The following publication Chen, Y., Tang, T., Li, Y., & Fan, D. (2021). Does interest alignment between hotels and online travel agencies intensify review manipulations? Industrial Management & Data Systems, 121(6), 1435-1456 and is available at https://doi.org/10.1108/IMDS-11-2020-0657.

Does interest alignment between hotels and online travel agencies intensify review manipulations?

Abstract

Purpose - This study examines whether a higher interest alignment between online travel agencies (hosting platform) and hotels (business owners) will intensify review manipulation activities.

Design/methodology/approach - With a panel dataset collected from a Chinese online travel agency and a travel search engine, we develop a matching-based difference-in-difference approach to examine the presence of partnership-intensified review manipulation.

Findings - We find that the ratings of agency's partner hotels (with a higher interest alignment) is abnormally higher than those of matched non-partner hotels (with a lower interest alignment), after benchmarked with their ratings on the search engine (without a partnership business model). Further, our ananlysis results indicate that this partnership-intensified manipulation deteriorates the hotel's sales performance because of damaged customer trust and satisfaction.

Originality/value - Previous studies implicitly assume that review manipulator is indepedent from the hosting platform. This is the first study examining the role of the hosting platform in review manipulaitons.

Keywords Review manipulation; Online travel agency; Partnership model; Interest alignment; Hotel performance

Paper type Research paper

1. Introduction

Hotels are increasingly relying on the internet platforms provided by online travel agencies (OTAs) as important sales channels. OTAs have also changed the way that consumers acquire related information about target hotels. Most OTAs host a platform for consumers to share their experiences by writing online reviews. Literature has substantially investigated the effects of these reviews on consumer booking behavior (Casado-Díaz et al. 2020, Filieri & McLeay 2014, Zhao et al. 2015) and hotel business performance (Öğüt & Onur Taş 2012, Xu et al. 2019, Ye et al. 2009). These studies generally concluded that positive reviews can lead to favorable business outcomes.

The positive effect of online reviews is based on the assumption that the reviews accurately reflect consumption experiences. However, recently, there is a growing concern over review manipulation (Hu et al. 2011, 2012, Lee et al. 2018, Luca & Zervas 2016, Mayzlin et al. 2014, Zhuang et al. 2018). Review manipulation is defined by Mayzlin et al. (2014) as "reviewers with a material interest in consumer's purchase decisions may post reviews that are designed to influence consumers and resemble the reviews of disinterested consumers". Later, Zhuang et al. (2018) point out "Despite the efforts by e-marketplace operators and review platforms to filter out fake reviews and the strengthening of guidelines and enforcement in various countries, manipulation of online reviews has persisted and taken more varied forms". Therefore, in this study, we extend the definition by Mayzlin et al. (2014) as "anyone with a material interest in consumer's purchase decisions may post, delete or modify reviews that are designed to influence consumers and resemble the reviews of disinterested consumers". Review manipulation has been found on TripAdvisor (Mayzlin et al. 2014, Zhuang et al. 2018), Yelp (Luca & Zervas 2016), and Twitter (Lee et al. 2018), and may mislead consumers' decision-making and impede review usefulness.

Previous studies implicitly assumed that review manipulators (e.g., hotels or their rivals) were independent from the hosting platform. They have largely overlooked the role of OTAs as the intermediary of hotel bookings and hosting platform for consumer reviews nowadays. On the contrary, this research aimed to explore the role of the hosting platform. In line with Mayzlin et al. (2014), our study does not attempt to distinguish whether any review is fake or not, instead we empirically examine whether the operating model of OTAs can be systematically intensifying review manipulation activities.

We drew from agency logic to explore this question. In the service supply chain of the hotel industry, consumers (the principal) delegate hospitality activities to a hotel (the agent) (Pavlou et al. 2007). From an agency perspective, such delegations facilitate the agent to conduct opportunistic behaviors and gain self-interest, while such behaviors may undermine the benefit of the principal (Jensen & Meckling 1976). The agency problem is primarily caused by a lack of interest alignment between agents and principals. We conceptualize review manipulation as a type of opportunistic behavior, and argue that the interests of OTAs are tied with hotels (through sales commissions), not with consumers. Thus, the higher interest alignment between hotels and OTAs may intensify review manipulation and thus undermine consumers' benefit. Specifically, we aimed to answer three research questions for both research and practice purposes:

1. Does a closer partnership (higher interest alignment) between hotels and OTAs intensify manipulations in the hotel's online review rating?

2. How does such partnership-intensified review manipulation affect hotels' online sales performance?

3. Which types of hotels are more affected by the partnership-intensified review manipulation?

The blooming of Chinese online OTA markets provided a fertile ground to answer our research questions. Using data collected from major OTAs in China, with a matching-based difference-in-difference (DID) design, we capture an abnormally higher consumer review rating in OTAs' partner hotels (with high interest alignment) than the matched non-partner hotels (with low interest alignment), after benchmarking to their ratings on a major Chinese travel search engine, Qunar.com. This observatoin indicates that the partnering business model of OTAs is likely intensifying review manipulation activities. Further, we conduct a regression analysis for panel data of these hotels over seven weeks. The results indicate that this partnership-intensified manipulation deteriorates the hotel's sales performance on the platform because of damaged customer trust and satisfaction. Moreover, the performance deterioration is more salient for large-scale, expensive, and prestigious hotels as a result of doubling the expectancy-violation effects, which implies that people react more strongly to greater violation of their previous expectation.

2. Theoretical background and hypotheses

2.1. Online reviews and review manipulation

Online reviews play an increasingly critical role in consumers' purchasing decisions. Previous studies typically reported a positive correlation between online review ratings and business performance in various industries, such as bookstores, hotels and restaurants (Chevalier & Mayzlin 2006, Mauri & Minazzi 2013, Öğüt & Onur Taş 2012, Ye et al. 2009, 2011). Therefore, stakeholders are tempted to promote the online reviews of their products or services to improve their business. Based on a qualitative study with 20 hotel managers in southern Sweden, Gössling et al. (2018) concluded that there exists a wide range of review manipulation strategies in practice. Moreover, this paper postulated that, as hotel managers compete increasingly over online reputation, they will eventually find that engaging in manipulation is the most rational choice.

There are several challenges in detecting review manipulation and quantifying their effect. First, because of social (un)desirability, it is almost impossible to directly observe review manipulation. However, empirical and technical methods were developed recently to capture review manipulation (Hu et al. 2011, 2012, Lee et al. 2018, Luca & Zervas 2016, Mayzlin et al. 2014, Zhuang et al. 2018). By examining the difference in review ratings for the same hotel on Expedia.com and TripAdvisor.com, Mayzlin et al. (2014) and Zhuang et al. (2018) captured empirical evidence about review manipulation on a travel review site - TripAdvisor. Luca & Zervas (2016) studied reviews on the review website Yelp and concluded that suspicious reviews has grown significantly over time. Lee et al. (2018) studied movie Tweets before and after the movie's release date and found that the proportion of positive Tweets exhibited a significant drop on the movie's release day. Based on these observations, they concluded that the movie industry might be actively managing online sentiment in a strategic manner.

Second, the effect of review manipulation is not static, but evolving over time and dependent on specific contexts. Using data from Expedia and TripAdvior, Zhuang et al. (2018) argued that review manipulating has an initially positive effect on sales and thereafter a negative effect as manipulation becomes more frequent and intensive. Some studies (Jin Ma & Lee 2014, Reimer & Benkenstein 2016) also show that as manipulation becomes more prevailing and consumers become more vigilant, suspicious reviews can have a greater adverse effect on consumers' perceptions.

However, there are several important research gaps in the literature to be addressed. First, most of the studies discussed above implicitly assumed that hotels are independent of the review hosting platform, while the role of OTAs in review manipulation has been largely overlooked. The case presented by Gössling et al. (2018) implies that some practices of OTAs may facilitate review manipulation of their partner hotels: the partnership between Shangri-La and TripAdvisor has significantly increased the number of page views and consumer reviews, hotel ratings, and market share. In addition, a recent study by Hunold et al. (2020), using data collected from Booking.com, Expedia, and Kayak, revealed that OTAs alter their search results to discipline hotels for price differences on competing channels, and therefore reduce search quality for consumers. Thus, our research applies a fresh perspective to systematically and quantitatively explore the role of the hosting platform in review manipulation.

In addition, our research extends existing methods of detecting review manipulation (examining either the average or ratio of review ratings (Hu et al. 2011, 2012, Lee et al. 2018, Luca & Zervas 2016, Mayzlin et al. 2014, Zhuang et al. 2018)). The robustness check of this study indicates that the variance of customer ratings can also help detect review manipulation. Finally, instead of using a proxy for online sales (Ye et al. 2011, Zhuang et al. 2018), the number of actual bookings collected from the OTAs allows us to investigate the direct effect of review manipulation on online business performance. In the following section, we draw from agency theory to conceptualize the role of OTAs and explain why manipulations can be intensified in OTA partnered hotels.

2.2. Partnership-intensified review manipulation on OTAs: an agency perspective

Agency theory investigates occasions in which one party (the principal) delegates authority to another party (the agent) (Jensen & Meckling 1976). In principal-agent relations, both the principal and agent are self-interested and seek to maximize their own profits by individually interpreting their contract relations (Fleisher 1991). This theory has been widely applied to explain the opportunistic behavior conducted by either principals or agents motivated by their own benefits (Bosse & Phillips 2016).

The literature has discussed the agency problems that arise in a business-to-business (B2B) context, where firms delegate sales, marketing, and advertising activities to agents. The agents may take advantage of the delegating firm's resources (e.g., brand equity and customer loyalty) to gain self-interest with guile (Zhang et al. 2015). Another smaller stream of literature uses the agency theory framework to understand the relations between product/service providers and consumers (Pavlou et al. 2007, Singh & Sirdeshmukh 2000, Tan & Lee 2015). In this business-to-consumer (B2C) context, the buyer (consumer) delegates responsibility to a seller (business) to deliver products/services, and the seller acts on behalf of the buyer (Pavlou et al. 2007). In this relation, out of consideration for short-term revenue-related goal, the business (agent) may be opportunistic and provide misleading information to induce consumers (principal) to purchase, thereby causing the agency problem.

Traditional hospitality transactions fit the B2C context. The hotel and consumer are opposing forces and have diverged interests: hotels seek the highest revenue, while consumers seek the maximum surplus. As a result of such diverged interests and information asymmetry, hotels may conduct opportunistic behaviors aimed at reaching a deal with a shorter time and higher price. Review manipulation is one typical example of opportunistic behavior that provides false information to consumers and affects their buying decisions.

When OTAs are involved as an intermediary in hotel booking and a hosting platform for customer reviews, would review manipulation be intensified or inhibited? Our hypothesized answer to this question is that the manipulations would be intensified as the interest alignment between the hotel and OTA becomes stronger. In an outcome-based contract, firms reward their sales forces based on measured performance outcomes (Ekanayake 2004), such as sales volume. Such risk- and revenue-sharing mechanisms are often used in contracts as incentives and reward strategies to stimulate short-term sales (Norrman 2008). For major OTAs, such as Ctrip and Fliggy, two types of hotels are listed on their platforms: partner hotels and non-partner hotels. Partner hotels typically pay a higher commission for each room sale. For example, to become a strategic partner hotel of Ctrip, hotels must pay a commission as high as 15% to 25%, compared with 8% to 10% for typical non-partner hotels (Liu 2019). This indicates a higher interest alignment between OTAs and their partner hotels, compared with non-partner hotels. Thus, OTAs are incentivized by higher commissions from their partner hotels, and their partner hotels try to make up for higher commissions with more room sales. Intuitively, higher hotel review ratings will lead to more room sales. Therefore, both the OTAs and their partner hotels are tempted to boost or help boost the partner hotels' review ratings. By doing so, they expect to promote these partner hotels' room sales and ultimately increase their own benefits.

Thus, the higher interest alignment (sales commission) between OTAs and their partner hotels likely tempts OTAs to loosen their vigilance in the review manipulation of these hotels. Their partner hotels may be emboldened because they believe that the partnered OTA will be more lenient toward their behavior, which leads to an additional intensity of review manipulation. Based on this discussion, we postulate that partnership relations will intensify review manipulation:

Hypothesis 1. A higher level of interest alignment between hotels and OTAs is associated with a higher review manipulation for the hotels (i.e., partnership-intensified review manipulation).

2.3. Effect of partnership-intensified review manipulation

Review manipulation is considered an opportunistic and unethical business practice because it generates false or misleading information that interferes with consumers' decision-making (Jin Ma & Lee 2014). Studies in consumer behavior reveal that unethical business practices greatly affect consumers' evaluation of the company and purchase intentions (Brown & Dacin 1997, Folkes & Kamins 1999, Jin Ma & Lee 2014, Mohr & Webb 2005, Sen & Bhattacharya 2001). A survey conducted by Brown & Dacin (1997) demonstrated that consumers' knowledge about a firm can influence their beliefs and attitudes toward the firm's products. Experiments of Folkes & Kamins (1999) showed that unethical behavior elicits consumers' negative attitude toward a company. Later, a study of Mohr & Webb (2005) also confirmed that a company's lack of social responsibility will lead to consumers' lower valuations and purchase intentions. Moreover, customers are sensitive and diagnostic to potential negative practices by firms (Sen & Bhattacharya 2001). These perceptions can seriously damage customer trust, which consequently undermines buying intention.

When hotels and platforms are tempted to boost review ratings, they may also cause customer suspicion. Prior research has found that consumers evaluate the credibility of online reviews in terms of various factors, such as grammar and mechanics (Ketron 2017) and reviewer identity (Akhtar et al. 2019). The power of review valence highly depends on consumers' perceptions of review credibility (Filieri 2015, 2016, Filieri et al. 2018, Jin Ma & Lee 2014, Reimer & Benkenstein 2016). Moreover, Ahmad & Sun (2018) found that psychological discomfort caused by distrust with reviews also strongly affects consumer purchase behavior. Experiment results of Zhuang et al. (2018) revealed that customer suspicion lead to a decrease in willingness to book. Apart from this, industrial data (Womply Research 2020), also shows that lodging places with a star rating between 3.5 and 4.5 earned more than any other ratings group, including the 5 rated. This indicates that consumers' trust can decrease when the rating is too positive.

Meanwhile, customers' perceived satisfaction is influenced by their perception and expectation. A study of Mauri & Minazzi (2013) showed a positive correlation between the valence of the review and the hotel service expectation. If customers do not sense a review manipulation and make a booking, this manipulated rating can inflate the customers' expectations. This may increase the likelihood of having an expectation-perception discrepancy that disconfirms the pre-purchase expectation. The disconfirmation leads to customer dissatisfaction (Anderson & Sullivan 1993), which will in turn be reflected in customers' negative post-purchase reviews (online or offline) and behaviors, such as reluctance to repurchase or complain to others.

Based on the discussion above, we argue that partnership-intensified review manipulation can undermine customer trust if customers identify the manipulation. Moreover, inflated ratings can expand the gap between customer expectation and perception, which worsens perceived service satisfaction. Both mechanisms will deteriorate the hotel's subsequent performance. Therefore, we posit that:

Hypothesis 2. Partnership-intensified review manipulation deteriorates hotels' subsequent online business performance.

2.4. Moderating role of hotel characteristics

H2 hypothesizes that partnership-intensified review manipulation worsen hotel performance because of damaged customer trust and satisfaction. It is essential to explore the circumstances in which a hotel is more vulnerable or resilient to this deteriorating effect. We further postulate that the hotel's reputation could be a liability, that makes the hotel more vulnerable to partnership-intensified review manipulation.

A firm's reputation creates consumer expectation about its product/service quality (Shapiro 1983). Organizational theorists find that highly reputed firms suffer more market penalties for product defects because expectations about product quality are more likely to be violated (Rhee & Haunschild 2006). In the hotel industry, customer dissatisfaction is considered a defect in the service, which can be caused by discrepancy between expectation and perception. If online reviews are boosted for OTAs' partner hotels, these hotels' guests may encounter a mismatch between the service quality and review rating, which results in an expectancy violation. The expectancy-violation effect in the communication literature points out that people react more strongly to violations under circumstances in which such violations are perceived to be less likely to occur (Bond et al. 1992, Burgoon & Le Poire 1993). This indicates that customers of high-reputation hotels may react more strongly because of reputational liability (Rhee & Haunschild 2006). Specifically, hotels' reputations can be viewed as an implicit promise to potential customers to offer good services, with a quality level commensurate with their word-of-mouth (Rhee & Haunschild 2006). This implies that the better the hotel's reputation, the greater the extent to which consumers expect the hotel's service to be consistent with their online review rating. When service quality does not match review rating, customers of high-reputation hotels respond more negatively toward the hotel. Similarly, marketing research has shown that different market segments react differently to expectancy violations (Heath & Chatterjee 1995). Experiments of Simonson & Tversky (1992) found that losing quality is generally more aversive in the higher-end market than the lower-end market.

In addition to creating expectations about product/service quality, a firm's reputation also generates consumer expectations about firms' behavior (Shapiro 1983). A good reputation is often associated with trust (Doney & Cannon 1997, Walsh & Beatty 2007) and integrity (Bick et al. 2003). Review manipulation is considered an unethical business practice that is less likely to occur with high-reputation hotels. If customers became aware of review manipulation after their stay, customers of high-reputation hotels may react more strongly because of the expectancy-violation effect discussed above. Next, we use hotel size, price, and prestige as proxy indicators for reputation, and examine their moderating effects on the manipulation-performance relation.

First, scholars associate organization size with organization reputation because larger organizations enjoy greater name recognition than do smaller organizations (Williams & Barrett 2000). Consumers tend to perceive that a large hotel is more trustworthy and hospitable than a small hotel (Ariffin & Maghzi 2012). Thus, consumers may be more disappointed if they learn that large hotels are manipulating their online reviews:

Hypothesis 3. The relation between partnership-intensified review manipulation and hotel performance is more negative when the hotel size is larger.

Second, the hotel price should be associated with the hotel reputation expected by customers because such price premiums should be a signal of good service quality. Yacouel & Fleischer (2012) found that reputable hotels enjoy a price premium. Consumer trust may be more seriously undermined if they are cheated by a hotel that is expensive. In addition, pre-purchase price perceptions are correlated with pre-purchase expectations of service quality (Voss et al. 1998). The raised expectations of higher hotel price would be more easily violated because of review manipulation, leading to undermined customer satisfaction and subsequent hotel sales:

Hypothesis 4. The relation between partnership-intensified review manipulation and hotel performance is more negative when the hotel price is higher.

Finally, the star rating of a hotel can be viewed as a recognition of a third party (e.g., governments and certification bodies) of the service quality of the hotel. Thus, the star rating is considered a reputation-based quality signal for consumers (Abrate et al. 2011). Consumers expect a better experience for their stay at a five-star hotel than at a three-star hotel, which increases the likelihood of expectancy violation if the hotel's online review is manipulated. Consumers would be more disappointed if they became aware of the review manipulation of a high-star-rated hotel, leading to a stronger deteriorating effect on future sales:

Hypothesis 5. The relation between partnership-intensified review manipulation and hotel performance is more negative when the hotel has a higher star rating.

Figure 1 contains a summary of our hypotheses and their directionality.

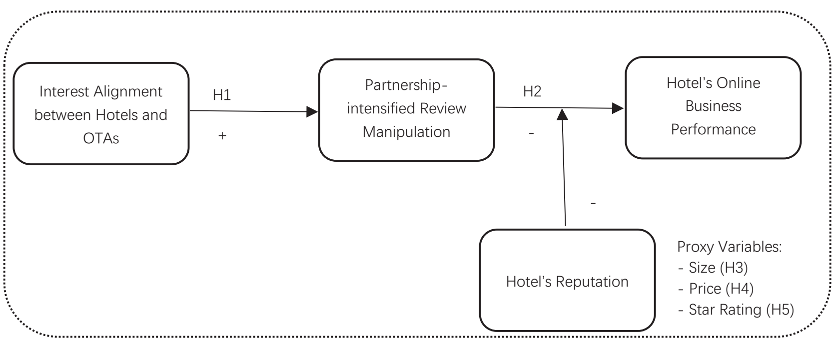

FIGURE 1: Research Model with Hypothese

3. Data and measurements

To test the hypotheses above, we collected data from one major online travel agency, Ctrip.com, and one major travel search engine, Qunar.com. Ctrip is the largest online travel agency in China, for which commission is a major part of its hotel booking service.

On Ctrip, only users who have booked a hotel through this platform within one year can post reviews. In addition, after posting reviews, users are not allowed to modify or delete them. In contrast, Qunar is a major Chinese travel search engine focusing on price comparison. Its revenue from hotel searching services mainly derives from advertising. In addition, for robustness checks, we also collected data from another major OTA in China, Fliggy.com, whose business model of hotel booking services is very similar to that of Ctrip.

3.1. Data collection

Our research design required comparison between an OTA (Ctrip/Fliggy) and a search engine (Qunar). The data collection process started by selecting the 10 most popular Chinese cities for tourism listed on Ctrip: Beijing, Shanghai, Guangzhou, Shenzhen, Nanjing, Hangzhou, Chengdu, Xiamen, Qingdao and Sanya. We then obtained a list of 21,103 hotels listed on all three websites (Ctrip, Qunar, and Fliggy) on January 3, 2019. This procedure excluded the hotels that were exclusively represented by a sole agent.

We collected the hotels' initial overall ratings, individual ratings from each user, and basic information. We then deleted the inactive hotels with an overall rating of less than 1 or a total number of reviews less than 10. This procedure removed hotels with an abnormal status or a number of reviews that did not provide sufficient reference information for customers. This left us with a total of 15,887 hotels.

Given that hotel sales on the OTA are not publicly available, we developed a crawler using Python to routinely monitor the Ctrip website to identify the latest sales condition. If a customer accessed the webpage of a hotel, Ctrip would notify with a pop-up window with the information 'Last booking: X minutes ago'. We accessed all the hotels' Ctrip pages every minute and tracked whether the information was reset to 'Last booking: one minute ago'. If so, we considered that the hotel had one sale in the last minute. In addition, we tracked the change of time-variant factors, including the individual hotel ratings and lowest price offering. This data collection process ran from January 5 to February 22, 2019. We then organized the data and developed a seven-week panel dataset.

3.2. Manipulation measurement: a DID approach

To measure the partnership-intensified review manipulation, we adopted a matching-based DID design to catch and quantify the rating difference between the matched partner and non-partner hotels. We first classified the hotels into two groups: partner hotels and non-partner hotels (based on each hotel's category marked as "partner hotel" or "non-partner hotel" on Ctrip.com). Our search found 2,838 partner hotels and 13,049 non-partner hotels from Ctrip. Following this, we employed a matching method to control the confounding effects of hotels' observable characteristics in the treated (partner hotels) and control (non-partner hotels) groups. For example, five-star hotels may simultaneously have a higher likelihood of being a partner hotel and a higher review rating. Specifically, we matched each partner hotel with a group of non-partner hotels based on the following criteria:

1. the hotels were in the same city

2. the hotels had the same star rating (e.g., four-star or five-star hotels)

3. the non-partner hotel had an offered price within $\pm 10\%$ of the price of the partner hotel.

Criterion 1 ensured that the matched hotels were in the same city, which mitigated the variation caused by geographical locations, such as service level standards . Criterion 2 ensured that the matched hotels had the same star rating. The hotels with the same star rating had similar physical attributes and quality signals. Criterion 3 controlled the price variation in the matched groups because price shapes consumer expectations, which could affect evaluation of service quality (Kopalle & Lehmann 2006). There are two approaches to control hotel price: (1) select one non-partner hotel for each partner hotel with the closest offered price (one-to-one nearest-neighborhood matching) or (2) select a group of non-partner hotels whose prices are within a certain range of the partner hotel's price (one-to-many matching). A common complaint about nearest-neighborhood matching is that it can suffer from discarding a large number of observations and lead to reduced power (Stuart 2010). Thus, we used the one-to-many approach, which selected non-partner hotels whose prices were within $\pm 10\%$ of the partner hotel. We considered that the selected non-partner hotels that met all three criteria should have similar characteristics to the matched partner hotel in terms of location, star rating, price and customer patterns.

The first difference in review rating between the treated (partner hotels, *i*) and control (non-partner hotels, *j*) groups is specified in Equation (1):

$$\begin{aligned} &Difference\ of\ Review\ Rating\ on\ Ctrip_i \\ =&Review\ Rating\ on\ Ctrip_i - Median\ Review\ Rating\ on\ Ctrip_j \end{aligned} \tag{1}$$

where $Review\ Rating\ on\ Ctrip_i$ and $Median\ Review\ Rating\ on\ Ctrip_j$ are the rating of partner hotel i on Ctrip and the median of all ratings of the matched non-partner hotel group j on Ctrip, respectively.

However, the first difference calculated from Equation (1) may still be confounded with unobservable factors. For example, the observed difference in Equation (1) may merely be a result of hotels' abundant promotion budgets. A hotel with a high promotion budget may simultaneously have a higher likelihood of being a partner hotel and have more fake or 'promotional' online reviews. We argue that these unobservable characteristics of partners and non-partners would be reflected on other major platforms, regardless of whether there is a partnership or not, such as the largest Chinese travel search engine, Qunar. If the manipulated review ratings are driven by unobservable factors, such as extra marketing budget, they should be observable on other non-partner platforms as well. Therefore, we benchmarked the first difference with the rating difference of the same hotels observed in Qunar, which is calculated in Equation (2).

$$\begin{aligned} &Difference\ of\ Review\ Rating\ on\ Qunar_i \\ =&Review\ Rating\ on\ Qunar_i - Median\ Review\ Rating\ on\ Qunar_j \end{aligned} \tag{2}$$

We based on following assumptions to select Qunar as the benchmark: 1) Commission is not applicable to hotel sales through search engine, thus revenue of search engine is not

TABLE I
Descriptive statistics of review ratings for partner hotels and non-partner hotels on Ctrip and Qunar (partner hotels vs. non-partner hotels, N=2,838 pairs)

	Partner Hotel		Non-partner Hotel	
	Ctrip	Qunar	Ctrip	Qunar
Mean Rating	4.599	4.553	4.302	4.318
Median of Rating	4.600	4.600	4.400	4.400
Variance of Rating	0.052	0.087	0.220	0.203

directly tied with hotel sales. Therefore, the partnership-intensified review manipulation (not all manipulations) should be insignificant on Qunar. 2) User behaviours should be similar on the two platforms. We verified this assumption by examining demographics of Ctrip and Qunar users using Baidu Index (Baidu 2020). Baidu Index is provided by Baidu, which is currently the largest search engine in China. Based on the behavioral data generated on Baidu, Baidu Index provides insight on online users searching for specific keywords and thereby helps companies understand their target markets. Figures 2, 3, and 4 in the Appendix show that Ctrip and Qunar users are similar in terms of gender, age, and habits. This evidence mitigates the concern that user groups are significantly different between these two websites.

The review rating difference calculated in Equation (2) reflects the unobservable difference between the two groups of hotels, while the effects of partnership are not included because Qunar has the same relationship with both groups of hotels.

Finally, we used Equation (1) (including both effects of unobservable factors and partnership) minus Equation (2) (including effects of unobservable factors only) to isolate the effects of partnership. Specifically, we calculated the partnership-intensified review manipulation for a partner hotel i with Equation (3):

$$\begin{aligned}
&Partnership_intensified\ review\ manipulation_i \\
=&Equation\ 1 - Equation\ 2 \\
=&Difference\ of\ Review\ Rating\ on\ Ctrip_i \\
&- Difference\ of\ Review\ Rating\ on\ Qunar_i \\
=&(Review\ Rating\ on\ Ctrip_i - Median\ Review\ Rating\ on\ Ctrip_j) - \\
&(Review\ Rating\ on\ Qunar_i - Median\ Review\ Rating\ on\ Qunar_j)
\end{aligned} \tag{3}$$

4. Analysis model and results

Table I provides the descriptive statistics of review ratings of matched partner hotels and non-partner hotel. Table II presented the paired t-test and non-parametric Wilcoxon signed-rank (WSR) test to examine H1. The results indicates the manipulation intensity is significantly larger than zero (the null effect). Thus, H1 is supported.

H2 to H5 examined the effects of partnership-intensified review manipulation on hotel online performance. We developed a hotel-week panel dataset and conducted regression analyses to test these hypotheses. The dependent variable was hotel online performance,

TABLE II
Testing results of partnership-intensified review manipulation (partner hotels vs. non-partner hotels, N=2,838 pairs)

	Paired t-test			WSR Sign Rank test		
	Mean	t	p	Positive: Negative	Z	p
H1	0.175	28.644	0.000	1.407	27.656	0.000

which was measured by the hotel's weekly sales. The sales data were based on the booking information collected from Ctrip's website introduced in Section 3.1. We used the number of bookings multiplied by the average price of the hotel in one week to obtain the weekly sales volume. Hotel size was measured by the number of rooms offered by the hotel (De Jorge & Suárez 2014). Hotel price was measured by the average price offered by the hotel in the week. Hotel star rating was rated by the CNTA (China National Tourism Administration) in an ordinal manner, ranging from one star (the lowest standard) to five stars (the highest standard).

We used control variables to increase the robustness of the analysis. First, we included the one-week lag value of the dependent variable (lag hotel performance) to create a dynamic panel data structure, which effectively controlled for the prior performance of the hotel. We included hotel age because customers may favor new facilities provided by new hotels. Further, Coenders, Espinet & Saez (2003) stressed the importance of hotel attributes related to facilities and amenities for business and leisure travelers. Thus, we controlled the hotel types by indicating whether a hotel was a business hotel or leisure hotel, based on the labels indicated by the hotel's Ctrip webpage. We included the number of room types and number of service types because consumers may favor hotels with additional services provided, which was also indicated on the hotels' Ctrip websites. We included the number of holidays in each week because sales may be higher on holidays. Finally, we included a dummy variable of observed time (week) and city of the hotel to control for effects relating to time and location. We performed natural logarithm transformation for hotel performance, lag hotel performance, hotel size, hotel price, and hotel age to correct for the skewness of these variables. The panel data analysis model was specified as follows,

$$\begin{aligned} ln(HotelPerformance_{it}) =& \beta_0 + \beta_1 ManipulationIntensity_{i,t-1} + \\ & \beta_2 ln(Size_i) + \beta_3 ln(Price_{i,t-1}) + \beta_4 Prestige_i + \\ & \beta_5 ln(HotelPerformance_{i,t-1}) + \beta_6 ln(Age_i) + \\ & \beta_7 BusinessHotel_i + \beta_8 ResortHotel_i + \\ & \beta_9 RoomTypes_i + \beta_{10} ServiceTypes_i + \\ & \beta_{11} Holidays_t + Week + City + u, \end{aligned} \tag{4}$$

where i indicates hotel, t denotes the week of observation, and u is the error term. We performed ordinary least squares to estimate the coefficients β in the specified model.

Table III presents the descriptive statistics and correlations of the variables. The maximum variance inflation factor was 2.42, which suggested that multicollinearity was not a serious concern in our analysis.

Table IV presents the results from the regression analysis. Model 1 included all the control variables and the standardized direct effects of the moderators. The adjusted R^2 was 75.38%, which suggested that these variables created satisfied controls. Model 2 examined H2 by adding the standardized variable of partnership-intensified review manipulation. The coefficient of manipulation intensity was significantly negative (-0.021, p <0.01). Adding the variable increased the goodness-of-fit of Model 2 compared with Model 1 (F=22.3, p <0.01). Thus, H2 was supported.

Model 3 examined H3 by adding the interaction term between standardized partnership-intensified review manipulation and hotel size. The coefficient of the interaction term was significantly negative (-0.013, p <0.01). Adding the variable increased the goodness-of-fit of Model 3 compared with Model 2 (F=7.50, p <0.01). Thus, H3 was supported.

Model 4 examined H4 by adding the interaction term between standardized partnership-intensified review manipulation and hotel price. The coefficient of the interaction term was significantly negative (-0.009, p <0.01). Adding the variable increased the goodness-of-fit of Model 4 compared with Model 2 (F=4.620, p <0.05). Thus, H4 was supported.

Model 5 examined H5 by adding the interaction term between standardized partnership-intensified review manipulation and hotel prestige (star rating). The coefficient of the interaction term was significantly negative (-0.053, p <0.01). Adding the variable increased the goodness-of-fit of Model 5 compared with Model 2 (F=17.17, p <0.01). Thus, H5 was supported.

TABLE III

Descriptive statistics and correlations (N=16,743 hotel-week observations)

	Variables	Mean	Standard Deviation	1	2	3	4	5	6	7	8	9	10	11
1	Hotel performance	8.918	1.098											
2	Lag performance	8.987	1.114	0.831										
3	Hotel size	4.554	0.831	0.452	0.458									
4	Hotel price	5.705	0.638	0.658	0.614	0.272								
5	Hotel prestige (star)	0.305	1.068	0.154	0.165	0.314	0.189							
6	Hotel age	1.576	0.864	0.089	0.097	0.330	0.108	0.431						
7	Business hotel	0.529	0.499	0.215	0.228	0.348	0.177	0.184	0.107					
8	Resort hotel	0.203	0.402	0.321	0.324	0.347	0.415	0.259	0.200	0.058				
9	Number of room types	10.253	4.293	0.157	0.150	0.085	0.096	0.068	0.165	-0.040	0.159			
10	Number of service types	3.341	.694	0.413	0.419	0.525	0.502	0.297	0.230	0.422	0.539	0.136		
11	Number of holidays	2.825	1.856	-0.005	-0.087	-0.001	0.118	-0.002	-0.003	-0.001	0.002	0.002	0.001	
12	OTA review manipulation intensity	0.175	0.793	-0.052	-0.035	-0.021	-0.045	-0.048	-0.015	-0.024	0.010	0.012	-0.020	0.048

TABLE IV

Regression analysis of the impacts of review manipulation by OTA (N=16,743)

	Dependent variable: Hotel performance at week t														
	Model 1			Model 2			Model 3			Model 4			Model 5		
Independent variables (t-1)	Coef.	S.E.	p	Coef.	S.E.	p	Coef.	S.E.	p	Coef.	S.E.	p	Coef.	S.E.	p
Lag performance	0.606	0.006	0.000	0.606	0.006	0.000	0.606	0.006	0.000	0.606	0.006	0.000	0.606	0.006	0.000
Hotel size	0.155	0.006	0.000	0.155	0.006	0.000	0.156	0.006	0.000	0.155	0.006	0.000	0.155	0.006	0.000
Hotel price	0.274	0.006	0.000	0.273	0.006	0.000	0.273	0.006	0.000	0.274	0.006	0.000	0.273	0.006	0.000
Hotel prestige (star)	-0.009	0.005	0.053	-0.010	0.005	0.035	-0.011	0.005	0.023	-0.011	0.005	0.027	-0.015	0.005	0.003
Hotel age	-0.036	0.006	0.000	-0.036	0.006	0.000	-0.035	0.006	0.000	-0.035	0.006	0.000	-0.036	0.006	0.000
Business hotel	0.025	0.010	0.014	0.025	0.010	0.015	0.026	0.010	0.012	0.025	0.010	0.014	0.025	0.010	0.013
Resort hotel	-0.046	0.013	0.001	-0.044	0.013	0.001	-0.043	0.013	0.001	-0.044	0.013	0.001	-0.045	0.013	0.001
Number of room types	0.007	0.001	0.000	0.007	0.001	0.000	0.007	0.001	0.000	0.007	0.001	0.000	0.007	0.001	0.000
Number of service types	-0.023	0.004	0.000	-0.024	0.004	0.000	-0.024	0.004	0.000	-0.024	0.004	0.000	-0.024	0.004	0.000
Number of holidays	-0.016	0.003	0.000	-0.015	0.003	0.000	-0.015	0.003	0.000	-0.015	0.003	0.000	-0.015	0.003	0.000
OTA review manipulation intensity				-0.021	0.005	0.000	-0.023	0.005	0.000	-0.022	0.005	0.000	-0.034	0.006	0.000
Manipulation × Hotel size							-0.013	0.005	0.006						
Manipulation × Hotel price										-0.009	0.004	0.032			
Manipulation × Hotel prestige													-0.053	0.013	0.000
Adjusted R^2	75.38%			75.41%			75.42%			75.41%			75.43%		

5. Robustness checks

In this section, we performed robustness checks to strengthen the validity of our findings.

5.1. Alternative detection of partnership-intensified review manipulation: variance

Generally, there are two possible ways to manipulate review ratings: adding positive reviews and deleting negative reviews. Previous studies have found that the adverse effect of negative reviews is greater than the favorable effect of positive reviews (Lappas, Sabnis & Valkanas 2016). In addition, deleting negatvie reivews is more disguised and difficult to be suspected (Zhuang et al. 2018). In practice, it is very risky for firms to conduct review manipulation. Once discovered, their reputation and credibility will be damaged. Moreover, adding positive reviews is physically much more difficult than deleting negative reviews, as it involves creating fraudulent accounts, feigning transaction records (as only guests can leave reviews), and posting fake comments. Therefore, compared with adding favorable reviews, deleting negative reviews is a more disguised and feasible long-term strategy to boost online ratings.

If this is the case, it will lead to lower variance observed in online customer ratings for partner hotels than for non-partner hotels. This distinguishes partnership-intensified manipulation from other types of review manipulation, which can only be conducted by adding positive/negative (positive by business owners or negative by competitors) reviews (users are typically not allowed to delete reviews to maintain the integrity of the review system). Adding fake reviews typically leads to more variance because the purpose of doing so is to change (elevate or decrease) the current overall rating and only extreme values (compared with normal review ratings) can serve this purpose effectively. Therefore, we posited that a lower variance would be observed in the customer review ratings for OTAs' partner hotels.

We conducted a paired t-test and WSR test to determine the difference in the variance of customer review ratings between matched hotels (Ctrip partner hotels versus matched non-partner hotels). The test t-statistic and p-value of the paired t-test were -5.503 and 0.000, respectively. The z- and p-values of the WSR test were -4.865 and 0.000, respectively. The average difference in the variance of the review ratings of the matched Ctrip partner and non-partner hotels was -0.0319. These results indicate a lower variance in customer ratings for Ctrip partner hotels than for non-partner hotels. This test provides additional evidence to indicate the intensified manipulated reviews for partner hotels.

5.2. Alternative data source: Fliggy

Given that we examined our hypotheses with data collected from Ctrip, some may argue that partnership-intensified review manipulation may depend on platform-level unobservable variables (e.g., tendency to choose partner hotels). Thus, we examined the sensitivity of our main analysis by replacing the data from Ctrip with data from Fliggy (the benchmark data from Qunar unchanged). Fliggy is the second-largest OTA in China—second only to Ctrip in number of active users. We created 2,007 pairs of matched Fliggy partner hotels and non-partner hotels for this robustness analysis.

The paired t-test about the rating difference in the matched Fliggy partner hotels and non-partner hotels, benchmarked with Qunar, indicated a statistically significant difference, with a t-statistic and p-value of 4.363 and 0.000, respectively. The average rating difference was 0.028. The paired t-test about the variance observed in customer ratings for Fliggy partner hotels and non-partner hotels also indicated a statistically significant difference, with a t-statistic and p-value of -6.858 and 0.000, respectively. The average difference in the variance was -0.54, which was similar to the results observed in Ctrip. These two tests provide additional evidence to support H1.

6. Conclusions

Online reviews of hotel services are critical in consumer purchasing decisions. However, manipulated reviews may be harmful. Although review manipulation aims to boost sales, it may backfire. Our study captured an abnormally higher rating for the OTA partnered hotels, which indicates that the higher interest alignment between the hotels and OTA was intensifying the review manipulation of these hotels. This conclusion was further strengthened by the finding that the variance in review ratings of partner hotels was significantly lower than that of non-partner hotels, which was likely caused by deleting extremely negative reviews.

After that, we examined the effect of the partnership-intensified review manipulation on hotels' sales performance. With scenario-based experiments, the previous literature (Reimer & Benkenstein 2016) has found that suspicious reviews have negative effects on business performance. We confirmed this notion with field data collected from realistic business processes. Our results suggest that partnership-intensified review manipulation deteriorates hotels' business performance by undermining customer trust and widening the gap between customer expectation and perception. Moreover, this deterioration of performance is more salient for large-scale, expensive, and prestigious hotels.

6.1. Theoretical contributions

This research contributes to the literature on online customer reviews and review manipulation. The previous literature has largely focused on the role of business owners and ignored the role of the hosting platform in review manipulation. Our research differs from previous studies by exploring the role of OTAs as the intermediary between hotels and consumers. Nowadays, hotel booking transactions increasingly rely on the platform provided by OTAs, yet it was unclear how the interaction between hotels and OTAs could affect the intensity of review manipulation. We entered this discourse by investigating whether the interest alignment between hotels and OTAs can facilitate review manipulation. OTAs perform sales and promotion activities on behalf of hotels, and perform information search activities on behalf of consumers. Ideally, OTAs should be fair and protect the interests of both opposing parties (hotels and consumers). However, this may not be true in practice (Hunold et al. 2020). The aligned interest between hotels and OTAs may disrupt this balance, and subsequently facilitate opportunistic behaviors against consumers. Specifically, by capturing the abnormally high rating of OTA partnered hotels (compared with non-partners), we provide evidence that such interest alignment through sales commissions can facilitate review manipulation.

This research also contributes to the agency theory. It is widely suggested in agency studies that interest alignment between the principal (i.e., buyer) and agent (i.e., supplier) can reduce the agent's opportunistic behavior (Eisenhardt 1989). Interest alignment resolves the goal conflicts between the two parties, so that the supplier is more likely to act on behalf of the buyer's interests. However, few studies have discussed how this opportunistic behavior may be affected when an intermediary is involved in the transaction. We have found that the interest ties between the intermediary and agent (i.e., hotels) will intensify opportunistic behavior toward consumers. This is likely to occur because the manipulation can increase the short-term sales of these hotels, which subsequently increases the commission income of the OTA. The agent-intermediary (i.e., hotel-OTA) partnership may intensify the myopic goal and short-term gain, yet compromise the long-term benefit of the hotel. This view is consistent with prospect theory, which hypothesizes that decision makers favor instant gain, rather than future gain (Tversky & Kahneman 1979). These findings call for a rethink of the merits of interest alignment in controlling transaction costs in outsourcing relationships.

6.2. Managerial implications

This research presents practical implications to hotels and OTAs to construct a better and healthier hospitality industry. First, our results provide evidence that partnership-intensified review manipulation will lead to a negative (not positive) effect on sales. Managers should not assume that consumers can be easily manipulated. Moreover, our results indicate that partnership-intensified review manipulation lead to a 0.2% decrease on hotels' online sales. Given Ctrip's gross merchandise volume jumped 30 percent year-on-year to hit ¥725 billion in 2018 (Zhu 2019), the magnitude of the effect on total online sales of Ctrip alone will be measured in billions. Moreover, the robustness check of this study indicates that, in addition to the average rating, the variance of customer ratings can also help detect review manipulation.

This evidence can also be used to educate hotel managers to avoid excess review manipulation. If the idea that review manipulation can lead to higher sales with little cost prevails among hotel managers, the manipulation behavior will enter managers into a "prisoner's dilemma"—the manager may consider that they are at a disadvantage if not manipulating reviews when others are doing so. However, our solid evidence can be an important reference indicating that hotels who are manipulating their reviews will be punished by the market. The hospitality industry will be healthier if the idea that review manipulation is harmful is widely accepted.

Last, OTAs should not lessen their monitoring of their partner hotels and allow review manipulation to prevail on their platform. The image of independence and fairness is vital for OTAs to gain consumer trust, given that they perform information search activities for consumers. Intensified manipulations will hurt consumer trust in both the hotel and OTA, which will subsequently undermine their sales performance.

6.3. Limitations

There are several limitations of this study. First, our detection of review manipulation was based on empirical evidence, rather than direct observation. Second, the number of bookings was used as a proxy for room sales, instead of the number of rooms booked. This may have caused some measuring errors. In addition, this message may also subject to manipulation. However, as long as the way of such manipulation is consistent, it will not impact our qualitative conclusions. In the future, there are certain research directions worth exploring. For example, it would be interesting to examine online and offline data together over the same time period to find out interplay of online reviews and offline customer behaviour. Also, it would be interesting and challenging to examine the role of OTAs and their partner hotels in partnership-intensified review manipulation. The power asymmetry between OTAs and these hotels and its correlation with manipulation intensity may help answer this question.

References

Abrate, G., Capriello, A. & Fraquelli, G. (2011), 'When quality signals talk: Evidence from the turin hotel industry', *Tourism Management* **32**(4), 912–921.

Ahmad, W. & Sun, J. (2018), 'Modeling consumer distrust of online hotel reviews', *International Journal of Hospitality Management* **71**, 77–90.

Akhtar, N., Ahmad, W., Siddiqi, U. I. & Akhtar, M. N. (2019), 'Predictors and outcomes of consumer deception in hotel reviews: The roles of reviewer type and attribution of service failure', *Journal of Hospitality and Tourism Management* **39**, 65–75.

Anderson, E. W. & Sullivan, M. W. (1993), 'The antecedents and consequences of customer satisfaction for firms', *Marketing science* **12**(2), 125–143.

Ariffin, A. A. M. & Maghzi, A. (2012), 'A preliminary study on customer expectations of hotel hospitality: Influences of personal and hotel factors', *International Journal of Hospitality Management* **31**(1), 191–198.

Baidu (2020), 'Baidu index.'. https://index.baidu.com.

Bick, G., Jacobson, M. C. & Abratt, R. (2003), 'The corporate identity management process revisited', *Journal of Marketing Management* **19**(7-8), 835–855.

Bond, C. F., Omar, A., Pitre, U., Lashley, B. R., Skaggs, L. M. & Kirk, C. (1992), 'Fishy-looking liars: deception judgment from expectancy violation.', *Journal of personality and social psychology* **63**(6), 969.

Bosse, D. A. & Phillips, R. A. (2016), 'Agency theory and bounded self-interest', *Academy of Management Review* **41**(2), 276–297.

Brown, T. J. & Dacin, P. A. (1997), 'The company and the product: Corporate associations and consumer product responses', *Journal of marketing* **61**(1), 68–84.

Burgoon, J. K. & Le Poire, B. A. (1993), 'Effects of communication expectancies, actual communication, and expectancy disconfirmation on evaluations of communicators and their communication behavior', *Human communication research* **20**(1), 67–96.

Casado-Díaz, A. B., Andreu, L., Beckmann, S. C. & Miller, C. (2020), 'Negative online reviews and webcare strategies in social media: effects on hotel attitude and booking intentions', *Current Issues in Tourism* **23**(4), 418–422.

Chevalier, J. A. & Mayzlin, D. (2006), 'The effect of word of mouth on sales: Online book reviews', *Journal of marketing research* **43**(3), 345–354.

Coenders, G., Espinet, J. & Saez, M. (2003), 'Predicting random level and seasonality of hotel prices: a latent growth curve approach', *Tourism Analysis* **8**(1), 15–31.

De Jorge, J. & Suárez, C. (2014), 'Productivity, efficiency and its determinant factors in hotels', *The Service Industries Journal* **34**(4), 354–372.

Doney, P. M. & Cannon, J. P. (1997), 'An examination of the nature of trust in buyer–seller relationships', *Journal of marketing* **61**(2), 35–51.

Eisenhardt, K. M. (1989), 'Agency theory: An assessment and review', *Academy of management review* **14**(1), 57–74.

Ekanayake, S. (2004), 'Agency theory, national culture and management control systems', *Journal of American academy of business* **4**(1/2), 49–54.

Filieri, R. (2015), 'What makes online reviews helpful? a diagnosticity-adoption framework to explain informational and normative influences in e-wom', *Journal of Business Research* **68**(6), 1261–1270.

Filieri, R. (2016), 'What makes an online consumer review trustworthy?', *Annals of Tourism Research* **58**, 46–64.

Filieri, R., Hofacker, C. F. & Alguezaui, S. (2018), 'What makes information in online consumer reviews diagnostic over time? the role of review relevancy, factuality, currency, source credibility and ranking score', *Computers in Human Behavior* **80**, 122–131.

Filieri, R. & McLeay, F. (2014), 'E-wom and accommodation: An analysis of the factors that influence travelers? adoption of information from online reviews', *Journal of Travel Research* **53**(1), 44–57.

Fleisher, C. S. (1991), 'Using an agency-based approach to analyze collaborative federated interorganizational relationships', *The Journal of applied behavioral science* **27**(1), 116–130.

Folkes, V. S. & Kamins, M. A. (1999), 'Effects of information about firms' ethical and unethical actions on consumers' attitudes', *Journal of consumer psychology* **8**(3), 243–259.

Gössling, S., Hall, C. M. & Andersson, A.-C. (2018), 'The manager's dilemma: a conceptualization of online review manipulation strategies', *Current Issues in Tourism* **21**(5), 484–503.

Heath, T. B. & Chatterjee, S. (1995), 'Asymmetric decoy effects on lower-quality versus higher-quality brands: Meta-analytic and experimental evidence', *Journal of Consumer Research* **22**(3), 268–284.

Hu, N., Bose, I., Gao, Y. & Liu, L. (2011), 'Manipulation in digital word-of-mouth: A reality check for book reviews', *Decision Support Systems* **50**(3), 627–635.

Hu, N., Bose, I., Koh, N. S. & Liu, L. (2012), 'Manipulation of online reviews: An analysis of ratings, readability, and sentiments', *Decision support systems* **52**(3), 674–684.

Hunold, M., Kesler, R. & Laitenberger, U. (2020), 'Hotel rankings of online travel agents, channel pricing and consumer protection.', *Marketing Science* **39**(1), 92–116.

Jensen, M. C. & Meckling, W. H. (1976), 'Theory of the firm: Managerial behavior, agency costs and ownership structure', *Journal of financial economics* **3**(4), 305–360.

Jin Ma, Y. & Lee, H.-H. (2014), 'Consumer responses toward online review manipulation', *Journal of Research in Interactive Marketing* **8**(3), 224–244.

Ketron, S. (2017), 'Investigating the effect of quality of grammar and mechanics (qgam) in online reviews: The mediating role of reviewer crediblity', *Journal of Business Research* **81**, 51–59.

Kopalle, P. K. & Lehmann, D. R. (2006), 'Setting quality expectations when entering a market: What should the promise be?', *Marketing Science* **25**(1), 8–24.

Lappas, T., Sabnis, G. & Valkanas, G. (2016), 'The impact of fake reviews on online visibility: A vulnerability assessment of the hotel industry', *Information Systems Research* **27**(4), 940–961.

Lee, S.-Y., Qiu, L. & Whinston, A. (2018), 'Sentiment manipulation in online platforms: An analysis of movie tweets', *Production and Operations Management* **27**(3), 393–416.

Liu, Z. (2019), 'Online travel agency leading company operates stably.'. https://m.gelonghui.com/p/246981.

Luca, M. & Zervas, G. (2016), 'Fake it till you make it: Reputation, competition, and yelp review fraud', *Management Science* **62**(12), 3412–3427.

Mauri, A. G. & Minazzi, R. (2013), 'Web reviews influence on expectations and purchasing intentions of hotel potential customers', *International Journal of Hospitality Management* **34**, 99–107.

Mayzlin, D., Dover, Y. & Chevalier, J. (2014), ‘Promotional reviews: An empirical investigation of online review manipulation’, *American Economic Review* **104**(8), 2421–55.

Mohr, L. A. & Webb, D. J. (2005), ‘The effects of corporate social responsibility and price on consumer responses’, *Journal of consumer affairs* **39**(1), 121–147.

Norrman, A. (2008), ‘Supply chain risk-sharing contracts from a buyers’ perspective: content and experiences’, *International Journal of Procurement Management* **1**(4), 371–393.

Öğüt, H. & Onur Taş, B. K. (2012), ‘The influence of internet customer reviews on the online sales and prices in hotel industry’, *The Service Industries Journal* **32**(2), 197–214.

Pavlou, P. A., Liang, H. & Xue, Y. (2007), ‘Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective’, *MIS quarterly* pp. 105–136.

Reimer, T. & Benkenstein, M. (2016), ‘When good wom hurts and bad wom gains: The effect of untrustworthy online reviews’, *Journal of Business Research* **69**(12), 5993–6001.

Rhee, M. & Haunschild, P. R. (2006), ‘The liability of good reputation: A study of product recalls in the us automobile industry’, *Organization Science* **17**(1), 101–117.

Sen, S. & Bhattacharya, C. B. (2001), ‘Does doing good always lead to doing better? consumer reactions to corporate social responsibility’, *Journal of marketing Research* **38**(2), 225–243.

Shapiro, C. (1983), ‘Premiums for high quality products as returns to reputations’, *The quarterly journal of economics* **98**(4), 659–679.

Simonson, I. & Tversky, A. (1992), ‘Choice in context: Tradeoff contrast and extremeness aversion’, *Journal of marketing research* **29**(3), 281–295.

Singh, J. & Sirdeshmukh, D. (2000), ‘Agency and trust mechanisms in consumer satisfaction and loyalty judgments’, *Journal of the Academy of marketing Science* **28**(1), 150–167.

Stuart, E. A. (2010), ‘Matching methods for causal inference: A review and a look forward’, *Statistical science: a review journal of the Institute of Mathematical Statistics* **25**(1), 1.

Tan, J. C. K. & Lee, R. (2015), ‘An agency theory scale for financial services’, *Journal of Services Marketing* .

Tversky, A. & Kahneman, D. (1979), ‘Prospect theory: An analysis of decision under risk’, *Econometrica* **47**(2), 263–291.

Voss, G. B., Parasuraman, A. & Grewal, D. (1998), 'The roles of price, performance, and expectations in determining satisfaction in service exchanges', *Journal of marketing* **62**(4), 46–61.

Walsh, G. & Beatty, S. E. (2007), 'Customer-based corporate reputation of a service firm: scale development and validation', *Journal of the academy of marketing science* **35**(1), 127–143.

Williams, R. J. & Barrett, J. D. (2000), 'Corporate philanthropy, criminal activity, and firm reputation: Is there a link?', *Journal of Business Ethics* **26**(4), 341–350.

Womply Research (2020), 'How do online reviews impact revenue for lodging places?'. https://www.womply.com/impact-of-online-reviews-on-small-business-revenue/.

Xu, Y., Zhang, Z., Law, R. & Zhang, Z. (2019), 'Effects of online reviews and managerial responses from a review manipulation perspective', *Current Issues in Tourism* pp. 1–16.

Yacouel, N. & Fleischer, A. (2012), 'The role of cybermediaries in reputation building and price premiums in the online hotel market', *Journal of Travel Research* **51**(2), 219–226.

Ye, Q., Law, R. & Gu, B. (2009), 'The impact of online user reviews on hotel room sales', *International Journal of Hospitality Management* **28**(1), 180–182.

Ye, Q., Law, R., Gu, B. & Chen, W. (2011), 'The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings', *Computers in Human behavior* **27**(2), 634–639.

Zhang, J. J., Lawrence, B. & Anderson, C. K. (2015), 'An agency perspective on service triads: Linking operational and financial performance', *Journal of Operations Management* **35**, 56–66.

Zhao, X. R., Wang, L., Guo, X. & Law, R. (2015), 'The influence of online reviews to online hotel booking intentions', *International Journal of Contemporary Hospitality Management* .

Zhu, S. (2019), 'Ctrip reports revenue and gmv growth in 2018.'. https://www.meadin.com/yj/101733.html.

Zhuang, M., Cui, G. & Peng, L. (2018), 'Manufactured opinions: The effect of manipulating online product reviews', *Journal of Business Research* **87**, 24–35.

Appendix: Demographics of Ctrip and Qunar users by Baidu index

Demographics of Ctrip and Qunar users using Baidu Index are illustrated in Figures 2, 3, and 4, which indicate that user behaviours are similar on these two platforms.

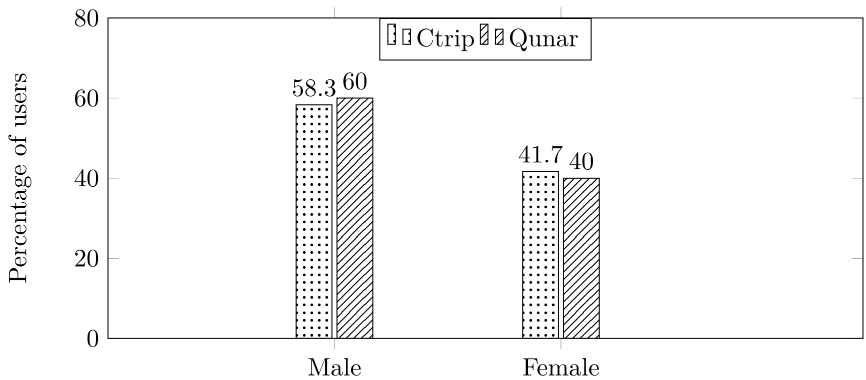

FIGURE 2: Gender distributions of Ctrip and Qunar users.

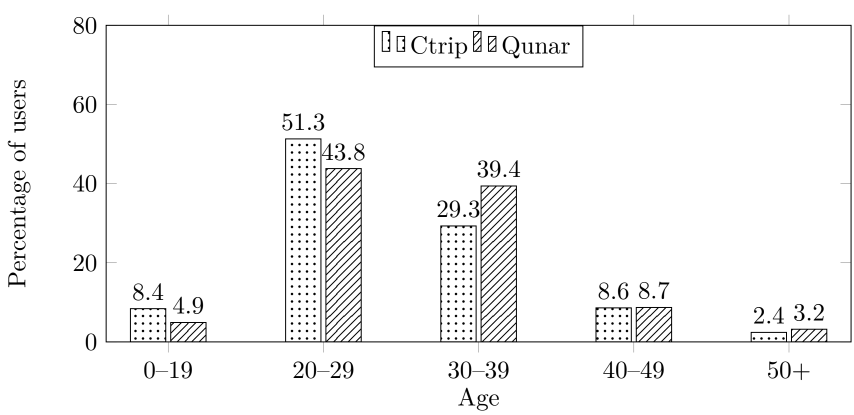

FIGURE 3: Age distributions of Ctrip and Qunar users.

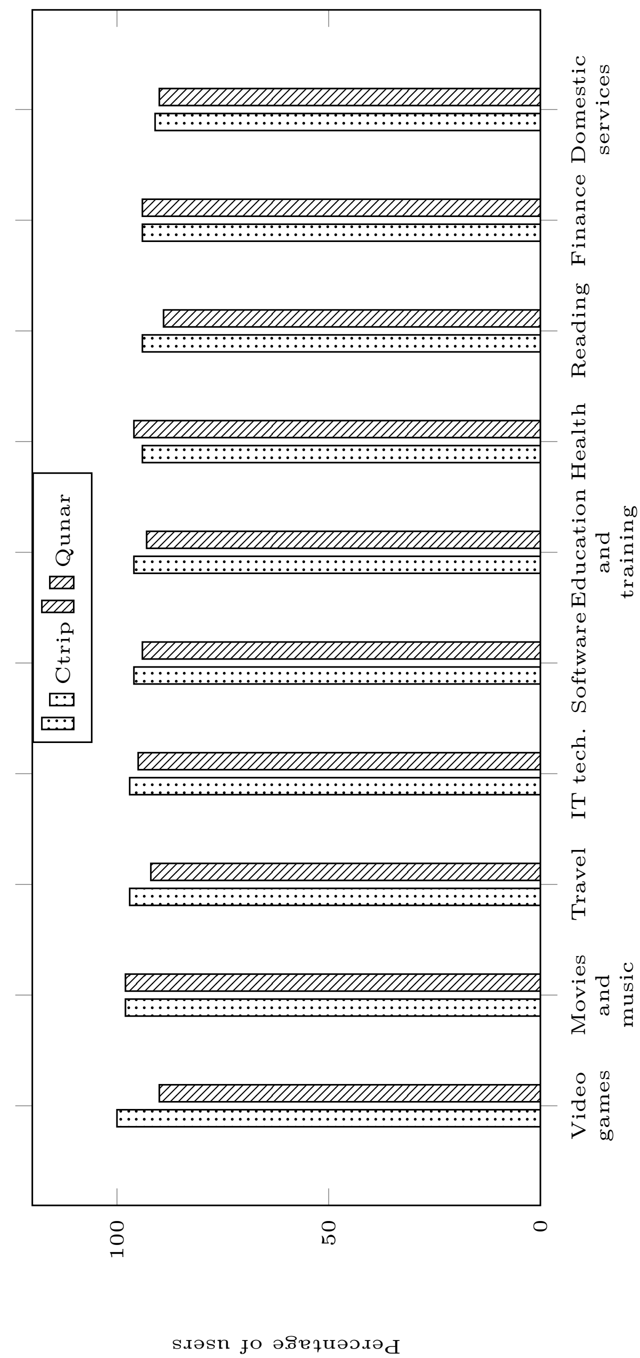

FIGURE 4: Hobby distributions of Ctrip and Qunar users.