibility varies depending on how consumers form their consideration sets. They posit that self-promotions are more effective when consumers consider only the top few choices in ranked results to form their consideration sets, while demotions are more effective when customers are willing to search further down the list.

In summary, hotels have incentives to manipulate reviews; further, it has been established that they engage in such practices and that they manipulate more in the face of fiercer competition. Further, hotels may utilize self-promotion and demotion differently, and manipulation actions may be heterogeneous across hotel types.

Identification of Review Manipulation

Identifying manipulative reviews is nontrivial. Several algorithms based on text mining have been developed to detect fake reviews (Jindal & Liu, 2008; Kumar et al., 2018;

[5] Mayzlin (2006) refers to such behavior as promotional chat.

Li et al., 2014) with varying degrees of success. Review websites like Yelp screen reviews using their proprietary algorithms.[6] Despite such endeavors, it remains a challenging task for a website to accurately detect fake reviews since manipulated reviews are designed to mimic truthful reviews. As mentioned earlier, a substantial number of fake reviews show up on review platforms despite the use of filtering algorithms. Since we lack ground truth regarding which reviews are genuine and which ones are fake, we do not use text mining approaches to classify reviews as fake or not. Instead, we use the identification approach proposed by Mayzlin et al. (2014). Their approach exploits the different regulations for users to post reviews between the two travel websites—TripAdvisor and Expedia. TripAdvisor allows any user, whether a real customer or not, to post reviews. Expedia, on the other hand, only allows customers who have stayed in a hotel (either booked through Expedia or its partners) to post reviews for the hotel on its site. Therefore, review manipulations will be more likely to occur on TripAdvisor's site than Expedia's because of the lower costs associated with fabricating a fake review on TripAdvisor. Thus, for hotels, the difference in review ratings between the two review platforms offers an indication of the level of review manipulation. Mayzlin et al. (2014) consider both the self-promotion type of review manipulation as well as demotion by competitors. Self-promotion activities are identified by examining the difference in the proportion of reviews with high ratings (5-star ratings) on TripAdvisor as opposed to Expedia, while demotion levels are identified using the net proportion of reviews with low ratings (1-star and 2-star ratings).

Strategic Group Lens

As of September 2021, Airbnb had hosted over 1 billion guest arrivals.[7] Similar to the way in which the sharing economy has changed car owners to Hertz competitors (Stein, 2015, p. 34), Airbnb has transitioned certain homeowners from persons with homes to hotel competitors. The encroachment of Airbnb listings into the territory of traditional hotels is clearly taking a toll on incumbent hotels. While the impact of Airbnb on hotel prices has been previously examined (Li & Srinivasan, 2019; Zervas et al., 2017), the competitive reactions of incumbent hotels in terms of review manipulation have not.

We draw on the theory of strategic groups, a central construct in the strategy literature, to examine the competitive behavior of firms in a market (e.g., Cool & Schendel, 1987; Fiegenbaum & Thomas, 1995; Short et al., 2007). Porter (1979) formalizes the notion of a *strategic group* as a group of firms in an industry that closely compete against each other and are similar to one another along key strategic dimensions (e.g., degree of vertical integration and investment in advertising and R&D). Fiegenbaum and Thomas (1995) note that a strategic group establishes a reference point for group members when they make strategic decisions. Strategic group theory has been widely used to study how firms compete in an industry (e.g., Mas-Ruiz et al., 2014; Mas-Ruiz & Ruiz-Moreno, 2011; Short et al., 2007).

Even though competition from Airbnb substitutes the demand for a hotel (akin to competition from another hotel), this does not mean that Airbnb's entry is identical to that of other competing hotels. Airbnb and hotels are quite different in terms of their asset bases, cost structures, and other dimensions of their strategic profiles, which are typically used to distinguish strategic groups (Peteraf, 1993). As a result, the competition from Airbnb and the competition from hotels are quite different.

To begin with, the offerings are quite different across these two types of providers. For example, hotels often need to provide amenities like meeting rooms, conference facilities, shuttle services, and gyms. These are typically not part of Airbnb listings. On the other hand, Airbnb listings often offer amenities such as full kitchen and laundry facilities, cozy living and dining areas, and local knowledge from Airbnb hosts. There is also a wide variety of Airbnb listings (e.g., treehouse, tent, and recreational vehicle) to accommodate travelers' unique preferences compared to the relatively standardized offerings from hotels (Kelleher, 2019). Importantly, because Airbnb does not own the physical properties it provides access to, its asset base is very different from that of traditional hotels. Instead, Airbnb's key assets are the underlying information technologies that enable effective transactions between hosts and guests.

The cost structures of hotels and Airbnb are very different as well. Hotels cannot quickly change their supply because of the long lead time needed for construction and employee training. In contrast, Airbnb can expand supply almost overnight, as demonstrated in the context of seasonal events like the SXSW festival in Austin, Texas (Zervas et al., 2017). Thus, Airbnb can better accommodate volatile demand because of the low capital costs necessary to add (or remove) marginal capacity (Li & Srinivasan, 2019). The regulation and compliance costs that Airbnb and hotels face are also different. Hotels must comply with a litany of health, safety, and zoning rules, in addition to registering with local agencies and paying taxes and other fees (Martineau, 2019). The regulations that Airbnb faces in different cities, if any, are mostly directed toward mitigating neighborhood impact rather than creating a level

[6] http://www.yelp-support.com/article/Why-would-a-review-not-be-recommended (last accessed December 11, 2021)

[7] https://news.airbnb.com/about-us/ (last accessed December 11, 2021).

playing field in the hospitality industry (Nieuwland & van Melik, 2020). Another driver of the existence of strategic groups is the presence of features that serve as mobility barriers across the two groups (Mas-Ruiz et al., 2014; Porter, 1979). The different regulations that apply, respectively, to hotels and Airbnb properties make it difficult for an entity to transition from one group to the other.

Because of these differences, the important strategic considerations and related actions of hotels and Airbnb are also quite different. For hotels, long-term strategic decisions include factors such as physical location, capacity, and the quality of accommodations; short-term decisions include pricing and promotional activities (Kim, 2018). Hotels typically locate their properties in pockets of local density, such as downtown areas. For pricing decisions, hotels must pay considerable attention to location, season, day of week, and other factors so that they can dynamically set prices for their offerings to maximize revenues. In contrast, an important long-term strategic imperative for Airbnb is to ensure that its platform attracts healthy participation from both hosts and guests, thereby generating strong network effects. To promote this, algorithms matching potential guests with hosts are an important aspect of Airbnb's growth strategy. Also, since guests and hosts typically do not know each other in advance, building trust between them is a very important consideration (Edelman & Luca, 2012). The platform uses a two-sided review system (reputation system) to alleviate such concerns (Proserpio et al., 2018). As far as revenues are concerned, Airbnb sets the commission fee rate for hosts and guests transacting on its system and provides complete flexibility to hosts in setting prices for their listings. All these considerations exemplify the different strategic behaviors of hotels and Airbnb.

Airbnb's Impact on Hotels' Review Manipulations

Strategic group theory asserts that firms within the same group recognize their mutual dependence and follow similar strategies in response to market opportunities or threats (e.g., Mas-Ruiz & Ruiz-Moreno, 2017; Porter, 1979). Cool and Dierickx (1993) noted that changes in the strategic group structure could lead to a shift from within-group rivalry to between-group rivalry. In our context, such a shift to between-group competition is expected to occur when incumbent hotels face competition from Airbnb listings.

The issue of central interest here is how competition from Airbnb led the incumbent group of hotels to adjust their review manipulation strategies (over and above their reaction to conventional dimensions such as price adjustment and lobbying). Importantly, the respective review platforms for hotels and properties listed on Airbnb differ in important ways. Reviewers evaluate Airbnb listings through Airbnb's own website whereas conventional review platforms such as Expedia, TripAdvisor, and Yelp do not include reviews for Airbnb listings.[8] Airbnb only allows users who have stayed at a property to post reviews for that property, and it stipulates a bilateral review system where the host also reviews guests (Proserpio et al., 2018). Therefore, reviewers are not anonymous to Airbnb.com, making reviewers identifiable. Further, a typical Airbnb listing likely comprises only a few rooms. The demand implications for a focal hotel from a new hotel competitor would be equivalent to that from a fairly large collection of neighboring Airbnb listings. This makes the economics of faking reviews for nearby Airbnb listings relative to that for a competing hotel markedly different, with the costs of manipulating reviews (i.e., by demoting competitors) an order of magnitude higher when dealing with competition from Airbnb listings. Thus, incumbent hotels cannot counter between-group competition from Airbnb listings by demoting them in the same way as is possible when dealing with competition from other hotels (i.e., within their own strategic group).

While recognizing that "strategic group membership is a predictor of the manner by which firms compete with one another" (Smith et al., 1997, p. 156), the literature is silent regarding how the emergence of a new strategic group could impact rivalry within an existing group. With the emergence of Airbnb listings, would hotels change their review manipulation strategies targeted toward other hotels? On the one hand, when Airbnb takes away a portion of demand from hotels, the rivalry between hotels should become more intense and the reaction across hotels may be to "instigate warfare" (Smith et al., 1997, p. 151). In our context, this implies that hotels may be incentivized to demote competing hotels more in order to seize a larger share of the remaining demand. For instance, it has been shown in both the hotel and restaurant industries (Luca & Zervas, 2016; Mayzlin et al., 2014) that demotion activities intensify in response to an increased number of conventional competitors.

On the other hand, competing hotels now face Airbnb as a common rival. As an ancient proverb goes: "the enemy of my enemy is my friend"; thus, competing hotels may find it beneficial to work together to fight against the common new enemy. There is considerable evidence that incumbents do team up to fight against sharing economy competition. For example, taxi companies have teamed up to fight Uber by taking collective legal actions against Uber's lack of regulations

[8] We observe that a very small portion of Airbnb listings are cross-listed on both Airbnb and TripAdvisor. Zervas et al. (2021) found that out of 466,000 properties on TripAdvisor and 381,000 listings on Airbnb, only around 2,000 properties (0.5%) were cross-listed.

(Goldstein, 2018). In the lodging business, the American Hotel and Lodging Association (AHLA), a trade group that oversees Marriott International, Hilton Worldwide, and Hyatt Hotels, has not taken Airbnb's incursions lightly. According to *The New York Times*, AHLA has backed efforts by the Federal Trade Commission and the state of New York to investigate Airbnb's impact on local housing prices since 2016 (Benner, 2017). The AHLA has also launched a campaign to portray Airbnb hosts as being commercial operators competing illegally with hotels (AHLA, 2017). Hotels collectively funded an anti-Airbnb mailer that claims that Airbnb has made local housing less affordable (Bredderman, 2018).

The literature on strategic groups recognizes that firms within a group may not always compete intensely with other firms in their own group. As noted by Porter (2008, p. 17), "if moves and counter moves escalate, then all firms in the industry may suffer." Indeed, it has been suggested that rivalry in such cases will be lower within a group because firms are better able to recognize their mutual dependence and thus cooperate or tacitly collude with one another (Caves & Porter, 1977; Peteraf, 1993). Tit-for-tat competitive interactions within the same group can be unstable and destructive (Smith et al., 1997). In our context, this means that mutual demotion between incumbent hotels might be counterproductive for all hotels.[9] Therefore, hotels demoting competing hotels may be wary of retaliation that could end up hurting the hotels altogether since consumers are able to switch to Airbnb alternatives. Thus, strategic group theory suggests that co-opetition rather than tit-for-tat is a viable choice for members of the same group when between-group competition exists. In our context, this amounts to incumbent hotels becoming less incentivized to demote each other in the presence of Airbnb competition.

If increasing mutual demotion is not an effective choice in such cases, what other review manipulation actions can incumbents take? One possibility is to self-promote more. According to Porter (2008a, p. 84), "if an industry does not distance itself from substitutes through product performance, marketing, or other means, it will suffer in terms of profitability—and often growth potential." Therefore, when competition resulting from Airbnb listings intensifies, hotels may need to self-promote more to better differentiate themselves; for example, such self-promotions could highlight the unique amenities offered by a hotel. Since Airbnb has shrunk the collective demand for hotels (Zervas et al., 2017), a hotel may need to bolster its self-promotion actions to fight other hotels for the shrinking demand.

The level of self-promotion may also depend on the nature of the ratings received. Luca and Zervas (2016) found that a firm receiving more negative reviews tends to self-promote more. Their finding also suggests that hotels might self-promote less if hotels receive fewer negative reviews. Two reasons may contribute to fewer negative reviews. One, as already discussed, hotels may demote each other less in response to the emergence of the common rival Airbnb. Second, customers whose needs are better suited to Airbnb listings (e.g., the cost of meals and rooms for a family of four may be significantly higher for hotels compared to Airbnb listings, see McCool, 2015) would be more likely to prefer such properties resulting in fewer poor ratings for hotels. In summary, it will be interesting to explore which of these counteracting forces dominates in the lodging business in the face of Airbnb competition.

Differential Impact on Hotel Types

The literature on quality signaling postulates that high-quality firms are expected to spend more advertising resources than low-quality firms to promote their products, where advertising serves as a credible signal of quality (see, e.g., Kihlstrom & Riordan, 1984). In the lodging business, Hollenbeck (2018) found that online reviews have emerged as a new type of quality signal. Due to the importance of online reviews, it has been documented that firms manipulate online reviews to realize financial gains (Luca & Zervas, 2016; Mayzlin et al., 2014). However, it is unclear whether high-end hotels and low-end hotels would respond similarly to competition from Airbnb listings.

Vertically differentiated firms (i.e., high-end vs. low-end) often need to choose different competitive strategies that are suitable for their needs. Michael Porter (2008b) posited that firms in the low-cost position are better off utilizing the "overall cost leadership" strategy to remain profitable after their competitors have competed away their profits. In contrast, firms at the higher end may adopt a "differentiation" strategy by providing unique products or services, enhancing customers' brand loyalty, and lowering their price sensitivity. For hotels, this implies that low-end hotels and high-end hotels may employ different strategies to counter competition.

[9] Along similar lines, the balance theory proposed by Heider (1958) conceptualizes a motive called "cognitive consistency," which drives the formation of friend and enemy relationships. Balance theory is aligned with the *tertius iungens* strategic orientation where a newcomer facilitates new coordination between incumbents (Obstfeld, 2005). The predictions from these theories are essentially the same as the prediction from strategic group theory in our context.

Regarding the nature of review manipulation in particular, Lappas et al. (2016) showed that the relative effectiveness of self-promotion or demoting others depends on the size of consumers' consideration sets, which could differ for different types of hotels. Also, firms have been found to increase their self-promotion to counter negative reviews (Luca & Zervas, 2016). Since the average ratings for low-end hotels are generally lower than those for high-end hotels, low-end hotels may need to self-promote more.

With regard to demotions, firms may increase such activities when facing intensified competition (Luca & Zervas, 2016; Mayzlin et al., 2014). That is, if the competition is more intense for one type of hotel compared to another because of the advent of Airbnb, then this type of hotel may be more likely to increase demotion activities. Zervas et al. (2017) have shown that while all hotels' revenues are negatively influenced by Airbnb, low-end hotels suffer more compared to high-end ones. Accordingly, we may expect low-end hotels to be more responsive to the challenge posed by Airbnb.

These studies suggest that different types of firms may adopt different self-promotion and demotion strategies, but how the quality dimension of firms plays a role remains unresolved. Because of the different forces leading to conflicting observations, it is unclear which one would dominate as Airbnb gains more popularity and whether the outcomes would be the same for different hotel types. To address this, we investigate Airbnb's impact on the change in review manipulation behavior for low-end and high-end hotels separately.

In summary, we ask whether the emerging competition from the sharing economy leads incumbents to manipulate reviews differently. Specifically, we examine whether hotels engage in more review manipulation (i.e., self-promotion and demotion) when facing the new type of competition presented by Airbnb. We also examine whether the change in review manipulation behavior is homogeneous across different types of hotels. The rapid emergence of the sharing economy provides an ideal opportunity to study these new competition dynamics across incumbent hotels.

Data

We obtained and synthesized data from six different sources: Airbnb.com, Expedia.com, TripAdvisor.com, AirDNA.co, Smith Travel Research (STR), and the Texas Comptroller's Office (comptroller.texas.gov). Each source provides complementary data items for our analyses.

We conducted analyses for hotels in the state of Texas. All data collected are from the period between January 2008 (the year of Airbnb's inception) to December 2015. We restricted our attention to hotels in cities with a population of over 50,000, as the number of hotels and Airbnb listings is typically low in smaller cities. There were 67 cities in Texas meeting this requirement for the period under consideration.[10] We wrote Python crawlers to scrape the review data on all hotels in these cities from the TripAdvisor and Expedia sites. We obtained the review ratings and review dates from each site. Expedia provides a link to each hotel's TripAdvisor page (if it exists). Therefore, matching the hotels on these two websites is straightforward. The STR Texas census data include the name, price tier, and address for each hotel. Based on STR's price tier information, we considered two categories of hotels: low-end (or budget hotels) and high-end (non-budget hotels).[11] The Texas Comptroller's Office provides public records on quarterly hotel tax filing records for all the hotels in the state of Texas,[12] in addition to hotel names and addresses. We identified the period of each hotel's operation based on tax filing records. We matched all the hotels identified on TripAdvisor and Expedia with their corresponding entries in the data provided by STR and by the Texas Comptroller's Office using the hotels' names and addresses. Because the tax filing data is available on a quarterly basis, our unit of analysis is the *hotel quarter*, i.e., the quarterly information for hotels in terms of reviews, competitors, etc.

In order to determine the extent of competition faced by a hotel from Airbnb, we wrote Python programs to collect all Airbnb listings from the cities identified (parts of the data, such as historical prices, are obtained from AirDNA.co). We recorded the location and the host's registration information on 14,922 distinct listings on Airbnb's website. Following prior research (e.g., Zervas et al., 2017), we used the host's registration date as the time a listing became available.

To match hotels with competing Airbnb listings, we calculated the distance between them based on the latitude and longitude of each hotel (available on Expedia.com) and that of each Airbnb listing (available in the HTML file for each listing on Airbnb.com). In accordance with Mayzlin et al. (2014), we identified competing properties (hotels as well as Airbnb listings) as those within a 1-kilometer radius of a focal

[10] https://en.wikipedia.org/wiki/List_of_cities_in_Texas_by_population (last accessed December 11, 2021).

[11] To reflect the different demand across cities, STR categorizes hotel tiers using different price brackets for different cities. The price brackets used in different markets are not available to us. But the results are robust to change of cutoff points for high-end versus low-end hotels

[12] https://comptroller.texas.gov/transparency/open-data/search-datasets/ (last accessed December 11, 2021).

hotel.[13] To control the level of competition from traditional hotels, we counted the number of competing hotels of the same type (i.e., low-end or high-end) for the focal hotel in each quarter. Likewise, we counted the number of distinct listings that appeared on Airbnb by that quarter to identify the level of competition resulting from the sharing economy. Our data consisted of 2,188 hotels that received reviews on both the TripAdvisor and Expedia websites. Three cities were dropped because none of the hotels in these cities received any reviews, leaving us with hotels from 64 cities. Hotels in 10 of the 64 cities did not have any competing Airbnb presence. Overall, 48% of hotels had at least one Airbnb competitor. Among all the cities included in our data, Houston had the largest number of hotels with 333, while McKinney had only one hotel. Table 1 provides summary statistics for the data.

Empirical Strategy

Identifying Review Manipulation

We identified review manipulations following Mayzlin et al.'s (2014) measure of self-promotion as the difference in the share of 5-star reviews on TripAdvisor (TA) and Expedia (EXP), respectively, for hotel *i* in year-quarter *t*:

$$\text{SelfPromotion}_{\text{it}} = \frac{\text{5Star Reviews}_{\text{it}}^{\text{TA}}}{\text{Total Reviews}_{\text{it}}^{\text{TA}}} - \frac{\text{5Star Reviews}_{\text{it}}^{\text{EXP}}}{\text{Total Reviews}_{\text{it}}^{\text{EXP}}}.$$

Similarly, they measure demotion as the difference in the share of 1-star and 2-star reviews on TripAdvisor and Expedia:

$$\text{Demotion}_{it} = \frac{\text{1Star Reviews}_{it}^{\text{TA}} + \text{2Star Reviews}_{it}^{\text{TA}}}{\text{Total Reviews}_{it}^{\text{TA}}} - \frac{\text{1Star Reviews}_{it}^{\text{EXP}} + \text{2Star Reviews}_{it}^{\text{EXP}}}{\text{Total Reviews}_{it}^{\text{EXP}}}.$$

One nuance is that in our sample, the average TripAdvisor (Expedia) rating was 3.0 (3.1) for low-end hotels and 4.0 (4.1) for high-end hotels. A 4-star rating could still promote an average low-end hotel but not an average high-end hotel. Therefore, the aforementioned measures of self-promotion and demotion are reasonable proxies of review manipulation for high-end hotels. For low-end hotels, however, we considered both 4-star and 5-star ratings as potential promotions and 1-star ratings as demotions. Thus, for a low-end hotel:

$$\text{SelfPromotion}_{it} = \frac{\text{4Star Reviews}_{it}^{\text{TA}} + \text{5Star Reviews}_{it}^{\text{TA}}}{\text{Total Reviews}_{it}^{\text{TA}}} - \frac{\text{4Star Reviews}_{it}^{\text{EXP}} + \text{5Star Reviews}_{it}^{\text{EXP}}}{\text{Total Reviews}_{it}^{\text{EXP}}}.$$

$$\text{Demotion}_{it} = \frac{\text{1Star Reviews}_{it}^{\text{TA}}}{\text{Total Reviews}_{it}^{\text{TA}}} - \frac{\text{1Star Reviews}it^{\text{EXP}}}{\text{Total Reviews}_{\text{it}}^{\text{EXP}}}.$$

Note that this demotion measure popularized by Mayzlin et al. (2014) only captures how a focal hotel is demoted. This measure is passive, in that a focal hotel does not directly control whether or how competing hotels demote it. In contrast, our interest is in understanding the review manipulation strategy in which a focal hotel actively engages. We thus propose and construct a measure to capture the level at which a focal hotel demotes other competing hotels as follows: (1) identify all the competitors for a focal hotel from the same category; (2) for each competitor, calculate the number of demoting reviews it receives ($\text{Demotion}_{it} \times \text{Total Reviews}_{it}^{\text{TA}}$); (3) attribute the demoting reviews evenly to the competitor's other competitors (of which the focal hotel is one);[14] and (4) take the average of the demoting reviews on competing hotels that are attributed to the focal hotel. We refer to this measure of review manipulation as $\text{DemotingOthers}_{it}$. Therefore, this measure differs from the demotion measure in Mayzlin et al. (2014) in that they capture the level of demotion received by a focal hotel instead of demotion activities pursued by the focal hotel.

At the aggregate level, TripAdvisor ratings increased while Expedia average ratings remained relatively flat during our observation period (Figure A1 in Appendix A). When differentiating hotels, we found that low-end hotels have relatively stable proportions of negative and positive ratings (relatively flat over time), while high-end hotels exhibit increasing proportions of positive ratings but decreasing proportions of negative ratings on TripAdvisor (Figure A2 in Appendix A).

Econometrics Analyses

To identify the impact of Airbnb on hotels' review manipulation behavior, we exploited the variability in the number of competing Airbnb listings with respect to each focal hotel (we refer to the number of competing Airbnb listings as *Airbnb supply*).

[13] In addition to using a fixed distance threshold, we also report in Appendix E the results of a robustness check where we use Gaussian kernels to model a gradual decrease in competition intensity as distance grows.

[14] We also conduct a robustness check by attributing the demoting reviews based on hotels' proximity (in terms of geographical distance). The results, discussed in Appendix E, are qualitatively similar.

Table 1. Summary Statistics at the Hotel-Quarter Level

	Mean	Standard deviation	Min	Max
Number of TripAdvisor reviews per quarter	10.89	18.00	1	509
Number of TripAdvisor 1-star reviews per quarter	0.71	1.43	0	31
Number of TripAdvisor 2-star reviews per quarter	0.76	1.51	0	28
Number of TripAdvisor 3-star reviews per quarter	1.47	2.58	0	61
Number of TripAdvisor 4-star reviews per quarter	2.97	4.96	0	98
Number of TripAdvisor 5-star reviews per quarter	4.98	10.91	0	373
Number of Expedia reviews per quarter	19.71	25.98	1	441
Number of Expedia 1-star reviews per quarter	1.16	3.23	0	92
Number of Expedia 2-star reviews per quarter	1.43	2.87	0	65
Number of Expedia 3-star reviews per quarter	2.83	4.70	0	109
Number of Expedia 4-star reviews per quarter	6.08	8.49	0	142
Number of Expedia 5-star reviews per quarter	8.21	12.96	0	287
Number of competing Airbnb listings per quarter	3.31	19.47	0	411
Number of competing hotels per quarter	4.97	7.24	0	48
Total number of hotels	2,188			
Total number of hotel-quarter observations	38,759			

Specifically, we asked whether the difference in review distributions between TripAdvisor and Expedia increased (or decreased) for a hotel, given an increase (or decrease) in the nearby Airbnb supply (i.e., within a specified radius). We estimate:

$$\text{ReviewManipulation}_{it} = \beta_0 + \beta_1 \log(\text{Airbnb}_{i,t-1}) + \beta_2 \log(\text{CompetingHotels}_{i,t-1}) + h_i + \lambda_t + \text{City}_i \times \text{Quarter}_t + \epsilon_{it}\,.$$

The dependent variable $\text{ReviewManipulation}_{it}$ represents either $\text{SelfPromotion}_{it}$ or $\text{DemotingOthers}_{it}$ for hotel i in quarter t. We begin with the simplest specification in Model 1, which only considers the competitive environment of a hotel by including the log of competing Airbnb supply and the log of competing hotels, i.e., $\log(\text{Airbnb}_{i,t-1})$ and $\log(\text{CompetingHotels}_{i,t-1})$.[15] It is important to note that our model specification uses two-way fixed effects that include both individual hotel-specific and time-specific (year-quarter) effects, as opposed to the cross-sectional estimation of Mayzlin et al. (2014). City-specific seasonality might be a confounding factor since it may impact both the Airbnb supply and hotels' review manipulation intensities. Therefore, we introduced controls for city-specific seasonality $\text{City}_i \times \text{Quarter}_t$ in the model. Incorporating these controls ensured that seasonal events in different cities, such as the South by Southwest festival in Austin in the spring and the Texas State Fair in Dallas in the fall, did not bias our estimation. Moreover, we mitigated simultaneity bias in the panel model by measuring the Airbnb supply *prior* to the measurement of self-promotion and demotion behaviors.

Our identification strategy is very similar to the difference-in-differences (DID) strategies used in Zervas et al. (2017) and Mayzlin et al. (2014). In our paper, the differences were implicitly and explicitly taken in three ways. The difference between TripAdvisor and Expedia is explicit, as in Mayzlin et al. (2014). This difference allowed us to control for unobservable qualities or popularity changes in hotels. We defined treated hotels as those hotels with nearby competing Airbnb listings, and untreated (control) hotels as those with no nearby Airbnb listings (as discussed in the Look-Ahead Propensity Score Matching subsection, an exception is the LA-PSM analysis, where control hotels eventually get competing Airbnb listings). The difference between treated and untreated hotels is measured implicitly because of the hotel-fixed effects, which account for time-invariant differences in review manipulation between treated and untreated hotels. Pre-treatment and post-treatment differences are also measured implicitly over time using year-quarter fixed effects, which allow for unobserved time-varying manipulation differences that are common across different hotels.[16]

[15] Since the variables Airbnb and CompetingHotels could have values equal to zero, we add one to them before the log transformation.

[16] We validate the pre-treatment parallel-trend assumption in Appendix B.

Since reviews in the previous period might impact self-promotion in the current period (Luca & Zervas, 2016), we also added controls for the reviews received in the previous period. In Model 2, we introduce controls that include the review ratios (ratios of 2-, 3-, 4-, and 5-star reviews) and review counts on TripAdvisor (controlling for review ratios and review counts on Expedia leads to qualitatively similar results).

$$\begin{aligned}&\text{ReviewManipulation}_{it} = \\ &\beta_0 + \beta_1 \log(\text{Airbnb}_{i,t-1}) + \beta_2 \log(\text{CompetingHotels}_{i,t-1}) \\ &+\beta_3 \log(\text{ReviewCount}_{i,t-1}) + B(\text{ReviewRatios}_{i,t-1}) \\ &+h_i + \lambda_t + \text{City}_i \times \text{Quarter}_t + \epsilon_{it}\,.\end{aligned}$$

We then investigated whether the impact of Airbnb on review manipulation is moderated by the type of hotel. Model 3 introduces the interaction between Airbnb supply and hotel types to capture the differential impact that Airbnb supply might exert on different types of hotels, i.e., high-end vs. low-end.

$$\begin{aligned}&\text{ReviewManipulation}_{it} = \\ &\beta_0 + \beta_1 \log(\text{Airbnb}_{i,t-1}) + \beta_2 \log(\text{CompetingHotels}_{i,t-1}) \\ &+\beta_3 \log(\text{ReviewCount}_{i,t-1}) + \beta_4 \log(\text{Airbnb}_{i,t-1}) \times \text{HotelType}_i \\ &+B(\text{ReviewRatios}_{i,t-1}) + h_i + \lambda_t + \text{City}_i \times \text{Quarter}_t + \epsilon_{it}\,.\end{aligned}$$

We should reiterate that the data used in Mayzlin et al. (2014) are cross-sectional while ours are panel data. It was unnecessary to include other controls on hotel characteristics used by Mayzlin et al., such as the official star categorization and location dummies (airport, interstate, resort, small-metro/town, suburban, urban), because these time-invariant features are subsumed by our hotel-specific fixed effects.

We controlled for the number of competing hotels, log(CompetingHotels) that might influence a focal hotel's review manipulation decisions, which are time-varying. The main coefficient of interest β_1 reflects the change in review manipulation in response to a change in competing Airbnb supply, and β_4 indicates the differential impact that Airbnb has on different types of hotels.

Addressing Endogeneity

There are several sources of endogeneity that could potentially bias the estimation results—for example, omitted (and relevant) variables. Although we controlled for two-way fixed effects and city seasonality, there may still be unobserved characteristics that could impact the hotel review manipulation level. The Airbnb supply could become endogenous if those unobservable characteristics also correlate with the Airbnb supply. One example is the advertising budget of hotels, which was unobservable to us. Along with review manipulation, hotels might use their advertising budget to promote themselves and demote their competitors through advertising on traditional channels. If the advertising budget correlates with the Airbnb supply, then the estimation on the impact of Airbnb supply might be biased.

In our context, it would be virtually impossible to tease out causal effects by running field experiments, because that would require coordinating the level of Airbnb supply across thousands of hotels. As a result, we first considered an instrumental variable (IV) approach. A desirable IV should be strongly correlated with the endogenous variable but must not be related to the hotel manipulation level in unobserved ways (i.e., through the error term). We identified the following IV for a focal hotel's competing Airbnb supply—the level of competing Airbnb supply for the focal hotel's competing hotels—which is defined as the distinct number of Airbnb listings for competing hotels, after excluding the competing Airbnb listings of the focal hotel. On the one hand, because the focal hotel's competing Airbnb listings were removed when constructing this instrumental variable for the Airbnb supply, the instrument is unlikely to impact the focal hotel's manipulation level. On the other hand, it should be highly correlated with the competing Airbnb supply of the focal hotel since they are in close proximity. Similar Hausman-type of IVs have been used to address endogeneity concerns (see, e.g., Bardhan et al., 2015).

We discern the strength of this IV based on the first stage least squares regression of the two-stage least square analysis (2SLS) using the Kleibergen-Paap (KP) *F*-statistic (Kleibergen & Paap, 2006). The KP *F*-statistic is 796.51, which is greater than the critical value (16.38) for the Stock-Yogo weak identification test at the 10% maximal IV relative bias (Stock & Yogo, 2005). While the exclusion restriction for the IV is untestable, there are some tests that can be performed to indirectly test the validity of the IV. In the Validity of the Instrument subsection, we provide further support for the instrument by running the test proposed by Barron et al. (2020). The test ensures that there is no correlation between the IV and the dependent variable in locations without Airbnb.[17]

Another relevant source of potential endogeneity could be self-selection: the treated and untreated hotels might be intrinsically different if they self-select into review manipulation levels. To alleviate this concern, we used look-ahead propensity score matching (LA-PSM) (Bapna et al., 2018) to balance the treated and untreated hotels. The details for how LA-PSM was implemented and the corresponding results are provided in the Look-Ahead Propensity Score Matching subsection.

[17] We thank an anonymous reviewer for suggesting this test to us.

We further address endogeneity by constructing synthetic controls for each treated hotel using generalized synthetic control (GSC) estimators (Xu, 2017). GSC applies to situations with multiple treated units and differential treatment timing, and it works even when the parallel-trend assumption is violated in difference-in-differences settings. The results of GSC analyses are reported in a later subsection.

Simultaneity could also cause endogeneity if Airbnb hosts were to base their decision to list their properties on hotels' review manipulation levels. This is unlikely for two reasons. First, it is very difficult for Airbnb hosts and guests to observe the review manipulation levels of neighboring hotels (short of conducting analyses, as in this paper). Second, we used a one-period lag in the Airbnb supply in all estimation models to capture the potentially delayed impact of Airbnb. Therefore, simultaneity is less of a concern in our context. Nevertheless, as discussed above, our IV estimation approach further alleviates this concern.

Results

We present the estimation results of review manipulation in response to the number of Airbnb listings. Specifically, we analyze Airbnb's impact on hotels' review manipulations in terms of self-promotion and demotion activities.[18]

Self-Promotion

Table 2 provides the results of 2SLS estimations for self-promotion. Since we used the panel data for estimating our specification, serial correlation may be present. To account for potential autocorrelation of review manipulation across time, we followed standard practice in clustering standard errors at the hotel level (Bertrand et al., 2004; Sun & Zhu, 2013) for all analyses.

Model 1 in Table 2 shows that estimated β_1 is 0.021, meaning that a 1% increase in nearby Airbnb listings is associated with a statistically significant increase of 0.021 percentage points ($p < 0.001$) in self-promotion. It implies that the impact of Airbnb over the five-year period of 2011-2015 would lead to an increase of 5.6 percentage points difference in the share of positive reviews across TripAdvisor and Expedia. This calculation is based on the increase of Airbnb supply from an average of 0.554 competing listings in Quarter 1 of 2011 to an average of 9.187 listings in Quarter 4 of 2015, which implies an increase in magnitude of $\log(9.187/0.554) \times 0.021 = 5.6\%$. Model 2 incorporates the additional control variables *review ratio*s and *review count*s. The estimate for the impact of Airbnb remains qualitatively unchanged. Thus, our results suggest that the competition from Airbnb offerings drives hotels to self-promote more in general.

A follow-up question is whether there are heterogeneous impacts of Airbnb supply on different hotel categories. Revenues of low-end hotels have been found to decrease more than those of high-end hotels after the entry of Airbnb (Zervas et al., 2017); therefore, low-end hotels would be expected to engage in more self-promotion because of the intensified across-group competition from Airbnb. However, this was not the case in our study. Column 3 provides estimates for Model 3 using the high-end hotel category as the reference level. A 1% increase in Airbnb competition drives high-end hotels to increase self-promotion by 0.020 percentage points (estimated β_1 is 0.020 in Table 2 Model 3), and the impact is statistically significant. What is interesting is that Airbnb's impacts on low-end hotels and high-end hotels are indeed different. As shown in Model 3, even though Airbnb supply drives high-end hotels to increase self-promotion, its impact on low-end hotels is weaker, as indicated by the significantly negative estimate on the interaction term (estimated β_4 is -0.054). To verify whether Airbnb has a significant net impact on low-end hotels, we also estimated Model 3 considering the low-end hotel category as the reference level; the results show that the net impact is statistically insignificant. It indicates that Airbnb supply does not drive low-end hotels to increase self-promotion. Taken together, with an increase in Airbnb supply, high-end hotels engage in significantly more self-promotion while low-end hotels do not increase self-promotion.

Our finding that high-end hotels engage in more self-promotion appears to be counterintuitive at first glance. However, this finding may not be surprising if we consider that online reviews may be of greater strategic importance for high-end hotels than low-end hotels. Lewis and Zervas (2019) show that the average rating of online reviews is more important for upscale to luxury hotels. This is also reflected in how hotels respond to reviews: hotel management teams frequently utilize management responses on online review platforms to directly respond to online reviews, especially the negative ones (Proserpio & Zervas, 2017; Yang et al., 2019). By looking at the percentages of reviews receiving responses from the hotels, we found that low-end hotels respond to only 4.1% of Expedia reviews while high-end hotels respond to 6.8% of such reviews (the difference is significant at the 1% level).

[18] SUR (seemingly unrelated regressions) models may seem more appropriate at first glance for the estimation since we have one equation for self-promotion and one equation for demotion activities. However, as noted in Greene (2008, p. 257), an SUR model is equivalent to equation by equation regressions when the equations have identical explanatory variables as is the case in our specifications.

Table 2. Self-Promotion with 2SLS

	Model 1	Model 2	Model 3
log(Airbnb)	0.021*** (0.006)	0.020** (0.006)	0.020*** (0.006)
log(CompetingHotels)	0.050 (0.031)	0.049 (0.030)	0.043 (0.030)
Log(ReviewCount)		0.005 (0.006)	0.004 (0.006)
log(Airbnb) × Low-end			-0.054* (0.022)
ReviewRatios	NO	YES	YES
Hotel-fixed effects	YES	YES	YES
Time-fixed effects	YES	YES	YES
Observations	32,122	32,122	32,122

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001; Robust standard errors are in parentheses (errors clustered at the hotel level.)

Further, we found that low-end hotels receive significantly fewer reviews, on average, on both Expedia and TripAdvisor, compared to high-end hotels. Along these lines, Lewis and Zervas (2019) argue that the importance of online review ratings is larger for high-end hotels because their customers have higher expectations. Our finding suggests that high-end hotels tend to utilize the "differentiation" strategy through increasing self-promotion activities in the face of across-group competition from Airbnb.

Demoting Competitors

We next turn to the specification where the dependent variable is DemotingOthers. We conduct 2SLS with the same instrumental variable described earlier and present the results in Table 3.

Models 1 and 2 in Table 3 show that when the competing Airbnb supply increases, hotels reduce demotion activities. Model 3 includes the interaction terms for hotel categories, showing the differential impact of Airbnb using high-end hotels as the reference level. The levels of demotion behaviors for high-end hotels are qualitatively similar to the previous two models. A 10% increase in Airbnb supply would drive high-end hotels to significantly decrease demotion activities by 0.0035 (estimated β_1 is 0.035 in Model 3). Considering that the mean of demotion activities is 0.189 per year-quarter, the decrease in the demotion activities that high-end hotels engage in against competing hotels amounts to about 1.85% each quarter because of the impact of Airbnb. Since the estimated coefficient for the interaction term log(Airbnb) × Low-end is insignificant, it shows that Airbnb influences high-end and low-end hotels similarly. Therefore, this suggests that both high-end and low-end hotels decrease their demotion behaviors as Airbnb supply increases.

Mayzlin et al. (2014) found that the presence of more competing hotels leads the focal hotel to receive more fake demoting reviews on TripAdvisor. Also, Luca and Zervas (2016) reported that more competition (from other restaurants) leads to more fake negative reviews in the restaurant industry as well. One may similarly expect that the intensified competition resulting from Airbnb supply would lead hotels to demote their competitors even more. But contrary to those findings, our results show that intensified competition from Airbnb actually led to fewer demoting reviews for high-end hotels. This contrasting finding lends support to our earlier argument that the nature of sharing economy competition is different. Our findings align with the predictions of strategic group theory (Caves & Porter, 1977): rivalry is lower within a group because firms are better able to recognize their mutual dependence and thus cooperate or tacitly collude with one another when facing competition from another strategic group or a common enemy like Airbnb, particularly because the tit-for-tat competitive interactions can be destructive for the whole group (Smith et al., 1997). Accordingly, it may not help hotels to demote each other in platforms like TripAdvisor given that customers have the option of Airbnb rentals. This finding indirectly echoes the "differentiation" strategy that may be attributed to self-promotion: by decreasing demotion activities, high-end hotels can indirectly boost their online ratings in a relative manner as a result of potentially reduced retaliation.

Mutual Demotion across Hotel Groups ■

Our main analyses used the behavior of individual hotels as the unit of analysis. In this section, we investigate whether the mutual demotion activities across *groups of hotels* decreased as Airbnb gained popularity, along the lines predicted by strategic group theory. Specifically, we look at hotel pairs and triplets. We present the analyses for hotel pairs here; the results for hotel triplets, presented in Appendix C, are qualitatively the same.

Table 3. Demotion Behavior with 2SLS

	Model 1	Model 2	Model 3
log(Airbnb)	-0.035*** (0.009)	-0.035*** (0.009)	-0.035*** (0.009)
log(CompetingHotels)	-0.297*** (0.044)	-0.294*** (0.044)	-0.295*** (0.044)
Log(ReviewCount)		-0.013 (0.010)	-0.013 (0.010)
log(Airbnb) × Low-end			-0.006 (0.049)
ReviewRatios	NO	YES	YES
Hotel-fixed effects	YES	YES	YES
Time-fixed effects	YES	YES	YES
Observations	24,713	24,713	24,713

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001; Robust standard errors are in parentheses (errors clustered at hotel level.)

The Identifying Review Manipulation subsection introduced the procedure to attribute demoting reviews to competing hotels. For each pair of hotels, we calculated the intensity of mutual demotion activities by computing the number of demoting reviews that the two hotels likely contributed to each other. For the hotel pair (A, B) the mutual demotion level is calculated as: $MutualDemoting(A,B) = Demoting(A \rightarrow B) + Demoting(B \rightarrow A)$.

When the unit of analysis is a hotel pair (two hotels) instead of an individual hotel, we needed to aggregate competing Airbnb supply and competing hotels for the hotel pair in a consistent manner. For example, to measure the intensity of Airbnb competition faced by a hotel pair (A, B), we considered the intersection of the Airbnb listings competing with Hotel A and the listings competing with Hotel B. The cardinality of the intersection is used as a measure of the intensity of Airbnb competition for the hotel pair. Similarly, we measured the intensity of competition arising from traditional hotels as the cardinality of the intersection of the two sets of competing hotels for A and B, respectively.[19]

The results are reported in Table 4. We found that high-end hotels decrease mutual demotion activities, given an increase in competing Airbnb supply, while low-end hotels do not significantly change their demotion behaviors. For high-end hotels, both Table 3 and Table 4 show that the reductions in demotion activities are consistent. However, for low-end hotels, Table 3 shows they would reduce demotion activities while Table 4 suggests they would not significantly change demotion activities. A conservative interpretation, then, is that low-end hotels do not increase demotion activities in response to Airbnb competition. The difference between high-end and low-end hotels might be explained by the fact that the reviews are of more strategic importance for high-end hotels as discussed in the Self-Promotion subsection.

There may be a concern that our findings could be the result of a customer shift, e.g., some hotel customers who used to give low ratings may have shifted to Airbnb listings. This putative shift in customer types could then lead to decreased demotion activities for hotels. However, it is unlikely that this alternative explanation is driving our results. First, our operationalization of review manipulation involves computing the difference in ratings between the two platforms Expedia and TripAdvisor. There is no reason to believe that the reduction in poor ratings from a shift in customer preferences would occur on one platform but not the other. Second, we examined whether the travel types of customers changed after the emergence of Airbnb and did not find any significant change during our observation period. This analysis is discussed in Appendix D.

Robustness Checks

We reinforced the causality inferences and robustness of our results by conducting analyses using several alternative approaches.

[19] The results are similar if we use the union instead of the intersection to aggregate the set of competing Airbnb listings and competing hotels.

Table 4. Mutual Demotion Behavior with 2SLS

	Model 1	Model 2	Model 3
log(Airbnb)	-0.107*** (0.008)	-0.092*** (0.008)	-0.092*** (0.008)
log(CompetingHotels)	-0.370*** (0.030)	-0.357*** (0.029)	-0.348*** (0.029)
Log(ReviewCount)		0.050*** (0.005)	0.050*** (0.005)
log(Airbnb) × Low-end			0.136*** (0.040)
ReviewRatios	NO	YES	YES
Hotel-fixed effects	YES	YES	YES
Time-fixed effects	YES	YES	YES
Observations	104,424	104,424	104,424

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; Robust standard errors are in parentheses (errors clustered at hotel level.)

Validity of the Instrument

If the instrument is valid, then it should only correlate with the review manipulation level through its effect on Airbnb competitors. Therefore, for hotels with no Airbnb competitors, we should not see a significant relationship between the IV and the hotel's review manipulation level. To test this, we regressed the review manipulation level on the instrument directly, using only data for hotels where no Airbnb competitors were observed. The first two columns of Table 5 report the results of these regressions. They show that conditional on the two-sided fixed effects and controls, there is no statistically significant relationship between the IV (labeled as log(Cmp_Airbnb)) and the review manipulation in hotels without Airbnb competitors. By contrast, Columns 3 and 4 of Table 5 show that if we regress the review manipulation level directly on the instrument for hotels with Airbnb competitors, there is a statistically significant relationship between the instrument and the self-promotion (demoting) level.

It may be possible that hotels with versus without Airbnb competitors may be fundamentally different. We therefore constructed a third sample of hotels with Airbnb competitors that are very similar to hotels without Airbnb competitors. To do so, along the lines proposed by Barron et al. (2020), we used propensity score matching (PSM) to match the treated hotels with untreated ones based on observable measures (the measures are detailed in the Look-Ahead Propensity Score Matching subsection). Columns 5 and 6 of Table 5 report the results when the review manipulation level is directly regressed on the instrument in the propensity score-matched sample with Airbnb competitors. The direct effect of the instrument is statistically significant, alleviating concerns that the null effect of the instrument in the non-Airbnb sample is only because hotels without Airbnb competitors are fundamentally different from hotels with Airbnb competitors.

Look-Ahead Propensity Score Matching (LA-PSM)

Since the treatments of Airbnb supply to hotels may not be assigned randomly (as in a controlled experiment), our estimations may be subject to systematic differences between the treated hotels and untreated ones. To alleviate this concern, we used the LA-PSM method (Bapna et al., 2018). A limitation of a standard PSM is that it only accounts for observed measures. It fails if the control group and the treatment group are systematically different in unobserved measures. In contrast, LA-PSM suggests using as the control group those hotels which are currently untreated but *will become treated in the future*. Thus, by construction, LA-PSM matches treated and untreated groups that share the same unobserved time-constant characteristics that may cause hotels to become treated. As a result, LA-PSM can account not just for the observed characteristics in the matching procedure but also for unobserved characteristics in our panel data.

We determined the treatment and control groups as follows. As shown in Figure 1, there are three groups of hotels based on whether they have Airbnb competitors, and if so when they start to have such competitors. We divided the time horizon into two periods. Group A denotes the set of hotels that have Airbnb competitors in both Periods 1 and 2, Group B hotels that have no Airbnb competitors in Period 1 but have Airbnb competitors in Period 2, and Group C hotels that have no Airbnb competitors in both Periods 1 and 2. In regular PSM, hotels in either Group A or Group B are considered treated hotels and are matched with untreated hotels in Group C. In LA-PSM, only hotels in Group A are considered treated hotels and are matched with hotels in Group B.

To make the number of samples between treated hotels and their matched hotels relatively balanced, we divided the 32 quarters into the first two thirds and the last third.

Table 5. IV Validity Check: Correlation Between Instrument and Review Manipulation

	Sample: Hotels w/o Airbnb ever		Sample: Hotels w/ Airbnb		Sample: PSM sample w/ Airbnb	
	(1)	(2)	(3)	(4)	(5)	(6)
	Promote	Demote	Promote	Demote	Promote	Demote
log(Cmp_Airbnb)	0.004 (0.019)	-0.009 (0.015)	0.012** (0.004)	-0.032*** (0.010)	0.013* (0.006)	-0.038** (0.012)
log(CompetingHotels)	0.030 (0.044)	-0.209*** (0.059)	0.062 (0.041)	-0.357*** (0.064)	0.043 (0.049)	-0.283*** (0.069)
Log(ReviewCount)	0.009 (0.009)	0.017 (0.014)	-0.001 (0.008)	-0.033* (0.013)	-0.013 (0.009)	-0.037 (0.019)
ReviewRatios	YES	YES	YES	YES	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	15,073	11,279	17,117	13,492	10,772	8,640

Note: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; Robust standard errors are in parentheses (errors clustered at hotel level.)

To calculate the propensity score (predicted probability of being treated), we used observable characteristics including price, ownership (independent or chain), whether a hotel has a restaurant, location type (airport, interstate, resort, small-metro/town, suburban, urban), and the number of rooms. Some of the characteristics are categorical variables such as a hotel's ownership status while others are continuous-valued variables such as the price. We used exact matching on the categorical variables and nearest-neighbor matching on the continuous ones as it provided better matching quality compared to using just one method. We grouped hotels that had an exact match on the categorical variables into subsets, and then matched the treated hotels with untreated ones that had the closest propensity score within each subset (without replacement). We found a good match of control hotels (untreated in Period 1 and treated in Period 2) for 307 of the 411 hotels which had competing Airbnb listings in Period 1.

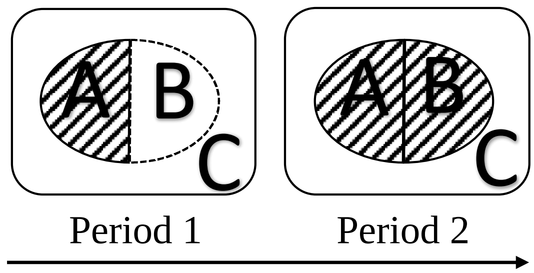
Because both the treatment and the matched control groups ultimately were treated (at different time periods), the matching procedure accounts not only for the observed measures using propensity scores, but also for unobserved time-invariant characteristics influencing the hotel's intrinsic propensity to be treated. The results, as presented in Table 6, remain consistent with the main results in the paper. In addition, the results are robust to alternative matching methods (coarsened exact matching, exact matching, nearest neighbor matching) and to the inclusion of other features for the matching (such as hotel average rating, standard deviation of rating, and the number of ratings).[20]

Generalized Synthetic Control

Besides LA-PSM, an alternative method that can help address the endogeneity concern is generalized synthetic control (GSC) (Xu, 2017). The challenge for causal inference is to come up with a credible estimate of what the outcome would have been for the treatment group in the absence of the treatment. This requires estimating a counterfactual change over time for the treatment group had the treatment not occurred. Instead of using a single control unit or a simple average of control units, the synthetic control approach proposed by Abadie et al. (2015) constructs a control by using a weighted average of a set of controls (thus the name synthetic). The synthetic control approach "is arguably the most important innovation in the policy evaluation literature in the last 15 years" (Athey & Imbens, 2017, p. 9). The traditional synthetic control approach applies to the case of one treated unit with a unique treatment time. GSC extends the traditional approach by allowing multiple treated units as well as differential treatment timing as is the case in our data.

GSC had been proposed in the traditional binary treatment context. Therefore, we needed a cutoff point to dichotomize the Airbnb supply. At the midpoint of the time span of our study (2011 Quarter 4), the mean Airbnb supply for hotels that face Airbnb competition is 5.21. We used this number as the threshold above which hotels were considered to be treated. This also ensured that we were left with sufficient observations with at least ten pre-treatment periods, as suggested by Xu (2017). Because GSC cannot handle time-invariant variables like hotel tiers, we conducted subsample analyses (i.e., analyzing high-end hotels and low-end hotels separately) to investigate how high-end and low-end hotels manipulate reviews differently.

[20] We also conducted a traditional PSM analysis. The results from using PSM and LA-PSM are qualitatively the same.



Note: The shaded left half oval represents the hotels that start facing Airbnb competition in Period 1 (Group A). The shaded right half oval represents the hotels that start facing Airbnb competition in Period 2 (Group B). Group C denotes the hotels which do not face Airbnb competition in either Period 1 or Period 2.

Figure 1. Treatment and Control Groups in LA-PSM

Table 6. LA-PSM-Matched Hotels

	Self-promotion			**Demoting others**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
log(Airbnb)	0.034* (0.014)	0.031* (0.014)	0.030* (0.014)	-0.084** (0.028)	-0.086** (0.029)	-0.087** (0.029)
log(CompetingHotels)	0.058 (0.050)	0.054 (0.048)	0.044 (0.049)	-0.309*** (0.077)	-0.303*** (0.076)	-0.300*** (0.076)
Log(ReviewCount)		-0.011 (0.010)	-0.012 (0.010)		-0.044* (0.021)	-0.044* (0.021)
log(Airbnb) × Low-end			-0.044 (0.023)			0.017 (0.058)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	10,759	10,759	10,759	8,630	8,630	8,630

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001; Robust standard errors are in parentheses (errors clustered at hotel level.)

As shown in Table 7, the analyses yielded results consistent with the main results in the paper. High-end hotels significantly increase self-promotion activities in response to Airbnb while significantly reducing demotion activities. Low-end hotels do not show any significant change in review manipulation activities in response to Airbnb.

Being Demoted

Since we wanted to understand the active role that hotels engaged in with respect to demotion, we analyzed the magnitude for demoting others in our analyses. Mayzlin et al. (2014) used the being-demoted measure to see how much hotels *were demoted* by their competitors. Although it is orthogonal to the focus of our paper, we nevertheless explore whether our results are consistent with this alternative way of viewing demotions.

We computed the number of fake reviews that a hotel received using the formula $Demoted_{it} = Demotion_{it} \times Total\ Reviews_{it}^{TA}$. We use the measure $Demoted_{it}$ to evaluate how much a hotel had been demoted by its competitors. The results of using the $Demoted_{it}$ variable as the dependent variable are shown in Table 8.

As shown in Model 3 of Table 8, high-end hotels are demoted more and the impact on low-end hotels is not statistically significant. These findings appear to be contradictory at first sight. Our main analyses and the several robustness checks show that high-end hotels decrease demotion activities with an increase in Airbnb supply, while the results in Table 8 show that high-end hotels are demoted more. Interestingly, as explained below, there is no contradiction.

Imagine that Hotels A and B are competing with each other. Further, let us assume that Hotel A has more competing Airbnb listings than Hotel B. Based on our analysis, Hotel A is likely to engage in fewer demotion activities compared to Hotel B.

Table 7. Generalized Synthetic Control Estimators

	Self-promotion			Demoting others		
	All	High-end	Low-end	All	High-end	Low-end
Airbnb Treatment	0.029* (0.013)	0.033* (0.015)	-0.003 (0.073)	-0.034 (0.022)	-0.037* (0.019)	0.192 (0.175)
log(CompetingHotels)	0.011 (0.028)	0.017 (0.028)	0.450 (0.533)	-0.434*** (0.047)	-0.436*** (0.045)	-0.316 (0.500)
Log(ReviewCount)	0.028*** (0.009)	0.032*** (0.008)	0.016 (0.026)	-0.005 (0.010)	-0.005 (0.009)	-0.001 (0.047)

Note: *p < 0.05, **p < 0.01, ***p < 0.001; Standard errors in parentheses.

Table 8. Being demoted with 2SLS

	Model 1	Model 2	Model 3
log(Airbnb)	0.123* (0.048)	0.137** (0.048)	0.139** (0.048)
log(CompetingHotels)	-0.145 (0.122)	-0.160 (0.121)	-0.176 (0.122)
Log(ReviewCount)		0.171*** (0.027)	0.170*** (0.027)
log(Airbnb) × Low-end			-0.161 (0.174)
ReviewRatios	NO	YES	YES
Hotel Fixed Effects	YES	YES	YES
Time Fixed Effects	YES	YES	YES
Observations	32,122	32,122	32,122

Note: *p < 0.05, **p < 0.01, ***p < 0.001; Robust standard errors are in parentheses (errors clustered at hotel level.)

This, in turn, implies that Hotel B will receive fewer demotions as compared to Hotel A. This is consistent with the findings in Table 8. The signs of the estimated coefficients differ because we are looking at the same phenomenon through the opposite lens.

Other Robustness Checks

We have conducted several additional analyses to ensure that our results are robust. We provide a summary of those analyses here and present the details in the Appendices.

Thus far, we have assumed that the competition between and across hotels and Airbnb listings is primarily constrained within a 1-kilometer radius with respect to each focal hotel. Competing hotels located farther away or nearer may have varying degrees of incentives to demote their competitors. In Appendix E, we consider alternatives with different competition radii and also relax the restrictions of requiring a fixed competition radius and of considering all competing hotels equally. We build on the idea of Luca and Zervas (2016) to model a gradual decrease in competition intensity due to increased distance. The results are consistent with the main results.

As mentioned in the Identifying Review Manipulation subsection, because of the difference in average ratings for high-end and low-end hotels, we measured self-promotion and demotion differently for high-end and low-end hotels. We also replicated our experiments by considering the same measures for both high-end and low-end hotels following Mayzlin et al. (2014). The results are presented in Appendix F.

Airbnb listings vary considerably in terms of their quality and price. In the main analyses, we considered all nearby Airbnb listings to be competing with a focal hotel regardless of the nature (i.e., price and quality) of those listings. In Appendix G, we validated that our estimation results are not sensitive to this assumption.

In our main analyses, we assumed that hotels are only competing with other hotels from the same category. In Appendix H, we relaxed this assumption by considering hotels as competitors regardless of their categories.

To further reinforce our findings, we used an alternative approach to investigate how Airbnb listings influence hotels' review manipulation behaviors differently. In Appendix I, we demonstrate that the growth of Airbnb did change how incumbent hotels respond to competing hotels. In sum, the main results presented are robust to many alternative methods of testing them and Airbnb competition does indeed change hotels' review manipulation behavior.

Discussion and Conclusions

An interesting outcome of the rise of the digital economy is the emergence of sharing economy firms that use technology-mediated platforms to compete with traditional firms. We use strategic group theory, a central construct in the strategy literature, to examine how the competition from such novel digital enterprises affects the strategic actions of incumbent firms. Because such firms differ fundamentally from traditional firms in terms of their asset bases and business models, they do not constitute rivals that can be considered part of the strategic groups of incumbents. This raises an interesting question—namely, how the emergence of a new strategic group can impact rivalry across firms within existing traditional groups.

We specifically examined how one type of firms' strategic communications—review manipulations—is impacted by the emergence of sharing economy firms. Previous literature has found that the emergence of Airbnb has intensified the competition for customers among hotels, and that hotels manipulate reviews in response to increased competition. Based on these findings, one might conclude that the problem of online review manipulation would worsen across the board after Airbnb gains popularity. Our work provides some surprising findings regarding incumbent firms' manipulation strategies in response to competition from sharing economy firms. We show that increased Airbnb supply leads to significantly more self-promotion activities for high-end hotels but does not lead to any increase in self-promotion behavior for low-end hotels. Regarding demotions, we find that increased Airbnb supply leads to significantly less demotion behavior for high-end hotels. Low-end hotels do not increase their demotion behavior with increased Airbnb supply. The findings regarding demotions are particularly surprising given the findings of Mayzlin et al. (2014) in the conventional lodging business and those of Luca and Zervas (2016) in the restaurant industry, both of which suggest that intensified competition leads firms to demote each other more. These works do not factor in the new type of competition coming from the sharing economy. Consistent with the prediction of strategic group theory, we find that the impact of the sharing economy on the group of incumbent hotels leads hotels to demote their competing hotels less in response to Airbnb.

Our findings contribute to the literature on the sharing economy by showing that the disruptive innovations from sharing economy firms are changing the landscape of competition among incumbents in unexpected ways. Our work also contributes to the strategic group literature by demonstrating how the entry of a new strategic group (i.e., Airbnb) can change the rivalry across firms within an extant group. In our context, we show that incumbent hotels cannot use demotion to counter the competition from Airbnb listings as they typically do to manage competition arising from other hotels (i.e., within their own strategic group). When this new group enters the market, intensifying competitive interactions within the extant group can quickly become destructive. We find that the within-group rivalry across the hotels decreases when a new group (Airbnb) joins the industry, as reflected by the decrease in demotion. Thus, when between-group competition emerges, co-opetition rather than tit-for-tat becomes a preferable option among members within the extant group.

Our findings have important implications for both review hosting platforms and customers. Review-hosting platforms like TripAdvisor can benefit from knowing that increased Airbnb supply drives high-end hotels to increase self-promotion while engaging in fewer demotion activities. Consequently, these platforms can potentially adjust their filtering algorithms to account for both the magnitude of Airbnb supply near a hotel and the type of the hotel. Customers need to be more circumspect in their choices of high-end hotels in areas with high Airbnb penetration, keeping in mind that the online review ratings may have been inflated because of abundant Airbnb listings in the area.

A limitation of our study is that the GSC implementation used here considers only a binary treatment scenario and we had to dichotomize our continuous treatment to apply GSC. Extending GSC to the setting of continuous treatment variables would be desirable. Our work also opens up other interesting avenues for future research. We analyzed an important strategy, review manipulation, which incumbent firms utilize when dealing with new forms of competition. It would be useful to examine the joint impact of such manipulations along with other strategies that incumbent firms may use, such as pricing, advertising, quality, and capacity management.

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Appendix A

Model-Free Evidence

We examine whether the average ratings of hotels change as Airbnb supply increases. Figure A1 shows that TripAdvisor ratings increase in the aggregate while Expedia average ratings stay relatively flat. At the aggregate level, hotels appear to increase self-promotion and decrease demotion (more positive ratings and fewer negative ratings on TripAdvisor relative to Expedia).

We also examine the trends in positive and negative reviews on TripAdvisor. We plot positive reviews (4-star and 5-star for low-end, 5-star for high-end hotels) and negative reviews (1-star and 2-star for high-end, 1-star for low-end hotels) for high-end and low-end hotels in Figure A2. We find that low-end hotels have relatively stable proportions of negative and positive ratings (relatively flat over time), while high-end hotels have increasing proportions of positive ratings and decreasing proportions of negative ratings on TripAdvisor. This is consistent with our main findings that high-end hotels tend to increase self-promotion and reduce demotion activities while low-end hotels do not increase manipulation activities. Note that these figures only show the trends in general while ignoring potential confounding factors.

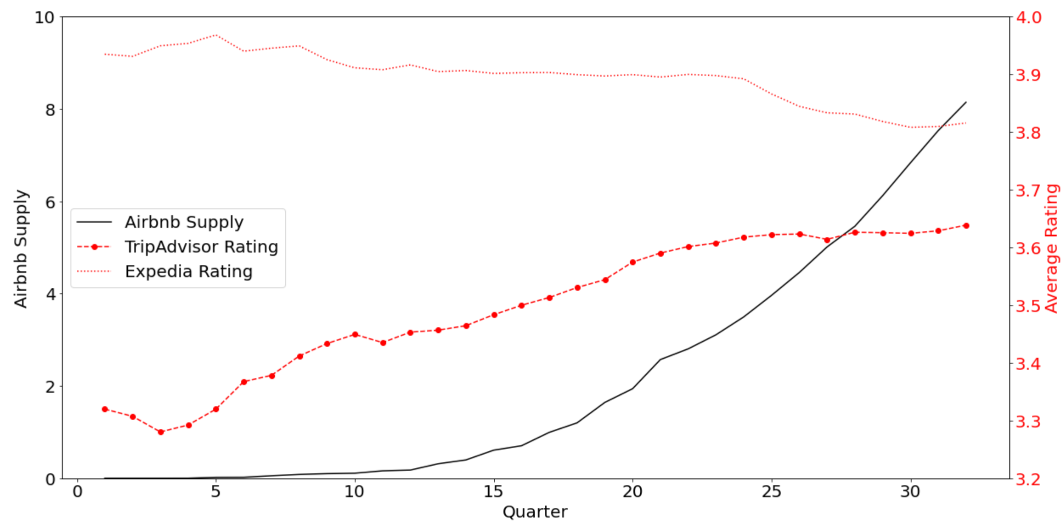
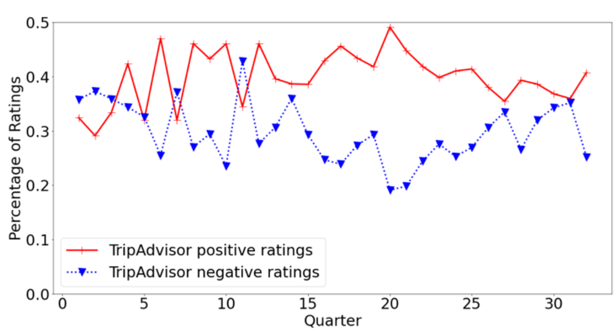
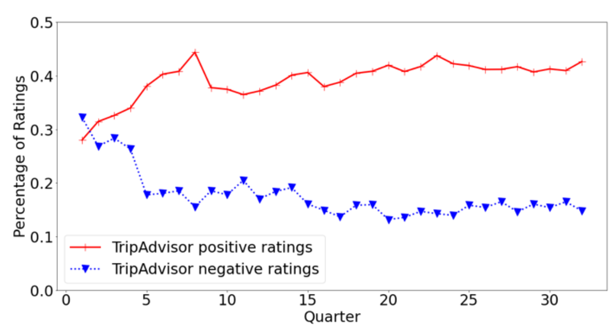


Figure A1. Changes in Average Ratings with Airbnb Supply



Low-end hotels



High-end hotels

Figure A2. Proportions of Negative and Positive Ratings on TripAdvisor

Appendix B

Validating the Parallel-Trend Assumption

In our context, we do not use a conventional DID setup where there is one binary treatment and a common event that occurs at the same instant of time for all hotels. Here Airbnb listings can enter at different times; further, there can be repeated entries (we use the count of Airbnb listings as the main independent variable rather than a binary treatment). This forms a staggered DID setting for which the parallel-trend assumption is not directly applicable. Nevertheless, by dichotomizing our independent variable into 0 and 1 (referred to as Airbnb_Binary hereafter), we are able to test the assumption of parallel trends using the relative time model proposed in Autor (2003).[21] The relative time model has been widely used in the literature to test the parallel-trend assumption (e.g., Chan et al., 2019; Greenwood et al., 2019; Lu et al., 2019). The idea is to add lead and lag treatment variables into the regression and investigate their coefficients. If the coefficient of any lead variable turns out to be significant, it would indicate there are pre-treatment trends in the data and so the parallel-trend assumption would be violated. We run the following relative-time model:

$$\begin{aligned}\text{ReviewManipulation}_{it} = \beta_0 &+ \sum_j \beta_{1j}\text{Airbnb\_Binary}_{i,t-1-j} + \beta_2 \log(\text{CompetingHotels}_{i,t-1}) \\ &+ \beta_3 \log(\text{ReviewCount}_{i,t-1}) + \beta_4 \text{Airbnb\_Binary}_{i,t-1} \times \text{HotelType}_i \\ &+ B(\text{ReviewRatios}_{i,t-1}) + h_i + \lambda_t + \text{City}_i \times \text{Quarter}_t + \epsilon_{it}\end{aligned},$$

where *j* is {-2, -1, 0, +1, +2, +3} following Autor (2003).[22] Note that in this model, both the treated and the control groups change every period as more hotels face Airbnb competitors over time. As a result, for any hotel that is treated at period *t* (i.e., starts to face Airbnb competition at period *t*), the comparison group would be those hotels that do not face any Airbnb competitors in that period (nor in any previous period). As shown in Table B1, none of the pre-treatment variables are significant in either the self-promotion or demoting others results. These results suggest that the parallel trends assumption is fulfilled, and the observed relationship between review manipulation and Airbnb supply is unlikely to arise as an artifact from events that occur in periods prior to the treatment. Importantly, the coefficients for the treatment period (i.e., $Airbnb\_Binary_{treat(0)}$) are significant (the shaded row in the table). The significant coefficients in this analysis yield consistent signs with the main analyses: i.e., self-promotion is positive and significant after the treatment, while demoting others is negative and significant after the treatment.

Table B1. Relative Time Model

	Self-promotion			Demoting others		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
$\text{Airbnb\_Binary}_{pre(-2)}$	-0.079 (0.234)	-0.071 (0.234)	-0.063 (0.235)	-0.042 (0.030)	-0.043 (0.030)	-0.043 (0.030)
$\text{Airbnb\_Binary}_{pre(-1)}$	-0.035 (0.025)	-0.034 (0.025)	-0.035 (0.025)	0.079 (0.043)	0.080 (0.043)	0.080 (0.043)
$\text{Airbnb\_Binary}_{treat(0)}$	0.060* (0.026)	0.058* (0.026)	0.063* (0.027)	-0.108* (0.054)	-0.107* (0.054)	-0.107* (0.052)
$\text{Airbnb\_Binary}_{post(1)}$	-0.046 (0.025)	-0.044 (0.025)	-0.045 (0.025)	0.050 (0.041)	0.049 (0.041)	0.049 (0.040)
$\text{Airbnb\_Binary}_{post(2)}$	0.010 (0.030)	0.009 (0.030)	0.010 (0.030)	-0.012 (0.036)	-0.011 (0.036)	-0.011 (0.036)
$\text{Airbnb\_Binary}_{post(3)}$	0.040 (0.025)	0.040 (0.026)	0.041 (0.025)	0.096 (0.061)	0.093 (0.061)	0.093 (0.060)
log(CompetingHotels)	0.009 (0.046)	0.009 (0.047)	0.007 (0.047)	-0.254* (0.106)	-0.251* (0.106)	-0.251* (0.106)
Log(ReviewCount)		0.021 (0.015)	0.020 (0.015)		-0.008 (0.026)	-0.008 (0.026)
$\text{Airbnb\_Binary}_{treat(0)}$ × Low-end			-0.042 (0.058)			0.003 (0.223)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	18,372	18,372	18,372	12,319	12,319	12,319

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001; Robust standard errors are in parentheses (errors clustered at hotel level.)

[21] We use zero as the cutoff point to dichotomize Airbnb treatment. The results are robust to alternative cutoff points.

[22] In the paper where the test for the parallel trend assumption was originally proposed (Autor, 2003, p. 24), *t-n* (*n* > 0) was used to denote *post-treatment* periods instead of *pre-treatment* periods. However, some other papers (e.g., Greenwood et al., 2019; Lu et al., 2019) used *relative time* dummies to indicate the relative chronological distance between time *t* and the treatment period, using *t-n* (*n* > 0) for *pre-treatment* periods. To eliminate such ambiguity, in Table B1, we adopt the notation $Airbnb\_Binary_{treat(0)}$ for the treatment period, $Airbnb\_Binary_{pre(-1)}$ for the one-period pre-treatment, $Airbnb\_Binary_{post(+1)}$ for one period post-treatment, etc.

Appendix C

Mutual Demotion Across Hotel Triplets

In the Mutual Demotion Across Hotel Groups section, we examined whether the mutual demotion across *groups of hotels* decreased with the emergence of Airbnb, using hotel pairs as the unit of analysis.

We now analyze how mutual demotion activities would change within a hotel triplet, where the unit of analysis becomes three hotels that are competing with each other. Denote the three competing hotels as A, B, and C, respectively. Then the mutual demotion among these competing hotels become: $MutualDemoting(A,B,C) = Demoting(A \rightarrow B) + Demoting(B \rightarrow A) + Demoting(A \rightarrow C) + Demoting(C \rightarrow A) + Demoting(B \rightarrow C) + Demoting(C \rightarrow B)$. Similar to the hotel-pair analyses, we measure the intensity of Airbnb competition faced by the hotel triplet as the cardinality of the intersection of the three sets of Airbnb listings that are competing with hotels A, B, and C, respectively. We measure the intensity of competition from conventional hotels as the cardinality of the intersection of the three sets of competing hotels for A, B, and C, respectively.

The results reported in Table C1 are qualitatively the same if we use the union instead of the intersection to aggregate the set of competing Airbnb listings and competing hotels for the hotel triplets. In sum, the mutual demotion analyses demonstrate that high-end hotels reduce their demotion activities within the incumbent hotels when they face Airbnb.

Table C1. Hotel Group Demotion Behavior with 2SLS (Hotel Triplet)

	Model 1	Model 2	Model 3
log(Airbnb)	-0.259*** (0.011)	-0.185*** (0.010)	-0.178*** (0.011)
log(CompetingHotels)	-0.797*** (0.036)	-0.661*** (0.032)	-0.640*** (0.033)
Log(ReviewCount)		0.141*** (0.004)	0.141*** (0.004)
log(Airbnb) × Low-end			1.667* (0.798)
ReviewRatios	NO	YES	YES
Hotel-fixed effects	YES	YES	YES
Time-fixed effects	YES	YES	YES
Observations	437,695	437,695	437,695

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Robust standard errors are in parentheses (errors clustered at hotel level.)

Appendix D

Change in Customer Travel Types

We examine whether the customer travel types changed with the emergence of Airbnb. For example, customers who travel with families or friends may shift to Airbnb listings. We verify if this is indeed the case from the data. During the observation period, many TripAdvisor reviewers revealed their travel as belonging to one of five types: as a couple, on business, solo, with family, and with friends; the type is recorded as "not specified" when no type is selected. The percentages of different types of travel remain relatively stable as shown in Figure D1.

We use a repeated measures ANOVA to test the null hypothesis that the population means of the ratios of each travel type do not change.[23] The resulting *p*-value is close to 1, which means we fail to reject the null hypothesis. We also consider an alternative to the ANOVA by testing if the time series of the six travel types are stationary. Using the KPSS test (Kwiatkowski et al., 1992) developed for this purpose, we find that all six categories of travel types are stationary. Thus, there is no evidence that hotel customers have changed their preferences during the observation period.

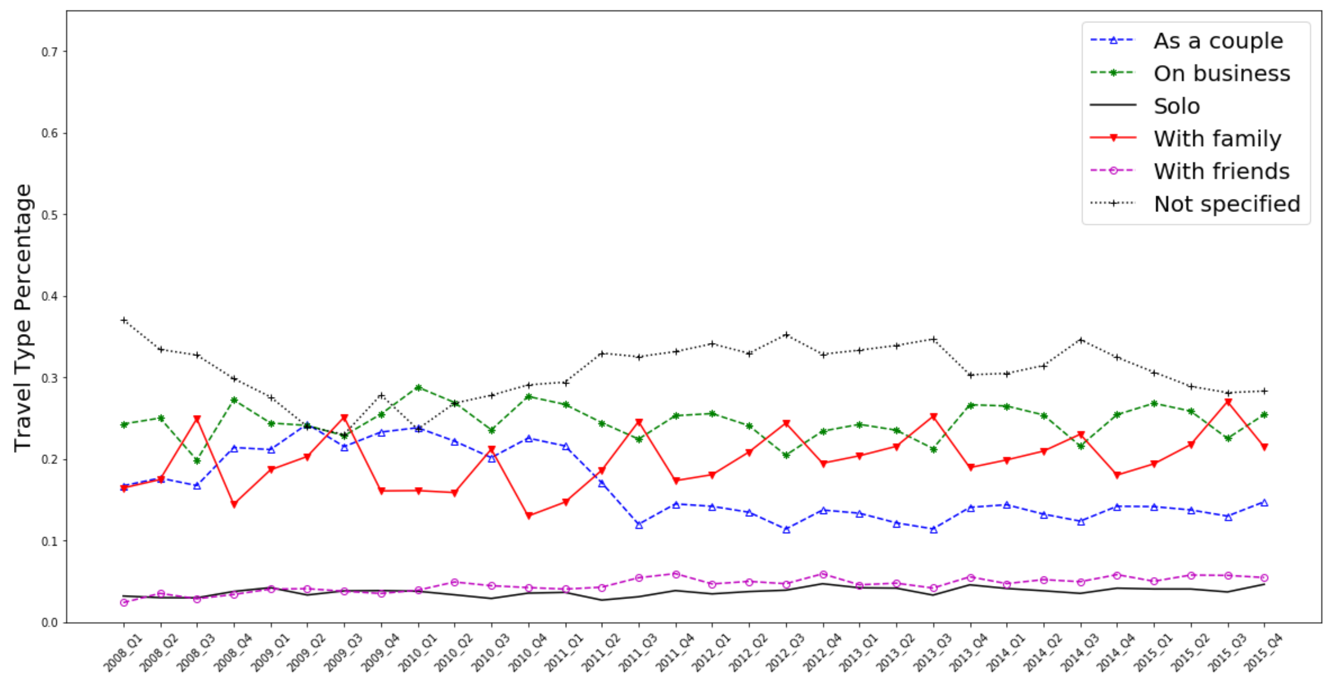


Figure D1. Changes in Proportions of Various Travel Types

[23] In our context, the proportions of each alternative travel type are measured at each quarter. The assumption of one-way ANOVA is violated due to the repeated measure for each ratio. Instead, we utilize the repeated measure ANOVA (as referred to as within-subject ANOVA) to examine whether the population means of these groups change (Jackman, 2009, p. 317).

Appendix E

Quantifying Competition Intensity Using a Smooth Kernel

Thus far, we have assumed that the competition between hotels and Airbnb listings is primarily constrained within a 1-kilometer radius with respect to each focal hotel. The results are not sensitive to this cutoff distance, and the estimations are qualitatively the same when we use 0.5km or 2km as the competition radius. However, we have not differentiated between the competing hotels within the radius and have attributed demoting reviews evenly across competitors. Competing hotels located farther or nearer may have varying incentives to demote their competitors. In this Appendix, we test an alternative where we relax such restrictions that all competing hotels are considered equal.

We build on the idea of Luca and Zervas (2016) to model a gradual decrease in competition intensity due to increased distance. To see if our results are robust, we use a Gaussian kernel with different values of bandwidths, where bandwidth corresponds to the standard deviation in the context of *z*-score calculation. More specifically, let the impact of hotel *j* on hotel *i* be

$$w_{ij} = K(\frac{d_{ij}}{h}),$$

where d_{ij} is the distance between the two hotels, K is a kernel function, and h is a positive parameter called the kernel bandwidth. Depending on the choice of K and h, w_{ij} provides different ways to capture the relationship between distance and competition. The hard cutoff using the competition radius h we consider in the Results section is a special case of this kernel weight when using a uniform kernel:

$$K_U(u) = 1_{\{|u| \le 1\}},$$

where $1_{\{...\}}$ is the indicator function; i.e., K_U assigns unit weight to competitors within a distance h, and zero to competitors farther away. The Gaussian kernel, on the other hand, produces spatially smooth weights that are continuous in u and follow the Gaussian density function:

$$K_U(u) = e^{-\left(\frac{1}{2}\right)u^2}.$$

When the 1-km bandwidth is used for the Gaussian kernel, it means that a competitor (an Airbnb listing or a hotel) at the exact location as the focal hotel would contribute 1 to the competition intensity, a competitor at a distance of 1 kilometer would contribute 0.61, one at a distance of 2 kilometers 0.14, and so on. This captures the intuition that competing hotels that are closer may have more incentives to demote a focal hotel. Therefore, we attribute the demoting reviews proportional to the competition intensity of a nearby hotel. We should point out that the IV is modified accordingly. As shown in Table E1, our findings using the kernel weights remain consistent with the main analyses. We test different alternatives of bandwidth choices to see if the results are robust. Both bandwidths of 1 km and 0.5 km (as used in Luca & Zervas, 2016) generate results consistent with those reported in the main analyses.

Table E1. Quantifying the Competition Intensity Using a Smooth Kernel

	Self-promotion			Demoting others		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
log(Airbnb)	0.012* (0.005)	0.011* (0.005)	0.011* (0.005)	-0.006* (0.002)	-0.006* (0.002)	-0.005* (0.002)
log(CompetingHotels)	0.058 (0.036)	0.057 (0.035)	0.054 (0.035)	-0.072*** (0.020)	-0.073*** (0.020)	-0.076*** (0.021)
Log(ReviewCount)		0.004 (0.006)	0.004 (0.006)		0.003 (0.003)	0.003 (0.003)
log(Airbnb) × Low-end			-0.010 (0.016)			-0.011 (0.010)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	32,122	32,122	32,122	24,713	24,713	24,713

Note: *p < 0.05, **p < 0.01, ***p < 0.001; Robust standard errors are in parentheses (errors clustered at hotel level.)

Appendix F

Alternative Operationalization of Self-Promotion and Demotion

As mentioned in the Identifying Review Manipulation subsection, because of the difference in average ratings for high-end and low-end hotels, we measure self-promotion and demotion differently for high-end and low-end hotels. We also replicate our experiments by considering the same measures that are used in Mayzlin et al. (2014): for all hotels (both high-end and low-end), the differences in the proportions of 5-star ratings on TripAdvisor and Expedia are considered as potential self-promotions and the corresponding differences in 1-star and 2-star ratings as demotions. The 2SLS results presented in Table F1 are consistent with our main results.

Table F1. Alternative Operationalization of Manipulation

	Self-promotion			Demoting others		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
log(Airbnb)	0.027^{***} (0.006)	0.025^{***} (0.006)	0.026^{***} (0.006)	-0.036^{***} (0.009)	-0.036^{***} (0.009)	-0.036^{***} (0.009)
log(CompetingHotels)	0.066^{*} (0.031)	0.064^{*} (0.030)	0.054 (0.030)	-0.289^{***} (0.044)	-0.286^{***} (0.044)	-0.290^{***} (0.044)
Log(ReviewCount)		0.012^{*} (0.006)	0.011 (0.006)		-0.014 (0.010)	-0.014 (0.010)
log(Airbnb) × Low-end			-0.095^{***} (0.020)			-0.037 (0.046)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	32,122	32,122	32,122	24,713	24,713	24,713

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; Robust standard errors are in parentheses (errors clustered at hotel level.)

Appendix G

Segmenting Airbnb Competitors

Airbnb listings are quite different in terms of their quality and price. In the main analyses, we considered all nearby Airbnb listings as competing with a focal hotel regardless of the nature (i.e., price and quality) of those listings. In this Appendix, we evaluate whether our estimation results are sensitive to this assumption.[24]

A common measure of quality is review rating. The user-generated reviews for Airbnb listings have very small variance and thus do not help to differentiate across those listings. For example, 95.7% of all listings boast an average user-generated rating of either 4.5 or 5 stars (highest); less than 0.3% of Airbnb listings have less than 3.5 stars. The mean and standard deviation of the user-generated ratings in Airbnb is 4.82 and 0.31 respectively. These statistics in our Airbnb listings sample are very similar to the ones reported in Zervas et al. (2021). Therefore, we did not use user-generated ratings as a control for the quality of Airbnb listings.

To obtain the price information of Airbnb listings, we obtained data from AirDNA.co that tracks the price information of each Airbnb listing over time. This enables us to categorize Airbnb listings as high-end or low-end and to examine the competition between similar segments of hotels and Airbnb listings (i.e., the competition between high-end hotels and high-end Airbnb listings, and the competition between low-end hotels and low-end Airbnb listings). To segment the Airbnb listings, we calculated the price per person (guest) for each Airbnb listing in our sample and then categorized the listings based on this price per person. Since 24% of all the hotels in our observations are low-end hotels, we use the 24th percentile of the Airbnb listing price per person as the cutoff point (which corresponds to $25 per person). The results, as presented in Table G1, are consistent with the main findings.[25]

Table G1. Segmenting Airbnb Competitors

	Self-promotion			Demoting others		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
log(Airbnb)	0.020** (0.006)	0.019** (0.006)	0.018** (0.006)	-0.034*** (0.008)	-0.034*** (0.009)	-0.033*** (0.008)
log(CompetingHotels)	0.049 (0.031)	0.048 (0.030)	0.049 (0.030)	-0.296*** (0.044)	-0.294*** (0.043)	-0.295*** (0.044)
Log(ReviewCount)		0.004 (0.006)	0.005 (0.006)		-0.012 (0.010)	-0.012 (0.010)
log(Airbnb) × Low-end			0.003 (0.012)			-0.006 (0.015)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	32,122	32,122	32,122	24,713	24,713	24,713

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Robust standard errors are in parentheses (errors clustered at hotel level.)

[24] We thank an anonymous reviewer for suggesting this analysis.

[25] Low-end hotels appear to increase self-promotions based on Model 3 for self-promotion in Table G1. However, such an increase is statistically insignificant when we use the low-end hotel as the reference level.

Appendix H

Combining Competitors Across Categories

In our main analyses, we assumed that hotels are only competing with other hotels from the same category; namely, low-end hotels are competing with low-end hotels while high-end hotels with other high-end hotels only. The rationale behind this is that a low-end hotel is unlikely to demote a nearby high-end hotel in order to capture a portion of the demand for the high-end hotel and vice versa. Next, we relax this assumption by considering hotels as competitors regardless of their categories. To incorporate this change, the competitor count, the count of demotion actions (i.e., negative reviews), and the instrumental variable measures are modified correspondingly. The results, as presented in Table H1, show consistency with our main findings.

Table H1. All Neighboring Hotels as Competitors

	Self-promotion			Demoting others		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
log(Airbnb)	0.022*** (0.006)	0.020** (0.006)	0.021*** (0.006)	-0.018* (0.007)	-0.018* (0.008)	-0.017* (0.008)
log(CompetingHotels)	0.057 (0.031)	0.055 (0.030)	0.054 (0.030)	-0.245*** (0.038)	-0.243*** (0.038)	-0.245*** (0.038)
Log(ReviewCount)		0.005 (0.006)	0.005 (0.006)		-0.007 (0.008)	-0.007 (0.008)
log(Airbnb) × Low-end			-0.021 (0.024)			-0.027 (0.014)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	32,122	32,122	32,122	26,748	26,748	26,748

Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001; Robust standard errors are in parentheses (errors clustered at hotel level.)

Appendix I

Difference between Airbnb and Hotel Competition

To further reinforce our findings, we used an alternative approach to investigate how Airbnb listings influence hotels' review manipulation behaviors differently.

The number of Airbnb listings started increasing rapidly around the middle of our observation period (i.e., Quarter 16 (2011 Q4) is an inflection point as shown in Figure A1). Prior to that point, the average number of competing Airbnb listings was 0.31. The average bumped to 4.62 after the middle point. Therefore, we use 2011 Q4 as the cutoff to split the data into two subsamples. We expect the impact of Airbnb to be minimal before it gains momentum, but its impact would become stronger as more Airbnb listings appear.

The subsample analyses, presented in Table I1, demonstrate that the growth of Airbnb did change how incumbent hotels respond to competing hotels. Before Airbnb listings became popular, the impact of competing Airbnb listings and competing hotels are both insignificant. After the inflection point, an increase in either competing Airbnb listings or competing hotels leads to significantly fewer demotion activities. This is consistent with the prediction from strategic group theory, that the incumbent group of hotels engaged in less destructive competitive behavior after Airbnb listings grew substantially.

Table I1. Demotion Behavior before and after the Inflection Point (2011 Quarter 4)

	Before 2011 Q4			After 2011 Q4		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
log(Airbnb)	0.010 (0.015)	0.010 (0.015)	0.005 (0.013)	-0.025* (0.013)	-0.026* (0.013)	-0.026* (0.013)
log(CompetingHotels)	-0.098 (0.159)	-0.097 (0.159)	-0.087 (0.159)	-0.258*** (0.056)	-0.256*** (0.056)	-0.256*** (0.056)
Log(ReviewCount)		0.010 (0.011)	0.011 (0.011)		-0.013 (0.015)	-0.013 (0.015)
log(Airbnb) × Low-end			0.255 (0.251)			0.001 (0.069)
ReviewRatios	NO	YES	YES	NO	YES	YES
Hotel-fixed effects	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES
Observations	5,305	5,305	5,305	19,226	19,226	19,226

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Robust standard errors are in parentheses (errors clustered at hotel level.)