Competing with the Sharing Economy: Incumbents' Reaction on Review Manipulation

Cheng Nie
Ivy College of Business, Iowa State University, Ames, IA U.S.A. {cheng@chengnie.com}

Zhiqiang (Eric) Zheng, Sumit Sarkar
Naveen Jindal School of Management, University of Texas at Dallas, Richardson, TX U.S.A.
{ericz@utdallas.edu} {sumit@utdallas.edu}

Abstract. The emergence of the sharing economy provides an untapped wealth of supplies to a market, posing a threat to the incumbents. In response to the competition from the sharing economy, incumbents have to adjust their competition strategies. In this paper, we focus our investigation on a nascent competition 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 (STR), 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 demoting when facing the common 'enemy' of Airbnb competition. But there is considerable heterogeneity among hotels in reaction to Airbnb competition. Low-end hotels do not increase their review manipulation activities for either self-promotions or demotions, while high-end hotels demote their competing hotels less and promote themselves more in the presence of higher levels of Airbnb competition.

Keywords: Sharing economy, online review manipulation, strategic groups

1. 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 of (potentially underutilized) goods or services to make them available to consumers. Recent years have witnessed a rapid growth of 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. They represent a different type of competitors to traditional firms, requiring revisiting models of competition to allow for the expanded and new competitive landscape (Eckhardt et al., 2019). Ways in which traditional firms may have 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) observe "… 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 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 the hosts set, 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 thousand cities.[1] Airbnb has a market cap of more than $100 billion in October 2021, exceeding several well-established hotel chains such as Marriott and Hilton.[2]

Online reviews have become an influential source of information to help 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 resort to manipulating reviews (He et al., 2021; e.g., 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 striving to counter the competition. For example, Zervas et al. (2017) document that hotels respond to the entrance of Airbnb by reducing prices.

Since Airbnb is intensifying the competition in the lodging business, and competition has been found to lead hotels to engage in review manipulation, we ask if hotels change their review manipulation actions upon the emergence of Airbnb. Is the problem exacerbating as Airbnb grows? We draw on the *strategic group theory* (e.g., Cool & Schendel, 1987; Fiegenbaum & Thomas, 1995; Mas-Ruiz et al., 2014) in framing 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, as well as review channels. These differences have important implications on the review manipulation strategies for incumbent hotels. Does the different nature of competition from the sharing economy lead to different review manipulation activities of incumbents? Specifically, the research question we address is whether conventional hotels change their review manipulation actions upon the emergence of Airbnb. We examine two types of manipulation strategies, self-promotions and demotions. We further investigate if the changes in manipulation behaviors are heterogeneous across different categories of hotels (i.e., high-end and low-end hotels).

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1 https://www.airbnb.com/about/about-us (accessed December 11, 2021).

2 https://companiesmarketcap.com/hotels/largest-hotel-companies-by-market-cap/ (accessed December 11, 2021)

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 STR.[3] We find that the supply of nearby Airbnb listings exerts significant impact on hotels' review manipulation actions and such impacts are not homogeneous across different types of hotels. Our main results are that high-end hotels promote themselves more after Airbnb penetrates their market; surprisingly, they demote each other less after the entry of Airbnb. The low-end hotels do not increase either their self-promoting or demoting actions as Airbnb became more popular. Our findings suggest that the disruptive innovations from sharing economy companies are changing the dynamics of competition among the incumbents in unexpected ways. These findings are aligned with the predictions from the strategic group theory.

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

2. Theoretical Framework

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

2.1. Incentives to Manipulate Reviews

Customer reviews have been found to be important drivers behind 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 to businesses, firms may even attempt to manipulate customer opinions by disguising their promotions as customer recommendations (Mayzlin, 2006).[4] Many firms have been found to resort to manipulating reviews (He et al., 2021; e.g., Tibken, 2013). Consequently, it is not uncommon to encounter fake (manipulated) reviews in 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 due to review manipulations by these retailers, 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 are found to be fake. The percentage of fake reviews has been estimated to be around 15% to 30% despite the best efforts of review platforms in combating 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, Dave Eggers, the author of *A Heartbreaking Work of Staggering Genius*, was found to have posted positive reviews for his own book to inflate its rating (Harmon, 2004). Similarly, Luca and Zervas (2016) find 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, a firm may be inclined to post disingenuous negative reviews for its competitors especially when their products are strong substitutes. For example, Luca and Zervas (2016) find that a restaurant is more likely to demote other restaurants

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

4 Mayzlin (2006) refers to such behavior as promotional chat.

when facing increased competition. In the lodging business before Airbnb became popular, Mayzlin et al. (2014) document 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 might also depend on a firm's own quality as demonstrated in two analytical modeling papers. Mayzlin (2006) argues that producers with lower quality will expend more resources on manipulating reviews. On the other hand, Dellarocas (2006) shows that there exists an equilibrium where the high quality producer will invest more resources into 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 only consider the top few choices in forming their consideration sets from the ranked results, while demotions are more effective when customers are willing to search further down the list.

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

2.2. Identification of Review Manipulation

Identifying manipulative reviews is non-trivial. Several algorithms based on text mining have been developed to detect fake reviews (Jindal & Liu, 2008; Kumar et al., 2018; Li et al., 2014) with varying degrees of success. Review websites like Yelp screen reviews using their proprietary algorithms.[5] Despite such endeavors, it is still 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 amount of fake reviews show up on the review platforms despite the filtering algorithms in place. Lacking ground truth regarding which reviews are genuine and which ones are fake, we do not resort to text mining approaches to classifying 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 that hotel on its site. Therefore, review manipulation, if any, will be more likely to occur at TripAdvisor's site than at Expedia's due to the lower cost needed to fabricate a fake review on TripAdvisor. Thus, for a hotel, the difference in review ratings between these 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 getting demoted by competitors. Self-promoting activities are identified by examining the difference in the proportions of reviews with high ratings (five-star ratings) in TripAdvisor as opposed to Expedia, while the getting-demoted levels are identified from the net proportions of the reviews with low ratings (one-star and two-star ratings).

2.3. Strategic Group Lens

Until September 2021, Airbnb had hosted over 1 billion guest arrivals.[6] Airbnb has transitioned some homeowners from "persons with homes" to "competitors with Hilton" (Stein, 2015). The encroachment by Airbnb listings into the territory of traditional hotels is taking a toll on incumbent hotels. While the impact of Airbnb on hotel prices has been examined (Li & Srinivasan, 2019; Zervas et al., 2017), the competitive reactions of incumbent hotels with respect to review manipulation has 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 to be a group of firms that closely compete against each other

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

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

within an industry, and where firms in the same group 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 (Mas-Ruiz et al., 2014; Mas-Ruiz & Ruiz-Moreno, 2011; e.g., 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 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 home-style kitchen and laundry facilities, cozy living and dining areas, complimentary breakfasts, and local knowledge from the 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 for which it provides access, their asset base is very different from that of traditional hotels. Its key assets, instead, 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 due to long lead time for construction and employee training. On the other hand, Airbnb can expand supply almost overnight as demonstrated for seasonal events like the SXSW festival in Austin, Texas (Zervas et al., 2017). Thus, Airbnb can better accommodate volatile demand due to low capital costs of adding (or removing) 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, as well as registering with local agencies and paying certain taxes (Martineau, 2019). The regulations that Airbnb face in different cities, if any, are mostly directed to mitigate neighborhood impact, rather than creating a level 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 nature of regulations that apply to hotels and to Airbnb properties makes 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 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 in 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. On the other hand, an important long-term strategic imperative for Airbnb is to ensure their platform attracts healthy participation from both hosts and guests, thereby generating strong network effects. To promote this, algorithms to match potential guests with hosts is an important aspect of their 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.

2.4. Airbnb's Impact on Hotels' Review Manipulations

The 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 (Mas-Ruiz & Ruiz-Moreno, 2017; e.g., Porter, 1979). Cool and Dierickx (1993) go on to note 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 the competition from Airbnb has led the incumbent group of hotels to adjust their review manipulation strategies (over and above their reactions on conventional dimensions such as price adjustment and lobbying). Importantly, the review platforms for hotels and for properties listed on Airbnb differ in important ways. Reviewers evaluate an Airbnb listing through Airbnb's own website, and conventional review platforms such as Expedia, TripAdvisor, and Yelp do not accommodate reviews for Airbnb listings.[7] Airbnb only allows those 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 the website host of Airbnb.com, making reviewers identifiable. Further, a typical Airbnb listing may comprise of 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 the 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 they were used to dealing with the 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), the literature is silent regarding how the emergence of a new strategic group could impact rivalry within an existing group. Would hotels change their review manipulation strategy targeted towards other hotels with the emergence of Airbnb listings? On one hand, because Airbnb has taken away a portion of demand from the hotels, the rivalry across hotels becomes more intense for the shrunk market, and the reaction across hotels could be to "instigate warfare" (Smith et al., 1997). In our context, it implies hotels may be incentivized to demote competing hotels more 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 demoting activities intensified due to an increased number of conventional competitors.

On the other hand, the competing hotels now face Airbnb as a common rival. As an ancient proverb goes "The enemy of my enemy is my friend," and competing hotels may find it beneficial to work together to fight against a common new enemy. There is considerable evidence that incumbents 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 (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 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 its 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 so they 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, it means that mutual demotion between incumbent hotels might be counterproductive for all hotels.[8] Therefore, hotels demoting their competing hotels may be wary of retaliation that could end up hurting the hotels altogether, now that consumers can switch to Airbnb alternatives. Thus the strategic group theory suggests that co-opetition, rather than tit-for-tat, is a viable choice among members within 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.

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7 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 thousand properties on TripAdvisor and 381 thousand listings on Airbnb, only around 2 thousand properties (0.5%) were cross-listed.

8 Along similar lines, the balance theory proposed by Heider (1958) conceptualizes a motive called "cognitive consistency," which drives the formations of friend and enemy relationships. The 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 the strategic group theory in our context.

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 a hotel offers. Since Airbnb has shrunk the collective demand for hotels (Zervas et al., 2017), a hotel may need to bolster its self-promotion actions to combat other hotels for the shrinking demand.

The level of self-promotion may also depend on the nature of ratings received. Luca and Zervas (2016) find 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 due to the emergence of the common rival Airbnb. Second, customers whose needs are better suited by Airbnb listings (e.g., the cost of meals and rooms for a family of four could be significantly higher with hotels than with Airbnb listings (McCool, 2015)) would be more likely to shift towards such properties, with the result that hotels would receive fewer poor ratings. In summary, because of these counteracting forces, it is interesting to explore which one dominates in the lodging business in the face of Airbnb competition.

2.5. 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 on promoting their products, where advertising serves as a credible signal of quality (see, e.g., Kihlstrom & Riordan, 1984). In the lodging business, Hollenbeck (2018) finds 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 gain financially (Luca & Zervas, 2016; Mayzlin et al., 2014). However, it is unclear whether high-end hotels and low-end hotels would respond similarly to the competition from Airbnb listings.

Vertically differentiated firms (i.e., high-end vs. low-end) often need to choose different competitive strategies suitable for them. Michael Porter (2008b) posits that firms at the low-cost position are better off utilizing the "overall cost leadership" strategy to remain profitable after their competitors have competed away their profits. On the other hand, 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, it implies that low-end hotels and high-end hotels may employ different strategies to counter competition.

With regards to the nature of review manipulation in particular, Lappas et al. (2016) show that the relative effectiveness of self-promoting or demoting others depends on the size of consumers' consideration sets, which could differ for different types of hotels. Also, firms are found to increase their self-promotion to counter the negative reviews they have received (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 hotels compared to the other because of the advent of Airbnb, then this type of hotels may be more likely to increase their demoting 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 from Airbnb.

These studies suggest that different types of firms may adopt different self-promoting and demoting 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 the different hotel types. To address this, we investigate Airbnb's impact on the change in review manipulation actions for low-end and high-end hotels separately.

In summary, we ask if 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 from Airbnb. We also examine if the change in review manipulation behavior is homogenous across different types of hotels. The rapid emergence of the sharing economy provides an ideal opportunity to study these new competition dynamics among incumbent hotels.

3. 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 (at comptroller.texas.gov). Each source provides complementary data items for our analyses.

Our analyses are conducted for hotels in the state of Texas. All data collected are for the period starting from January 2008 (the inception year of Airbnb) up to December 2015. We restrict our attention to hotels in cities with a population over 50,000, as the number of hotels as well as Airbnb penetration is quite low in smaller cities. There were 67 such cities in Texas for the period under consideration.[9] We wrote Python crawlers to scrape the review data on all hotels in these cities from the TripAdvisor and Expedia sites. From each site, we obtained the review ratings and the review dates. 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 includes, for each hotel, its price tier and address. Based on STR's price tier information, we consider two categories of hotels: low-end (or Budget hotels) and high-end (non-Budget hotels).[10] The Texas Comptroller's office provides public records on quarterly hotel tax filing records for all the hotels in the state of Texas,[11] in addition to the hotel names and addresses. We identified the period during which a hotel has been operating based on the tax filing records. Both the STR Texas census data and the Texas Comptroller's office tax filing data include the name and address of each hotel. We matched all the hotels identified in 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 hotel-quarter, i.e., the quarterly information for hotels in terms of reviews, competitors, etc.

In order to determine the extent of competition a hotel faces from Airbnb, we wrote Python programs to collect all the Airbnb listings from the cities identified (part 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 starting time when a listing became available.

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 one-star reviews per quarter	0.71	1.43	0	31
Number of TripAdvisor two-star reviews per quarter	0.76	1.51	0	28
Number of TripAdvisor three-star reviews per quarter	1.47	2.58	0	61
Number of TripAdvisor four-star reviews per quarter	2.97	4.96	0	98
Number of TripAdvisor five-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 one-star reviews per quarter	1.16	3.23	0	92
Number of Expedia two-star reviews per quarter	1.43	2.87	0	65
Number of Expedia three-star reviews per quarter	2.83	4.70	0	109
Number of Expedia four-star reviews per quarter	6.08	8.49	0	142
Number of Expedia five-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			

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

10 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

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

To match hotels with their competing Airbnb listings, we calculated the distance among them based on the latitude and longitude of each hotel (which is available in Expedia.com) and those of each Airbnb listing (which is available in the HTML file for each listing in Airbnb.com). Along the lines of Mayzlin et al. (2014), we identified competing properties (hotels as well as Airbnb listings) as those that were within one kilometer radius from a focal hotel.[12] To control the level of competition from the traditional hotels, we counted the number of competing hotels of the same type (i.e., low-end or high-end) for a focal hotel in each quarter. Likewise, we counted the number of distinct listings that have appeared on Airbnb up to that quarter to identify the level of competition resulting from the sharing economy. Our data consist of 2,188 hotels that received reviews on both the TripAdvisor and Expedia websites. Three cities were dropped because none of the hotels there received any review, and so we were left with hotels from 64 cities. Hotels in 10 of these 64 cities did not have any competing Airbnb presence. Overall, 48% of the 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.

4. Empirical Strategy

4.1. Identifying Review Manipulation

We identify review manipulations following Mayzlin et al. (2014) where they measure self-promotion as the difference in the share of five-star reviews in TripAdvisor (TA) and in Expedia (EXP), respectively, for hotel *i* in year-quarter *t*:

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

Similarly, they measure demotion as the difference in the share of one-star and two-star reviews in TripAdvisor and Expedia:

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

One nuance is that in our sample, the average TripAdvisor (Expedia) rating is 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 demotions are reasonable proxies of review manipulation for high-end hotels. For low-end hotels, we consider both 4-star and 5-star ratings as potential promotions and 1-star ratings as demotions. Thus, for a low-end hotel:

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

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

Note that this demotion measure popularized by Mayzlin et al. (2014), only captures how a focal hotel gets demoted. This measure is passive, in that a focal hotel does not directly control whether and how its competing hotels demote it. In contrast, our interest is to understand the review manipulation strategy that a focal hotel is actively engaged in. 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

12 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.

evenly to this competitor's other competitors (of which the focal hotel is one);[13] and 4) Take an 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) where they capture the level of demotion received by a focal hotel instead of demoting activities exerted by the focal hotel.

At the aggregate level, TripAdvisor ratings increase while Expedia average ratings stay relatively flat in our observation period (Figure A1 in Appendix A). When we differentiate hotels, we find 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 in TripAdvisor (Figure A2 in Appendix A).

4.2. Econometrics Analysis

To identify the impact of Airbnb on hotels' review manipulation behavior, we exploit 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*). Specifically, we ask whether the difference in review distributions between TripAdvisor and Expedia increases (or decreases) for a hotel with an increase (or decrease) in nearby Airbnb supply (i.e., within a specified radius). We estimate:

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

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 that 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 $\log(\text{CompetingHotels}_{i,t-1})$.[14] It is important to note that our model specification uses two-way fixed effects that include both individual-hotel specific and time (year-quarter) specific ones, 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 introduce controls for the city-specific seasonality $\text{City}_i \times \text{Quarter}_t$ in the model. Seasonal events in different cities like the South by Southwest festival in Austin in Spring, and the Texas State Fair in Dallas in Fall would not bias our estimation with these controls incorporated. Moreover, simultaneity bias is mitigated in the panel model because we measure the Airbnb supply *prior* to the measurement of self-promoting and demoting 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 are taken in three ways implicitly and explicitly. The difference between TripAdvisor and Expedia is explicit as in Mayzlin et al. (2014). This difference allows us to control for the unobservable quality or popularity change in hotels. We define treated hotels to be those hotels with nearby competing Airbnb listings, and untreated (control) hotels to be those with no Airbnb listings nearby (an exception as discussed in the subsection of Look-Ahead Propensity Score Matching is the LA-PSM analysis where control hotels eventually have competing Airbnb listings). The difference between treated and untreated hotels are taken implicitly through the hotel fixed effects, which accounts for time-invariant differences in review manipulation between treated and untreated hotels. The difference between pre-treatment and post-treatment are also taken implicitly over time using year-quarter fixed effects, which allow for unobserved time-varying manipulation differences that are common across different hotels.[15]

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

13 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.

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

15 We validate the pre-treatment parallel-trend assumption in Appendix B.

$$\begin{aligned}\text{ReviewManipulation}_{it} = \beta_0 + \beta_1 \log(\text{Airbnb}_{i,t-1}) + \beta_2 \log(\text{CompetingHotels}_{i,t-1}) \\ +\beta_3 \log(\text{ReviewCount}_{i,t-1}) + B(\text{ReviewRatios}_{i,t-1}) \\ +h_i + \lambda_t + \text{City}_i \times \text{Quarter}_t + \epsilon_{it}.\end{aligned} \tag{2}$$

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

$$\begin{aligned}\text{ReviewManipulation}_{it} = \beta_0 + \beta_1 \log(\text{Airbnb}_{i,t-1}) + \beta_2 \log(\text{CompetingHotels}_{i,t-1}) \\ +\beta_3 \log(\text{ReviewCount}_{i,t-1}) + \beta_4 \log(\text{Airbnb}_{i,t-1}) \times \text{HotelType}_i \\ +B(\text{ReviewRatios}_{i,t-1}) + h_i + \lambda_t + \text{City}_i \times \text{Quarter}_t + \epsilon_{it}.\end{aligned} \tag{3}$$

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

We control for the number of competing hotels, log(CompetingHotels), that might influence a focal hotel's review manipulation decisions, which is 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.

4.3. Addressing Endogeneity

There are several sources of endogeneity that could potentially bias the estimation results. Omitted (and relevant) variables could be such a cause. Though we have controlled for the two-way fixed effects and city seasonality, there might still be some unobserved characteristics that impact the hotel review manipulation level. The Airbnb supply could become endogenous if those unobservable characteristics also correlate with the Airbnb supply. An example is the advertising budget of hotels that is 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 this advertising budget is correlated with the Airbnb supply, then the estimation on the impact of Airbnb supply could be biased.

In our context, it would be virtually impossible to tease out the causal effects by running field experiments, because that would need to coordinate the level of Airbnb supply across thousands of hotels. As a result, we first consider to an instrumental variable (IV) approach. A desirable IV should be strongly correlated with the endogenous variable while it must not be related with the hotel manipulation level in unobserved ways (i.e., through the error term). We identify the following IV for a focal hotel's competing Airbnb supply: the level of competing Airbnb supply for the focal hotel's competing hotels. It is defined as the distinct number of Airbnb listings for competing hotels, after excluding the competing Airbnb listings of the focal hotel. On one hand, because the focal hotel's competing Airbnb listings are removed when constructing this instrumental variable for 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 percent maximal IV relative bias (Stock & Yogo, 2005). While the exclusion restriction for the IV is untestable, there are some tests that can be done to indirectly test the validity of the IV. In the subsection of Identifying Review Manipulation, we provide further support for the validity of the instrument by running the test proposed by Barron et al. (2020) that ensures there is no correlation between the IV and the dependent variable in places without Airbnb.[16]

Another relevant source of potential endogeneity could be self-selection: the treated and untreated hotels could be intrinsically different when they self-select into review manipulation levels. To alleviate this concern, we used the Look-Ahead Propensity Score Matching (LA-PSM) (Bapna et al., 2018) to balance the treated and untreated hotels.

16 We thank an anonymous reviewer for suggesting this test to us.

The details for how LA-PSM is implemented and the corresponding results are provided in the subsection of Look-Ahead Propensity Score Matching.

We further address endogeneity by constructing synthetic controls for each treated hotel using the *Generalized Synthetic Control* (GSC) estimators (Xu, 2017). GSC applies to situations that have 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 base their decisions to list their properties on hotels' review manipulation levels. This is unlikely to be the case for two reasons. First of all, it is very difficult for Airbnb hosts and guests to observe the review manipulation levels of neighboring hotels easily (short of conducting analyses as is done in this paper). Second, we have 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, our IV estimation approach as discussed has further alleviated this concern.

5. Results

We present the estimation results of review manipulation in reaction to the number of Airbnb listings. Specifically, we analyze Airbnb's impact on hotels' review manipulations in terms of self-promotion and demotion activities.[17]

5.1. Self-promotion

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

Column 1 (Model 1) in Table 2 shows 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 point (p<0.001) in self-promotion. It implies the impact of Airbnb over the five-year period 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 2011 Quarter 1 to an average of 9.187 listings in 2015 Quarter 4, which implies an increase in magnitude of log(9.187/0.554)×0.021=5.6%. Column 2 (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.

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 hotel level.)

17 SUR (Seemingly Unrelated Regressions) models may seem more appropriate at first glance for the estimation since we have one equation for the self-promotion and one equation for the demoting 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.

A follow up question is whether there is heterogenous impact of Airbnb supply on different hotel categories. The revenues for low-end hotels have been found to decrease more than that of high-end hotels after the entry of Airbnb (Zervas et al., 2017), and therefore, one might expect that low-end hotels need to engage in more self-promotion due to the intensified across-group competition from Airbnb. However, this is not the case. Column 3 provides estimates for Model 3 using the high-end hotel category as the reference level. A 1% increase in Airbnb competition would drive high-end hotels to increase self-promotion by 0.020 percentage point (estimated β_1 is 0.020 in Table 2 column 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 column 3, even though Airbnb supply drives high-end hotels to self-promote more, 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 estimate 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 levels. Taken together, with an increase in Airbnb supply, high-end hotels engage in significantly more self-promotion while low-end hotels do not increase their self-promotion levels.

Our finding of higher self-promoting behavior of high-end hotels appears to be counterintuitive at first glance. However, it may not be surprising when we consider that online reviews might be of greater strategic importance to high-end hotels than to 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 hotels' actions regarding responding to reviews: hotel management teams frequently utilize management response in 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 find 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). Further, we find that low-end hotels receive significantly fewer reviews on average in both Expedia and Trip Advisor as compared to high-end ones. Along these lines, Lewis and Zervas (2019) argue that the importance of online review ratings looms larger for high-end hotels because customers have higher expectations from them. Our finding suggests that high-end hotels tend to utilize the "differentiation" strategy through increasing self-promoting activities in face of the across-group competition from Airbnb.

5.2. 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.

Table 3: Demoting Behavior with 2SLS

	(1)	(2)	(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.)

Columns 1 and 2 in Table 3 show that, when the competing Airbnb supply increases, hotels reduce demotions for competitors. Column 3 includes the interaction terms for hotel categories, showing the differential impact of Airbnb using high-end hotels as the reference level. The estimates of demoting behaviors for high-end hotels are qualitatively similar to the previous two columns. A 10% increase in Airbnb supply would drive high-end hotels to significantly decrease demoting activities by 0.0035 (estimated β_1 is 0.035 in column 3). Considering the mean of demoting activities is 0.189 per year-quarter, the decrease in high-end hotels demoting their competing hotels amounts to about 1.85% each quarter due to 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 demoting behaviors as Airbnb supply increases.

Mayzlin et al. (2014) find that the presence of more competing hotels leads to a focal hotel receiving more fake demoting reviews in TripAdvisor. Also Luca and Zervas (2016) report 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 the intensified competition from Airbnb actually led to fewer demoting reviews for high-end hotels. The contrasting finding lends support to our earlier argument that the nature of sharing economy competition is different. Our findings align with the predictions of the strategic group theory (Caves & Porter, 1977): rivalry is lower within a group because firms are better able to recognize their mutual dependence and so they cooperate, or tacitly collude with one another, when facing competition from another strategic group or a common enemy like Airbnb, and because the tit-for-tat competitive interactions can be destructive (Smith et al., 1997). According to its prediction, it may not help hotels to demote each other in platforms like TripAdvisor given that customers now have the option of Airbnb rentals. This finding indirectly echoes the "differentiation" strategy that may be attributed to self-promotion: by decreasing demoting activities high-end hotels can indirectly boost their online ratings in a relative manner as a result of potentially reduced retaliation.

6. Mutual Demotion Across Hotel Groups

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

The subsection of Identifying Review Manipulation introduced the procedure to attribute demoting reviews to their competing hotels. For each pair of hotels, we calculate the intensity of mutual demoting 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 need 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 consider the intersection of the Airbnb listings that are 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 measure 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.[18]

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

One might be concerned that our findings might be a result of customer shift, e.g., some hotel customers, who used to give low ratings, now shift to Airbnb listings. This shift in customer types might lead to the decreased demoting activities for hotels. However, this alternative explanation is unlikely to be 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 occurs only in one platform but not in the other. Second, we examine whether the travel types of

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

customers changed after the emergence of Airbnb, and do not find any significant change during our observation period. This analysis is discussed in Appendix D.

Table 4: Mutual Demoting Behavior with 2SLS			
	(1)	(2)	(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.)

7. Robustness Checks

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

7.1. Validity of the Instrument

If the instrument is valid, then it should only be correlated 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 hotels' review manipulation level. To test this, we regress 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 review manipulation in hotels without Airbnb competitors. By contrast, columns 3 and 4 of Table 5 show that if we regress 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 could be fundamentally different. We therefore construct a third sample of hotels with Airbnb competitors which are very similar to the 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 section of Look-Ahead Propensity Score Matching where we discuss LA-PSM). Column 5 and 6 of Table 5 report the results when we regress review manipulation level directly 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 the hotels with Airbnb competitors.

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.)

7.2. Look-Ahead Propensity Score Matching (LA-PSM)

Since the treatments of Airbnb supply to hotels may not be assigned randomly (as opposed to a controlled experiment), our estimations may be subject to systematic differences between the treated hotels and untreated ones. To alleviate this concern, we use the LA-PSM method (Bapna et al., 2018). A limitation of a standard PSM is that it only accounts for observed measures. It would fail 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 the 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 for our panel data.

We determine 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 divide 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 had no Airbnb competitors in both Periods 1 and 2. In regular PSM, hotels in either group A or 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 and their matched hotels relatively balanced, we divide the 32 quarters into the first two-thirds and the last one-third. To calculate the propensity score (predicted probability of being treated), we use 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 such as the price. We use exact matching on the categorical (dummy) variables and nearest neighbor matching on the continuous ones as it provides better matching quality compared to using just one method. We group hotels that have an exact match on the categorical variables into subsets, and then match the treated hotels with untreated ones that have 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 got treated (at different time periods), the matching procedure accounts not only for the observed measures using propensity-scores, but also for the unobserved time-invariant characteristics influencing hotel's intrinsic propensity to get 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 including other features for the matching (such as hotel average rating, standard deviation of rating, and the number of ratings).[19]

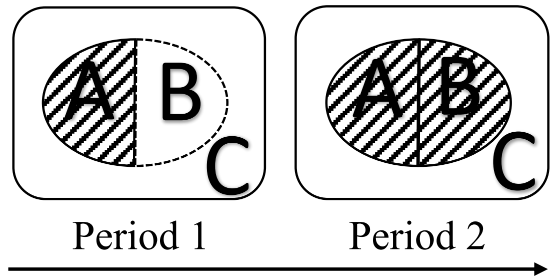

Figure 1. Control Group in LA-PSM
Note: The shaded left half oval represents the hotels that start facing Airbnb competition in Period 1 (Group A). Shaded right half oval represents the hotels that start facing Airbnb competition in Period 2 (Group B). Group C denotes the hotels which do not face Airbnb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

Table 6: LA-PSM – Matched Hotels

	Self-Promotion			Demoting-Others		
	(1)	(2)	(3)	(4)	(5)	(6)
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.)

7.3. Generalized Synthetic Control

Besides LA-PSM, an alternative method that can help address 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 like the case in our data.

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

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

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

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.

7.4. Getting Demoted

Since we want to understand the active role that hotels engaged in with respect to demotion, we have analyzed the magnitude for demoting others in our analyses. Mayzlin et al. (2014) used the getting-demoted measure to see how much hotels *have been demoted* by their competitors. Although it is orthogonal to the focus of our paper, we nevertheless explore if our results are consistent to 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 this 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 column 3, high-end hotels get demoted more and the impact on low-end hotels are 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 demoting 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 two hotels A and B are competing with each other. Further, let us assume that Hotel A has more competing Airbnb listings than does Hotel B. Based on our analysis, Hotel A is likely to engage in less demoting activities compared to Hotel B. 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 an opposite lens.

Table 8: Getting-demoted with 2SLS			
	(1)	(2)	(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.)

7.5. Other Robustness Checks

We have conducted several additional analyses to ensure 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 are primarily constrained within a one-kilometer radius with respect to each focal hotel. Competing hotels located farther 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 also of considering all competing hotels equally. We build on the idea of Luca and Zervas (2016) to model a gradual decease in competition intensity due to increased distance. The results are consistent with the main results.

As mentioned in the subsection of Identifying Review Manipulation, due to the difference in average ratings for high-end and low-end hotels, we measure self-promotion and demotion differently for the high-end and for the low-end hotels. We also replicate 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 consider all nearby Airbnb listings as competing with a focal hotel regardless of the nature (i.e., price and quality) of those listings. In Appendix G, we validate our estimation results are not sensitive to this assumption.

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

To further reinforce our findings, we use 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.

8. Discussion and Conclusions

An interesting outcome of the rise of the digital economy has been 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 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 the 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, are impacted by the emergence of the 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 reaction to increased competition. Based on these, 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-promotions for high-end hotels, while not leading to any increase in self-promotion behavior for low-end hotels. Regarding demotions, we find that increased Airbnb supply leads to significantly less demoting behavior for high-end hotels. Low-end hotels do not increase their demoting behavior with increased Airbnb supply. The findings regarding demotions is particularly surprising given the findings of Mayzlin et al. (2014) in the conventional lodging business and 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 the 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 the face of 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, incumbent hotels cannot counter the competition from Airbnb listings by demoting them in the same way as they dealt with the 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 demotions. Thus, co-opetition, rather than tit-for-tat, becomes a preferable option among members within the extant group, when between-group competition emerges.

Our findings have important implications for both review hosting platforms and customers. Review-hosting platforms like TripAdvisor can benefit from knowing that the increased Airbnb supply drives high-end hotels to self-promote more while engaging in less demoting activities. Consequently, these platforms can potentially adjust their filtering algorithms to account for both the magnitude of Airbnb supply around 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 manipulated because of abundant nearby Airbnb listings.

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 opens up other interesting avenues for future research as well. We have 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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About the Authors

Cheng Nie is an assistant professor of information systems and business analytics at the Ivy College of Business at Iowa State University. He received his PhD from the Jindal School of Management, University of Texas at Dallas. His current research interests are in sponsored search, sharing economy, and user-generated content.

Zhiqiang (Eric) Zheng is the Ashbel Smith Professor in Information Systems at the Jindal School of Management, University of Texas at Dallas. He received his PhD from the Wharton School of Business. His current research interests focus on fintech, blockchain, and healthcare analytics. He currently serves as a senior editor for *Information Systems Research*.

Sumit Sarkar is the Charles and Nancy Davidson Chair and Professor of Information Systems in the Naveen Jindal School of Management at the University of Texas at Dallas. He received his PhD from the Simon School of Business at the University of Rochester. His current research interests are in the sharing economy, crowdsourcing, recommendation systems, sponsored search, data privacy, and information quality. He is a Distinguished Fellow of the Information Systems Society at INFORMS.

Appendix A: Model-free Evidence

We examine if 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 demoting (more positive ratings and less negative ratings in TripAdvisor relative to in Expedia).

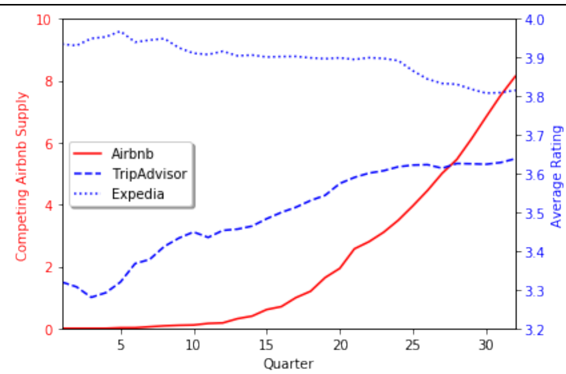
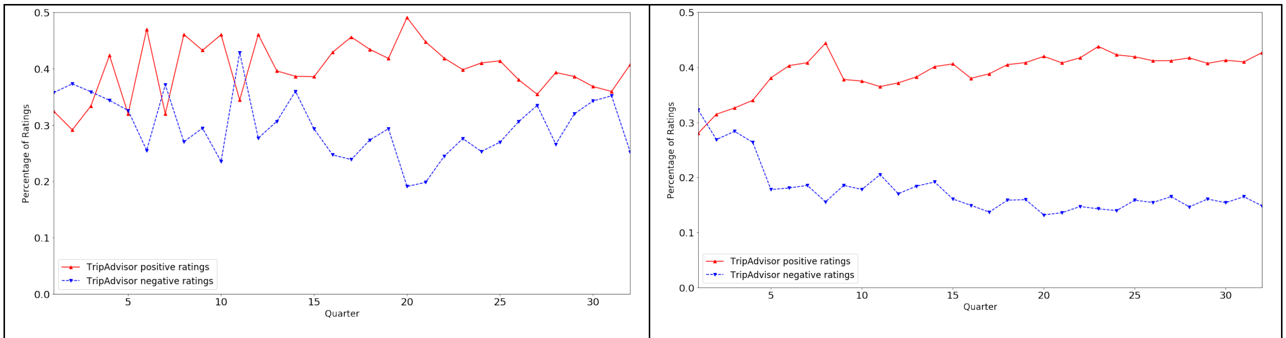


Figure A1. Changes in Average Ratings with Airbnb Supply

We also examine the trends in positive and negative reviews on TripAdvisor as compared to Expedia. 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.



Low-end hotels **High-end hotels**

Figure A2. Proportions of Negative and Positive Ratings in TripAdvisor

We find that the low-end hotels have relatively stable proportions of negative and positive ratings (relatively flat over time), while the high-end hotels have increasing proportions of positive ratings and decreasing proportions of negative ratings in TripAdvisor. This is consistent with our main findings that the high-end hotels tend to increase self-promotion and reduce demoting 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.

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, and 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).[20] The relative time model has been widely used in the literature to test the parallel-trend assumption (Chan et al., 2019; Greenwood 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).[21]

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

[21] 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; Y. 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 the *pre-treatment* periods. To eliminate such ambiguity, we adopt in Table B the notation $Airbnb\_Binary_{treat(0)}$ for the treatment period, $Airbnb\_Binary_{pre(-1)}$ for one period pre-treatment, $Airbnb\_Binary_{post(+1)}$ for one period post-treatment, etc.

Table B: Relative Time Model						
	Self-Promotion			Demoting-Others		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Airbnb\_Binary_{pre(-2)}$	-0.079 (0.234)	-0.071 (0.234)	-0.063 (0.235)	-0.042 (0.030)	-0.043 (0.030)	-0.043 (0.030)
$Airbnb\_Binary_{pre(-1)}$	-0.035 (0.025)	-0.034 (0.025)	-0.035 (0.025)	0.079 (0.043)	0.080 (0.043)	0.080 (0.043)
$Airbnb\_Binary_{treat(0)}$	0.060^{*} (0.026)	0.058^{*} (0.026)	0.063^{*} (0.027)	-0.108^{*} (0.054)	-0.107^{*} (0.054)	-0.107^{*} (0.052)
$Airbnb\_Binary_{post(1)}$	-0.046 (0.025)	-0.044 (0.025)	-0.045 (0.025)	0.050 (0.041)	0.049 (0.041)	0.049 (0.040)
$Airbnb\_Binary_{post(2)}$	0.010 (0.030)	0.009 (0.030)	0.010 (0.030)	-0.012 (0.036)	-0.011 (0.036)	-0.011 (0.036)
$Airbnb\_Binary_{post(3)}$	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)
$Airbnb\_Binary_{treat(0)}$ × 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.)

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 who do not face any Airbnb competitors in that period (nor in any previous period). As shown in Table B, none of the pre-treatment variables are significant in either the self-promoting 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 (shaded rows in the table). The significant coefficients in our 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.

Appendix C: Mutual Demotion Across Hotel Triplets

In the section of Mutual Demotion Across Hotel Groups, we examined if 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 the mutual demoting 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, C, respectively. Then the mutual demoting 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 C 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 demoting analyses demonstrate that high-end hotels reduce their demoting activities within the incumbent hotels when they face Airbnb.

Table C: Hotel Group Demoting Behavior with 2SLS (Hotel-Triplet)			
	(1)	(2)	(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 if 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 remains relatively stable as shown in Figure D.

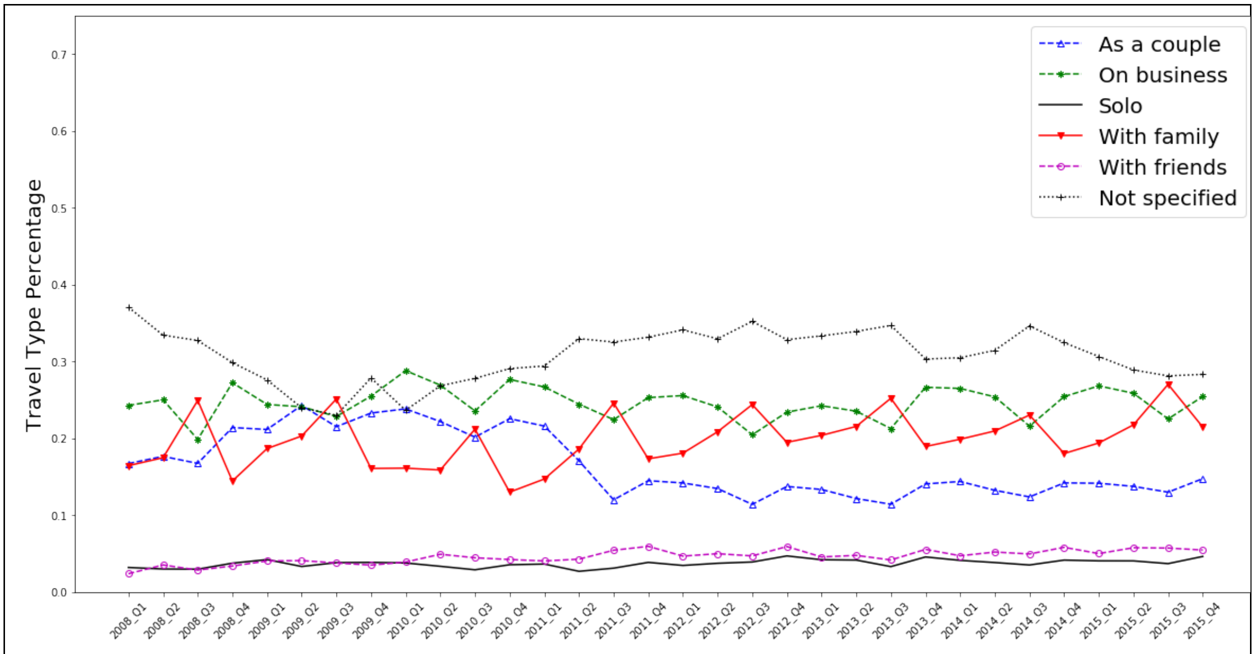


Figure D. Changes in Proportions of Various Travel Types

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.[22] The resulting p-value is close to 1, which means we fail to reject the null hypothesis. We

[22] In our context, the proportions of each alternative travel types 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

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 the six categories of travel types are stationary. Thus, there is no evidence that hotel customers have changed their preferences during the observation period.

Appendix E: Quantifying Competition Intensity Using a Smooth Kernel

Thus far, we have assumed that the competition between hotels and Airbnb listings are primarily constrained within a one-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 decease 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:

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

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 one kilometer would contribute 0.61, one at a distance of two kilometers 0.14, and so on. This captures the intuition that competing hotels with higher competition intensity 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 E, 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.

ANOVA (as referred to as within-subject ANOVA) to examine whether the population means of these groups change (Jackman, 2009, p. 317).

Table E: Quantifying the Competition Intensity Using a Smooth Kernel						
	Self-Promotion			Demoting-Others		
	(1)	(2)	(3)	(4)	(5)	(6)
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 subsection of Identifying Review Manipulation, due to the difference in average ratings for high-end and low-end hotels, we measure self-promotion and demotion differently for the high-end and for the 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 in TripAdvisor and in 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 F are consistent with our main results.

Table F: Alternative Operationalization of Manipulation						
	Self-Promotion			Demoting-Others		
	(1)	(2)	(3)	(4)	(5)	(6)
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 consider 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 if our estimation results are sensitive to this assumption.[23]

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

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

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 do not resort to the user-generated ratings as a control for the quality of Airbnb listings.

Table G: Segmenting Airbnb Competitors

	Self-Promotion			Demoting-Others		
	(1)	(2)	(3)	(4)	(5)	(6)
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.)

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 calculate the price per person (guest) for each Airbnb listings in our sample and then categorize 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 G, are consistent with the main findings.[24]

Appendix H: Combining Competitors Across Categories

In our main analyses, we have 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 are competing with high-end hotels only. The rationale behind this is that a low-end hotel is unlikely to demote a close-by 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 demoting actions (i.e., negative reviews), and the instrumental variable measures are modified correspondingly. The results, as presented in Table H, show consistency with our main findings.

[24] The low-end hotels appear to increase self-promotions based on column 3 of Table G1. However, such an increase is statistically insignificant when we use the low-end hotel as the reference level.

Table H: All Neighboring Hotels as Competitors						
	Self-Promotion			Demoting-Others		
	(1)	(2)	(3)	(4)	(5)	(6)
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 use 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 inflexion 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 get stronger as more Airbnb listings appear.

The subsample analyses, presented in Table I, 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 inflexion point, an increase in either competing Airbnb listings or competing hotels lead to significantly fewer demoting activities. This is consistent with the prediction from the strategic group theory, that the incumbent group of hotels engaged in less destructive competitive behavior after Airbnb listings grew substantially.

Table I: Demoting Behavior Before and After the Inflexion Point (2011 Quarter 4)						
	Before 2011 Q4			After 2011 Q4		
	(1)	(2)	(3)	(4)	(5)	(6)
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.)