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Clash of reputation and status in online reviews

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Abstract
This study extends the heterogeneous effectiveness of market signals by examining when textual sentiments have the most influence on purchasing decisions. Specifically, we argue that reputation and status, two distinct theoretical constructs, which are difficult to disentangle in practice, may influence the effectiveness of textual sentiments on customers' decision making process in opposite directions. Reputation refers to the quality trajectory for a product whereas status sets a societal expectation from a product based on the social standing of that product among its peers. In this study, we examine reputation and status as contingencies that affect how electronic word of mouth (e-WoM) is perceived by customers in the context of review platform. To demonstrate the impact of textual sentiments and the moderation effects of reputation and status, we used an online platform to crawl review and reservation data at the same time of everyday over a period of 100 days on 310 hotels located in New York City. We found that customers are more sensitive to the sentiment of textual reviews on hotels of high status but less receptive when reviews are on hotels of high reputation. Our robustness tests and two identification strategies are all consistent with these findings. This research offers a strategic guideline to businesses and platforms in terms of how much they should rely on e-WoM, contingent upon their reputation and status.

Keywords Reputation · Status · e-WoM · Subjectivity

1 Introduction

Extant studies about online consumer reviews, also known as electronic word of mouth (e-WoM), have highlighted the empirical evidence that online product review texts and ratings affect decision-making process of prospective customers [7, 10, 19, 36, 65]. In general, customers may use textual comments and aggregated e-WoM metrics such as the volume, mean, or variance of ratings from online platforms to reduce information asymmetry about products' quality. While it is well known that e-WoM contributes to purchasing decisions on online platforms as a signal, it is still underdeveloped on which factors the effects of e-WoM are contingent.

An online platform creates an opportunity for a product to create a quality record by accumulating customer ratings and evaluations over time. This archival record of ratings, reviews, and complaints may collectively vary the simple effect of a current rating on how a product's quality is perceived. Furthermore, a product's perceived standing with respect to other products in market place may also affect the contribution of e-WoM [6, 35, e.g.,]. In literature, the collective evaluation of the quality or the value of a product constitutes that product's '*reputation*', whereas the relational signal about a product's standing with respect to other similar products forms a measure for that product's '*status*' [40]. Thus, in this study, contrary to the extant literature that mostly examines the reputation and status as two similar forms that affect e-WoM [14, 16, 60], we examine them as two contingencies that affect the relationship between e-WoM and the success of products on online platforms.

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While the reputation and status both take the similar role in reducing quality uncertainty of a product, they have been regarded as two distinct theoretical constructs in strategy literature [61]. Reputation, an economic concept, has been defined as track record of the quality or capabilities of a focal actor within a specific domain [37, 41], capturing merits that generate performance-based rewards. Firm reputation originates from that firm's history on supplying high quality products and services; in that sense, reputation signals the consistency in firms' product quality. Status, on the other hand, a sociological concept, has been defined as relative social standing, capturing differences in social rank which stems from social position [61]. Status finds its roots at social position and social standing of a firm with respect to other similar firms competing in the marketplace or to the firms related to each other by a group affiliation or membership [57]; in that sense, status signals how a firm's product is perceived relative to other firms' similar products.

In this study, we explore firm reputation and status as disparate conditions that affect how e-WoM influence the product success on online platforms. Specifically, we use text reviews that provide more comprehensive and individualized content than star ratings and analyze how perceived sentiments based on textual reviews are moderated by the status and reputation of a firm. In doing so, we show that reputation and status are two distinct moderators in understanding the effect of e-WoM on firm sales growth. Recognizing reputation and status as two separate moderators may be important from the perspectives of firms that sell products or services because while firms are well aware of the influence of e-WoM, it is difficult for them to interpret and assess the significance of e-WoM in enhancing their sales performance. Understanding the conditions that make the influence of e-WoM more sensitive may be the first step to address the e-WoM in their daily business. Since reputation and status are often mixed with one another and it is not a trivial task to clearly identify them as two distinct signals, we created and used different metrics as a proxy to measure the magnitude of status and reputation. We corroborate our hypotheses using a novel dataset from hotels.com, a popular online platform in the hotel industry.

In the context of hotel business, we measure reputation in terms of hotel star rating that is posted on the hotel booking platforms. Note that, these ratings are different than customer ratings. Different entities such as hotel associations, online travel platforms, and volunteering organizations around the globe assign star ratings to the hotels. For example, in the US, hotel booking platforms such as hotels.com or booking.com, or, a non-profit independent organization, the American Automobile Association (AAA), provides rating information for the travelers. As stated at booking.com website, "(o)verall, the star classification is a representation of how the Provider compares to the legal requirements (if applicable) or, if not regulated, the sector or (customary) industry standards in terms of price, facilities, and available services" [4]. Another online booking platform Expedia.com states about its the star rating that "(t)his overview outlines what guests can generally expect from motels, hotels, and resorts displaying a Star Rating assigned by us" [15]. There is not any standardized star rating system, however, to the customer's perception, a four-to-five star hotel will be more appealing and luxurious than a three-star hotel [25]. Since consumers use a booking platform to read others' text reviews, understand reputation of any hotel, and then book a hotel, in this study, we use the star ratings issued on the same platform as a proxy to hotel reputation.

To determine the status of a hotel in terms of social standing and affiliation with a group, we examine if a hotel is associated with any hotel chain. A chain affiliation, such as Hilton, Hyatt, and Marriott, which uses the same logo, imagery, and marketing promotion, helps a hotel signal its specific quality expected from the overall quality of the affiliated hotels [31]. We measured the status with three metrics: (1) the ratio of number of hotels in an affiliated group to the total number of hotels in our dataset, (2) number of hotels within a chain to identify the general awareness of that chain in the market, and (3) an indicator variable to show whether hotels in a particular chain operate over four major continents, following AC Nielsen's definition of a global brand [46][1]. Following the definition of the reputation and status above, Hilton San Francisco and Hilton Garden Inn Gilroy are both Hilton affiliated hotels located around the Bay Area in the United States. They both are high status hotels but the former is also a high reputation hotel with a 4-star rating whereas the latter is a lower reputation hotel with a 3-star rating.

In this study, we find that potential customers show heterogeneous interpretation of text reviews depending on the reputation and status of hotels. The result of the baseline analysis shows that positive sentiment in textual reviews results in an increase in hotel bookings, confirming with the previous literature. However, the impact of the sentiment changes depending on the reputation and status of a hotel. When the reputation of a hotel is high, this gives a strong signal to the customers about the quality consistency of that hotel and the sentiment of text reviews become less important for potential customers. Thus, the impact of sentiment on bookings will weaken for high reputation hotels. A high status hotel is required to attain a certain level of standing in its socially agreed ranking and

[1] AC Nielsen: Founded in 1923, AC Nielsen Corporation is a global company that was founded in 1923 and provides comprehensive information on consumer research for corporate customers in various industries around the world.

has to live up to the expectations of the society. Customers would examine reviews on a hotel closely to infer if that hotel actually matches its actions to its promise in terms of its associated brand name and thus the impact of sentiment on sales will be strengthened for high status hotels. Therefore, potential customers are to evaluate the sentiment from a textual comment based on two signals: reputation and status. Our additional analysis shows that when the reputation and status are not in the same direction, customers' reactions to the sentiment of text review vary. When a hotel has both reputation and status in the same direction, both are low or high, customers exhibit a moderate reaction to the review sentiment. However, when the signals are in opposite direction, customers demonstrate a surprising reaction to the review sentiments. Customers become increasingly sensitive to review sentiments for hotels with high reputation and low status. This reaction is particularly observed for local hotels with high ratings. More notably, customers express a slightly more negative reaction to positive sentiment from textual reviews about hotels with low reputation and high status.

Our findings make two primary contributions to the literature on understanding of the impacts of text reviews in the online platforms. First, we introduce into the e-WoM literature in information systems domain the reputation and status as two distinct constructs and challenge the difficulty to disentangle their confounding influences on prospective customers' reaction to online reviews. We conceptualize the two constructs from the established literature on strategy, then dissect the two concepts in the online review landscape, and finally we provide robust empirical evidence on their occasionally contradicting moderating roles. Second, utilizing recently developed machine learning-based textual analysis, we introduce a new measurement for sentiments of customer text reviews, which mitigate the concern that simple numeric ratings may collapse the nuanced assessment of customers on product. This new metric for sentiment subjectivity is offered as a new instrumental variable for sentiment score, which may have an endogeneity issue due to a high quality product may receive a more preferable rating.

Our study also provides implications for businesses and practitioners. To accrue the full benefit of chain membership from reviews in the online review domain, the affiliated business should also be consistent in the quality of their product and services. A poorly managed member can have a free ride from positive reviews on the other members of the chain up to a certain point. For that reason, in order to create a positive externality from a review on one member firm on its other affiliated members, franchising brands should push aggressively their affiliated members to maintain an acceptable quality. Recognizing the impact of reputation and status, online platforms hosting customer reviews may strategically design the review layout depending on the focal firm's characteristics. For example, for a high status and low reputation firm, it may not be the best strategy to emphasize the most recent positive reviews, as our findings suggest that such an approach creates a negative perception of that firm for the customers.

In addition to the hotels, our findings also have some implications for the platforms that accommodate customer reviews. First, a platform, as an information service provider, facilitates interactions among the parties involved with that platform. Our findings may help a platform to give customized service to the businesses based on the customers' comments. This customized service will depend on the status and reputation of the businesses, in the way that a business with high reputation and low status should be more aware of the dynamics of their customers' reviews. Also, our findings differentiate the impact of e-WoM on hotel sales based on the reputation and status of the hotels. Thus, given the reputation and status information, one can predict the impact of e-WoM on hotel sales with more accuracy. Last, depending on the markets the platform mainly targets, the platform can decide where the e-WoM information should be provided and whether the information should be conspicuous.

The rest of this paper is organized as follows. In Sect. 2, we discuss previous literature and lay out the theoretical framework. In Sect. 3, we explain data collection process as well as pose our hypotheses. In Sect. 4, we provide an overview of econometric analysis and empirical results estimated from the analysis. Finally, in Sect. 5, we conclude the paper with limitations of this study and our suggestions for future research.

2 Literature review and hypotheses development

2.1 Aggregated numerical review rating and textual review comments

The e-WoM has been a significant component of shopping experience for both buyers and sellers on online platforms. Consumers use e-WOM to make purchasing decision. As consumers informally propagate signals to the market through e-WoM about the quality of products and services [28], companies also use e-WoM as a powerful tool to track customer sentiment [66]. Before evaluating their decision process, consumers form an ex-ante expectation about a good or service, and decide writing reviews based on how much their expectations are confirmed [49]. Customers mainly use three aggregate metrics to evaluate e-WoM about a product: number of postings (volume), average of ratings (valence), and the spread of ratings (variance). A higher volume of e-WoM is shown to have a positive effect on sales [5, 7, 13, 44]. Research on valence reveals mixed results, with some documenting a positive effect on sales [8], whereas others showing no significant impact [13, 17, 48]. The impact of variance is found to be heterogeneous across different types of products and how they are rated. [59] finds that a high variance improves the sales if the ratings are also high and [45] finds that customers prefer movies that are rated with high variance.

In addition to the aforementioned three metrics, with the recent advances on Artificial Intelligence (AI) and the development of natural language processing (NLP) techniques, both academicians and practitioners take a profound interest on how the textual reviews also influence the customers' intention to purchase [10, 20, 34, 56]. The textual comments are different from aggregate metrics mainly in three aspects. First, unlike aggregate metrics, a textual comment may reflect an individual's subjectivity, and thus the textual comment itself may have heterogeneous influence on consumers' decision depending on the subjectivity. Second, the textual comments may interplay with the strength of other signals such as the aggregate metrics or organizational attributes. That said, the textual comments, depending on the context, might take a complementary or a substitute role for those other signals. Third, due to its potential subjectivity and manipulation, a textual review with extreme sentiment, especially when it is negative, may not have as significant impact as a negative individual numeric rating.

Owing to the multi-dimensionality of review text [52], customers have a tendency to prefer text information to aggregate numerical information [21]. For instance, [38] investigates how dimension-specific (e.g., star, genre, and plot) sentiments have heterogeneous effects on movie sales. The research on diverse contexts has shown that review information attract customers' attention while providing a variety of information [22, 56], and help increase product sales [3, 7, 10, 20]. Several different methods, such as, keyword-based, lexicon-based, machine-learning, hybrid, linguistic rule based, natural language processing, and case-based reasoning ones, were developed and used to identify and analyze sentiment extracted from text [11, 39, 42, 55]. In literature, the impact of sentiment reflected in review texts on sales performance is straightforward: the greater positive sentiment, the higher sales of products [1, 30, 33, 36, 43, 64, 65]. The related studies on sentiment analysis have also reflected the linkage of sentiment embedded in review texts and sales forecasts. For instance, [47] show that sentiment from blogs leads to a better prediction on movie sales. In addition, [2] find that the sentiment extracted from twitter messages has a sales predicting power. Accordingly, to verify the prior literature and establish ground for our main findings, in the context of hotel business, we present the following baseline hypothesis.

Hypothesis 1 The positive sentiment of review texts on a hotel is associated with an increase in the number of bookings of that hotel.

2.2 Moderation on the impact of e-WoM on Sales

The firm reputation and status has been widely studied in various fields of business literature such as sociology and economics [57]. The definitions of two concepts were often used or studied without certain boundaries. However, there has been a perspective that two constructs are independent and should be considered differently and separately [61]. The concepts of two constructs are distinct in the following respects: First, reputation is a relative concept [51], accompanied by external evaluations throughout the historical records and performance from the past [57]. On the other hand, status is a network-centered concept that is accepted within a group [53, 61]. It refers to the social status and position in the specific network [53, 57, 58].

To clarify the difference between these two constructs, we borrow the following example from [40]: For instance, an opening for an academic job attracts tens of applications from job candidates with diverse backgrounds and academic records. The number of publications and citations, the quality of the journals the candidate chose as an outlet, number of years of experience on teaching and the teaching evaluations, form the track record of a candidate. Since comparing the candidates based on their individual merits alone can be time consuming and unreliable, a search committee may also check - mostly- the status of the candidates which may be determined by the doctoral program that they graduated from.

The strength of the sentiment of textual reviews would be different depending on who is sending the signal, who receives the signal, and under what conditions it has been delivered [26, 62]. Thus, social identities such as reputation and status may moderate the effectiveness of how the signal is interpreted [29]. [30] shows that brand strength moderates the effects of positive and negative consumer reviews on sales. It has also been shown that positive and negative consumer reviews have differential roles on the growth of chain and independent hotels [12]. While positive reviews promote the growth of independent hotels more than the chain hotels, negative reviews unfavorably affect the independent hotels but has no impact on the branded hotels. Despite the similarities to the mentioned study, our research differs in clarifying between the reputation and status, and exploring the moderating effects of these two constructs on the review sentiment on hotel bookings rather than firm growth.

[40] examines borrowers' reputation based on credit score and status based on group affiliation affect their obtaining loans and the reputation and status are complementary in obtaining loans. Different from [40], we investigate the

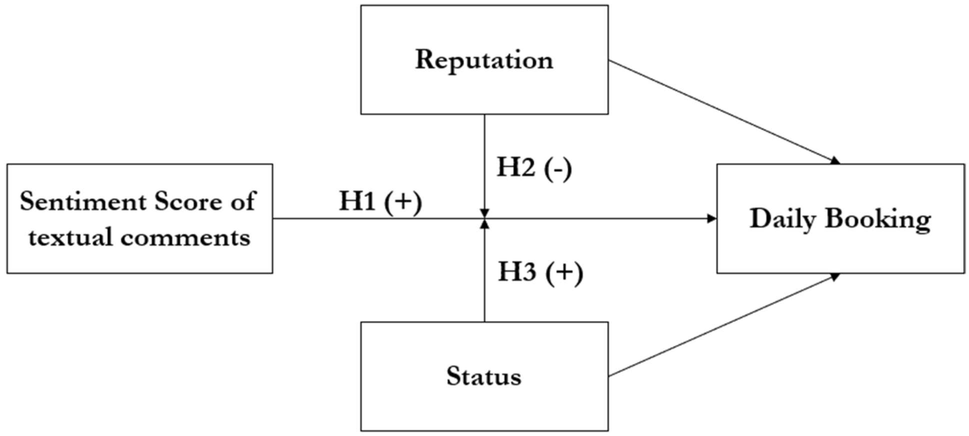

Fig. 1 Conceptual model

moderating effect of these two constructs on the impact of e-WoM on hotel bookings. A more recent study, [31], states that online reputation mechanisms decrease the value of chain affiliation. This study demonstrates that the increasing utilization of online reputation mechanisms helped independent hotels that are not affiliated with any other hotel chains. These independent hotels substantially increased their revenues compared to chain affiliated hotels. In our study, we investigate how reputation and status moderates the way customers perceive the sentiments derived from text reviews.

Reputation has been interpreted as an objective standard determined by star rating scored by either independent organizations such as Forbes Travel Guide and AAA, or online platforms such as hotels.com or booking.com. A high star rating for a local or a chain-brand hotel implies a high reputation. Reputation depends on the historical achievement of a hotel on various metrics such the quality of services and facilities [32]. For a high reputation hotel, a consistency in the quality of attributes and services implies a similar experience for a future customer of that hotel. Consequently, when customers observe a signal on high reputation for a hotel, they take this as a strong indicator of quality and they rely less on the information shared via text reviews. In other words, consumers' perception of e-WoM will be negatively moderated by the reputation, therefore, we present the following hypothesis.

Hypothesis 2 The impact of sentiment on the hotel booking is negatively moderated by the reputation in such a way that the positive effect of sentiment in textual reviews on the hotel bookings is weaker when the hotel possesses a higher level of reputation.

Reputation can be considered as ex-post. It is the actual returns of a firm in the forms of reviews in exchange for its service quality. Status, on the other hand, can be considered as ex-ante. It is related to the expectations from a firm on its service and product quality in relation to its standing. Status places a hotel in a socially accepted rank among its peers. It is a high status hotel's duty to live up to the standards of its social rank in the hotel industry. Customers would compare how close a hotel's service quality, room amenities, and standards of facilities are to the level of their expectations. If reputation is 'action', status can be resembled to 'words'. Since action speaks louder than words, customers scrutinize the reviews about a high status hotel to measure the distance between what is said and what is set for that hotel. Therefore, consumers become more sensitive towards the reviews and buy more of the review text for a hotel of high status because the e-WoM may influence the receiver who needs a concrete credible signal on the quality of that hotel. Thus, the following hypothesis is presented.

Hypothesis 3 The impact of sentiment on the hotel booking is positively moderated by the status in such a way that the positive effect of sentiment in textual reviews on the hotel bookings is stronger when the hotel possesses a higher level of status (Fig. 1).

3 Data, measurement, and model

We gathered data regularly at the same time every day from *hotels.com*, a hotel reservation platform, using customized crawlers programmed by Python 2.6, in the time period from October 31, 2017 to February 7, 2018 for hotels located in New York, USA. We chose hotels as our context because hotels have their own reputation and status as a business organization and customers often share their experience in terms of an evaluation and a textual comment. Our data collection was concentrated on New York City because the city does not have strong seasonality of hotel sales[2] and thus the sub-sample allows us to focus on the changes in sales before and after the individual textual reviews, without the influence of potential geographical characteristics. For the 310 hotels listed in the platform, for a duration of 100 days, we collected data including hotel reservations, customer rating, hotel specifications, price, and textual comments.

Prior literature confronts difficulty on finding appropriate proxies for sales due to the data limitation [63]. For instance, ranking information is mostly used as a proxy of sales [7, 18]. As a proxy to sales figure of a hotel, following the work of [63], we crawled the number of bookings in the last 24 hours from a popped-up yellow window from the platform at exactly the same time of every day. This window reports the number of bookings made through the platform within the last 24 hours.

To measure a hotel's status, we used three metrics. First, we created a variable, namely '$GloStat_i$', capturing how globally a hotel i chain is operating. For this purpose, we manually searched hotel's name on the Google Trends and find out people's interest on the hotel. The Google Trends offer visualized world map to show whether a specific keyword has been searched in a specific region. We were able to identify where the keyword has been searched from the map and measure the people's awareness on a specific hotel name. Therefore, we set $GloStat_i$ to 1 if hotel i is operating in a chain for which users around the world are making searches from more than four continents, and 0 otherwise [50]. Among 310 hotels in our dataset, there are 122 hotels which are searched by users from over four continents. Second, we counted the number of hotels within a chain to identify general awareness for the chain since franchise brand hotels are more likely to be noticed and perceived as high quality by potential customers. The maximal (minimal) numbers of local hotels in a hotel franchise is 2,726 (1) and the average is 299. Variable '$ChainStat_i$' denotes the number of hotels across the globe in a hotel chain for a specific hotel i. If, say, a hotel j does not belong to any hotel chain and operate as an independent entity, then we have $GloStat_j = 0$ and $ChainStat_j = 0$. Third, variable '$RatioStat_i$' denotes the size of a hotel chain with which a focal hotel i is associated. In this study, we define that a hotel chain is also considered as a sub-chain, since an umbrella chain may embrace multiple sub-chains. For instance, in our dataset, Accor has three hotel sub-chains (brand) such as the plaza, Sofitel, and Novotel. When we counted the total number of a hotels within a hotel chain for variable '$ChainStat_i$', we considered the total number of hotels in 'Novotel', instead of 'Accor'. However, variable '$RatioStat_i$' stands for the particular hotel chain's proportion out of the total number of hotels within all the chains presented in our dataset. That is, the size of a particular hotel chain is normalized by the total number of hotels in our dataset. For instance, if a hotel j belongs to a chain that is represented by 10 hotels and the total number of hotels including all hotel chains in our data set is 310, then we have $RatioStat_j = 10/310 = 0.0322$. We use '$RatioStat_i$' to further examine the relative magnitude of the chain's awareness which implies the total number of hotels in that chain (sub-chain) within the total number of hotels that appeared in our data by considering the standing of that chain out of the umbrella chain.

For measuring the reputation, we referred to the star rating reported on the reservation platform. We acknowledge that third party organizations such as AAA also report hotel star or diamond ratings. However, customers visiting the platform to make reservations are observing the star ratings posted on the same website. Note that the star ratings are different from the customer ratings posted on the same platform. We denote the reputation for hotel i as '$Reput_i$', where its range is in between 2 and 5.

For mining the textual review comments, we extracted the 10 recent reviews from the platform for each hotel. These reviews are available on the first page of the textual comment section of the platform at the time of the data collection. For the crawled textual comments, we utilized *Google Cloud Natural Language API* [23]. Google-Natural Language API measures the sentiment and magnitude scores based on a method called 'analyzeSentiment'. To describe the features based on the information provided by Google, sentiment analysis examines a given text and identifies dominant emotions (positive, neutral, negative) within that text. The sentiment score in a text represents the overall emotion within the text. The magnitude of the text represents how proportionally emotions within the text are presented. The magnitude value is considered to be correlated to the length of the text. Therefore, we included the magnitude of the emotion in our main models, but excluded text length variables. Since both the expression of mixed emotions and neutral emotions receive a sentiment score of '0', we also included the magnitude variable in our analysis. With the combination of sentiment score '0' and magnitude, we were able to separate the neutral and mixed emotions. Eventually, using Google API, for each comment, we captured the number of words, the sentiment score, and the magnitude of the sentiment. The number of words in each review ranges from 0 to 297, and averaged at 8.81. The variable $Length_{it}$ denotes the log transformation of word count of the most recent textual comment for hotel i at day t in the analysis. Sentiment score represents a numerical score of polarity ranging from -1 to 1. The value closer to 1.0 shows more positive sentiment but that closer to -1.0 means a negative one. On the other hand, the magnitude indicates the overall strength of sentiment and

[2] To control any seasonality and daily effects, we considered daily- and monthly- fixed effects.

Table 1 Summary statistics of key variables

Variable	Description	Mean	St.Dev	Min	Max
$Reput_i$	Star Ratings reported on platforms for Hotel$_i$	3.751	.739	2	5
$Price_{it}$	Price offered on the platform for Hotel$_i$ on day$_t$	\$272.4	\$182.7	\$41.49	\$9677.6
$Sales_{it}$	Number of bookings for Hotel$_i$ at day$_t$	6.383	8.7103	0	179
$Rating_{it}$	Aggregated numerical rating for Hotel$_i$ at day$_t$	8.257	.8884	4.4	10
$GloStat_i$	1 if the hotel chain for Hotel$_i$ is operating over 4 continents, 0 otherwise	.39	.488	0	1
$ChainStat_i$	The number of hotels across the globe within the chain that Hotel$_i$ is associated with	299.64	604.52	1	2726
$RatioStat_i$	The ratio of the number of hotels in the chain that Hotel$_i$ is associated with to the number of all hotels	.00645	.0139	.00002	.059
$AvgSenti_{it}$	Average sentiment score of the most recent textual review for Hotel$_i$ at day$_t$, $\in [-1, 1]$	.385	.493	−.9	.9
$Magni_{it}$	The average strength of the most recent textual review for Hotel$_i$ at day$_t$, $\in [0, +\infty)$	2.357	1.684	.1	13.4
$Length_{it}$	Log transformation of Average count of Words in the most recent textual comment for Hotel$_i$ at day$_t$	3.3	1.02	0	5.7
$Subj_{it}$	The average rate of subjectivity within the most recent text reviews for Hotel$_i$ at day$_t$	.463	.156	.06	.934

its range is between 0.0 and ∞. In Table 9, an example of a comparison between the review sentiment score and review magnitude is provided. We also list the summary statistics of the key variables in Table 1.

We focus on how the sentiment score extracted from review texts affects hotels' performance index, which is the number of booking rates daily. In addition, we also study how organizational attributes, such as reputation and status, interplay with review texts and eventually affect hotel performance.

4 Results

In this section, we present our results regarding the effect of a textual review, specifically the review's sentiment, on hotel booking and also the moderating impact of hotels' organizational attributes such as reputation and status on the impact of textual reviews. First, we applied the Poisson and negative binomial regression model to present our main results. Second, we made robustness analysis (1) by discretizing the reputation and status variables and assigning into buckets to normalize them, (2) by substituting the proxy variable to status with two other measures, (3) by considering the average sentiment scores from N different most recent textual reviews, and finally (4) by fragmenting reviews based on positive and negative sentiments. To address endogeneity issues, we ran instrumental variable estimation with subjectivity of the review, and also extended our analyses by only using the sentiment of the most recent review.

4.1 Main results

Given that our dependent variable is a count, we develop a zero-truncated Poisson model with day or month fixed effects. We cluster our standard errors at the hotel level since the effect of our interest is applied to hotel level. One key limitation of a Poisson model is that the Poisson parameters are assumed to be homogenous across hotels, which may not hold. For example, two hotels with the same observed attributes may be perceived differently by the customers. Such heterogeneity results in overdispersion, i.e., the variance exceeding the mean, and this is a violation of the Poisson property that the variance equals the mean. In our dataset, the variance of the sales (8.7103) is larger than the mean (6.383). Ignoring heterogeneity in the Poisson parameters may result in biases in the estimates of covariate coefficients.

To cope with this problem, one approach suggested in the literature is using negative binomial (NB) model. NB is derived from the Poisson model under the assumption that the random variation in the Poisson parameters is described by a gamma distribution. For an extended discussion of these models we refer to [24] and [9].

We begin our analysis with developing a baseline model to capture the impact of a hotel's status and reputation on its daily booking numbers. We also included in our model the average sentiment and magnitude of the most recent ten reviews as well as the hotel room price. Since daily booking numbers are highly correlated with the previous day's booking numbers, we included the lagged booking value to control for the auto-correlation. Variables $Rating_{it}$ and $Reput_i$ are both signaling the historical record of hotel quality and giving a VIF score of over 49, suggesting a high multicolliniearity. Therefore, we kept $Reput_i$ in and excluded $Rating_{it}$ from the model for two reasons: First, since $Reput_i$ is assigned by a third party other than the customers, we decided to keep this variable in the model to reduce the possible endogeneity problem between the ratings and the sales. Second, $Rating_{it}$ is reflecting customer satisfaction and may not include a comprehensive evaluation of hotel attributes.

Table 2 Baseline model for average 10 recent reviews

	Poisson Regression		**Negative Binominal**	
Variables	Model 1	Model 2	Model 3	Model 4
$AvgSenti_{it}$	0.048***	− 0.007	0.227***	0.164***
	(0.015)	(0.015)	(0.035)	(0.033)
$AvgMagni_{it}$	0.199***	0.143***	0.196***	0.146***
	(0.004)	(0.004)	(0.010)	(0.009)
$Reput_i$	0.246***	0.303***	0.157***	0.165***
	(0.005)	(0.005)	(0.010)	(0.010)
$RatioStat_i$	0.004***	0.007***	0.007***	0.005***–
	(0.001)	(0.001)	(0.002)	(0.002)
$Price_{it}$	− 0.001***	− 0.002***	− 0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{i(t-1)}$	0.031***	0.032***	0.089***	0.090***
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.420***	1.219***	0.014	0.600***
	(0.020)	(0.027)	(0.045)	(0.062)
Month (LSDV)	Yes	N/A	Yes	N/A
Day (LSDV)	N/A	Yes	N/A	Yes
Observations	21,358	24,085	21,358	24,085

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3 Main models for average 10 recent reviews

	Poisson regression		**Negative binominal**	
Variables	Model 5	Model 6	Model 7	Model 8
$AvgSenti_{it}$	2.242***	1.759***	2.017***	1.656***
	(0.0825)	(0.0791)	(0.183)	(0.169)
$AvgMagni_{it}$	0.202***	0.146***	0.205***	0.150***
	(0.004)	(0.004)	(0.010)	(0.009)
$Reput_i$	0.318***	0.365***	0.242***	0.232***
	(0.006)	(0.006)	(0.014)	(0.013)
$RatioStat_i$	− 0.044***	− 0.025***	− 0.015***	− 0.014***
	(0.002)	(0.002)	(0.004)	(0.004)
$Reput_i \times AvgSenti_{it}$	− 0.237***	− 0.222***	− 0.326***	− 0.258***
	(0.018)	(0.017)	(0.040)	(0.037)
$RatioStat_i \times AvgSenti_{it}$	0.154***	0.110***	0.070***	0.064***
	(0.005)	(0.005)	(0.012)	(0.011)
$Price_{it}$	− 0.001***	− 0.002***	− 0.000***	− 0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{i(t-1)}$	0.031***	0.032***	0.088***	0.090***
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	− 0.272***	0.703***	− 0.494***	0.190**
	(0.031)	(0.035)	(0.068)	(0.076)
Month (LSDV)	Yes	N/A	Yes	N/A
Day (LSDV)	N/A	Yes	N/A	Yes
Observations	21,358	24,085	21,358	24,085

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

As indicated in Table 2, average review sentiment and its magnitude, the hotel's status, and its reputation have significant positive relationship with the dependent variable of hotel bookings. When comparing the impact of status with reputation, considering the range of values these two variables are taking, one can infer that reputation matters significantly higher than status for guests making reservations from "hotels.com" platform. For instance, one unit of increment in reputation results in a 22.8% more increase in bookings than status. This finding confirms the conclusions in [31] that the quality signal broadcasted by online reputation mechanisms give a way to independent hotels when they compete with their chain-affiliated peers.

As said earlier, one important open question in the baseline model is whether reviews have the same degree of effect for hotels with different reputation and status states. For example, how would a customer react to a positive review made for a 3-star independent hotel versus a 3-star chain affiliated one. Would a customer tone down the e-WoM signal when it is about a high reputation hotel? To examine how the impact of review sentiments change with status and reputation, we included interaction terms into our baseline model. Table 3 presents the results for the parameters of our main interest: (1) the sentiment in a textual comments has a positive effect on hotel's daily reservation, (2) both status and reputation moderate the impact of sentiment on the daily number of bookings on a platform, and (3) moderation effects of status and reputation are opposite, as hypothesized earlier.

In Figs. 2 and 3, we compare the impact of review sentiment on sales for different levels of reputation and status as these two variables interact with the sentiment. Our first observation is that, considering the plots for Model 3 in both figures, there is an interesting disparity between different levels of reputation and status, respectively. As seen in these figures, for high reputation, the change in sales with respect to review sentiment is not as substantial as the case when reputation is lower. For their low, medium, and high levels, both reputation and status allow review sentiment positively impact the sales. We note that this impact has a difference of 0.35 between high status and low status, significantly wider than 0.02, which is the sentiment impact difference for high and low reputation. This difference begs for an explanation on why reputation and status behave so differently and whether we should look into this gap closer and investigate how status and reputation interacts with the review sentiment.

In Figs. 2 and 3, we also plotted sentiment versus sales when interaction terms for reputation and status are also

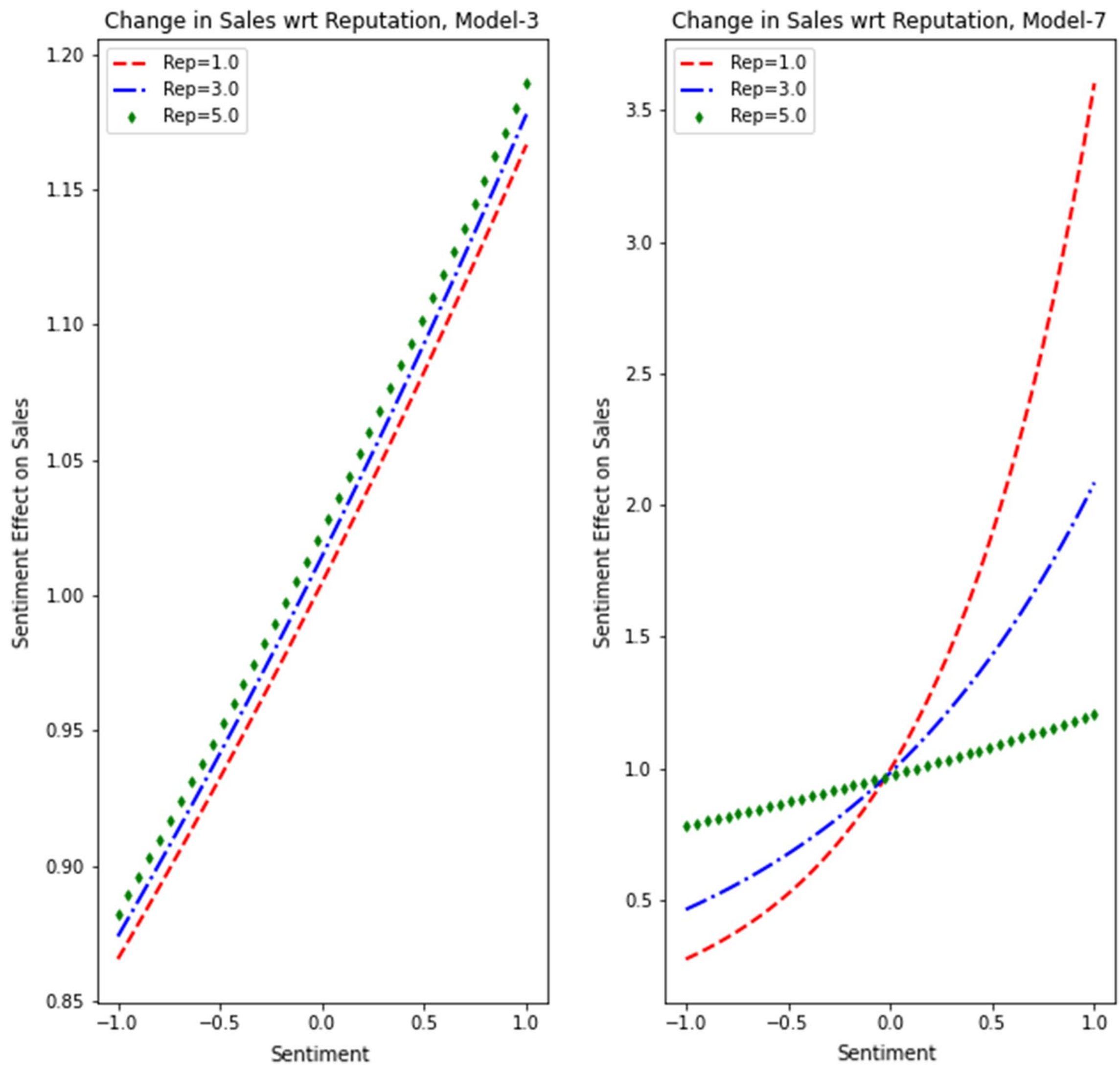

Fig. 2 Sentiment versus continuous reputation

incorporated in Model 7. According to the plot for Model 7 in Fig. 2, as the reputation decreases, the impact of review sentiment becomes more significant on the sales. When sentiment score is 1, that is, when we have maximum positive sentiment, the low reputation score of $Rep = 1$ has approximately three times more impact on sales than the high reputation score of $Rep = 5$. In other words, consumers do not put too much weight on review sentiment when the review is about a highly reputable hotel. However, this behaviour is modified when the hotel does not have a high reputation. On the other hand, as shown in the plot for Model 7 in Fig. 3, review sentiment becomes more effective on sales as the status increases. When the sentiment score is at its maximum, low status score of $Stat = 0$ has almost twice the impact on sales than high status score of $Stat = 0.0169$. Customers put more weight on review sentiments because reviews reduce the uncertainty on whether the true hotel quality matches the growing expectations from a high-status hotel.

We have examined the moderating effect of reputation and status on the sales when we silence one of the two. We now examine how these two variables interact when they moderate the effect of sentiment on the sales. We considered pairs of $(1,\ 0.0001)$ and $(5,\ 0.059)$ as low and high values for reputation and status $(Rep,\ Stat)$, respectively. For example, a reputation score of $Rep = 5$ and status score of $Stat = 0.0001$ are considered as high reputation and low status case, that is, $(Rep = H, Stat = L)$. As shown in Fig. 4, when we have $(Rep = H,\ Stat = H)$ or $(Rep = L,\ Stat = L)$, the review sentiment has minimal effect on the sales as these two variables work against each other and cancel one another. When we have $(Rep = H,\ Stat = L)$, we observe the highest effect of review sentiment on sales, because an independent hotel (low status) with high reputation requires more verification

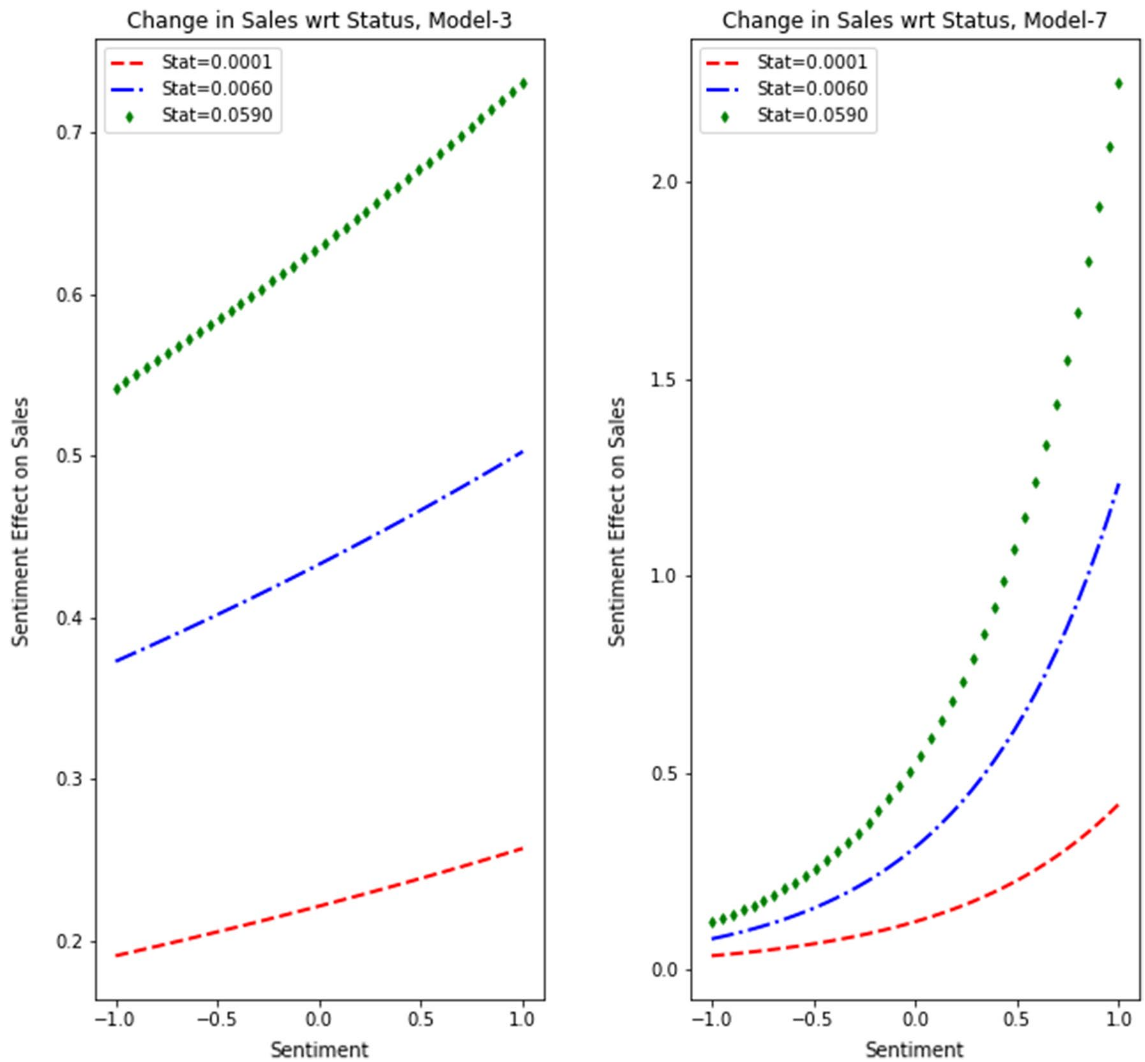

Fig. 3 Sentiment versus continuous status

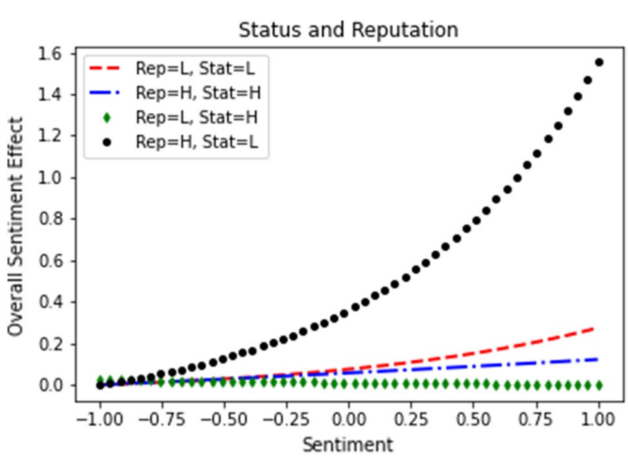

Fig. 4 Reputation and status comparison

for the potential customer and each positive increment in review sentiment brings more sales. Finally, when we have ($Rep = L,\ Stat = H$), a hotel affiliated with a chain receiving low reputation establishes a negative quality perception on the customers to a degree that any positive sentiment only makes the impact of reviews on the sales slightly worse.

4.2 Robustness tests

We conducted a variety of robustness checks, in order to assess the stability of our main results. We began by discretizing the reputation and status measures, then re-estimated the main model using alternative proxies for status and using N number of recent comments.

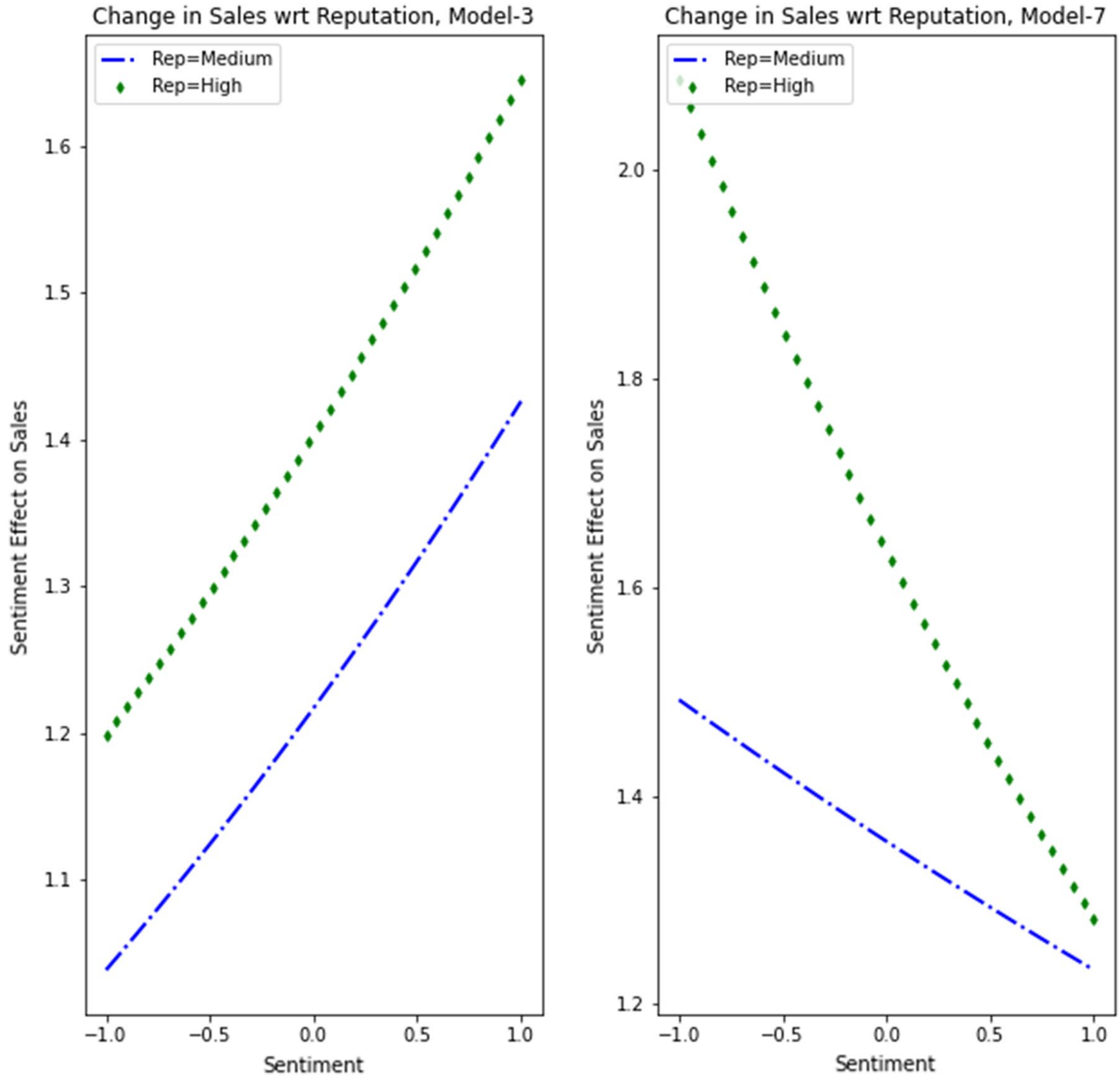

Fig. 5 Sentiment versus discretized reputation

4.2.1 Reputation and status discretized

To check the robustness of this interesting finding, since status and reputation take values from a different range of numbers, we normalized both reputation and status by dividing them into buckets of Low, Medium, and High based on their 25 and 75 quartiles. We therefore focused on how medium and high subgroup of each variable affects the sales by comparing them with their low value subgroups. We retrained our model and measured the effect of each variable by silencing the other. As it is shown in Figs. 5 and 6, the main essence of our result remained the same: Customers are influenced by review sentiments about a product (firm) more as the product's reputation decreases and its status increases.

4.2.2 Alternative measures of status

To assuage potential concern about relevance of the proxy to the status, we explore the robustness of the results by substituting $RatioStat_i$ with two variables: (1) $GloStat_i$, which is a dummy variable that takes the value of 1 if hotel i belongs to a hotel chain that operates in at least four continents, and (2) $ChainStat_i$, which is the number of hotels around the world which belongs to a chain that hotel i is affiliated with. The results are summarized in Table 4. We only list the base model with negative binomial regression. Our results for models both with and without status/reputation interaction terms qualitatively remain the same.

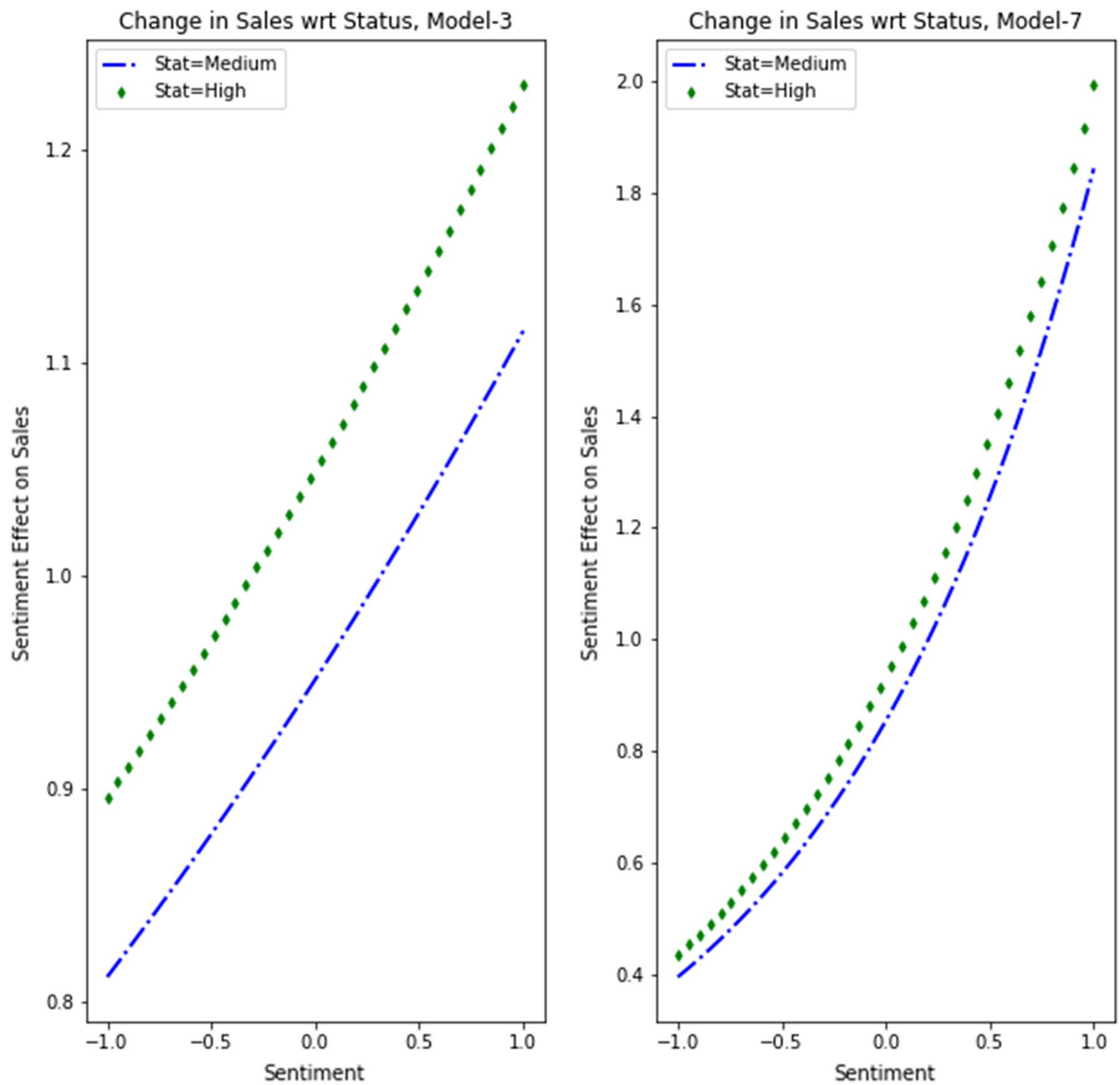

Fig. 6 Sentiment versus discretized status

4.2.3 N-recent textual comments

As mentioned earlier, the hotel.com platform displays up to ten most recent textual reviews. In our earlier analysis of our panel data set, since customers may prefer checking out the reviews displayed on the platform's landing page, we used the average sentiment perceived from up to ten most recent reviews. However, inclusion of too many textual comments to capture the customer sentiment for a single day may increase the correlation between the sentiment score and reputation as well as -if any- unobserved hotel quality, leading to both multicollinearity and endogeneity issues. To test the robustness of our results, we derived the average sentiment based on five, six, seven, and eight most recent reviews. All the results are qualitatively the same, but with the increasing number of textual comments, the moderation and the textual comment effects become more influential on the sales.

4.2.4 Considering only positive and negative sentiment

The impact of reviews on the sales might significantly differ depending on the polarity of review sentiments. Instead of using a single variable for sentiment, we created two variables, $SentPosOnly_{it}$ and $SentNegOnly_{it}$, which denote the positive or negative average sentiment for hotel i at day t, respectively. Note that we used the sentiment of the most recent review to introduce enough variance in the reviews. Our main results qualitatively hold for this new model and we present the individual effects of status and reputation in Figs. 7 and 8.

Table 4 Base models of average 10 recent reviews, Alternatives Status

	Using Global Status		Using No of Hotels within a Chain	
	Negative Binominal Regression		Negative Binominal Regression	
Variables	Model 9	Model 10	Model 11	Model 12
$AvgSenti_i$	0.234***	0.167***	0.237***	0.167***
	(0.035)	(0.033)	(0.035)	(0.033)
$AvgMagni_{it}$	0.196***	0.146***	0.196***	0.146***
	(0.010)	(0.009)	(0.010)	(0.009)
$Reput_i$	0.155***	0.164***	0.159***	0.169***
	(0.010)	(0.010)	(0.011)	(0.010)
$GloStat_i$	0.039***	0.039***		
	(0.013)	(0.012)		
$ChainStat_i$			0.000*	0.000**
			(0.000)	(0.000)
$Price_{it}$	−0.000***	−0.001***	−0.000***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{t-1}$	0.089***	0.090***	0.089***	0.090***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−0.050	0.549***	−0.060	0.533***
	(0.043)	(0.060)	(0.046)	(0.062)
Month(LSDV)	Yes		Yes	
Day(LSDV)		Yes		Yes
Observations Observations	21,358	24,085	21,358	24,085

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.3 Identification strategy

The endogeneity issue in e-WoM models is often stemming from unobserved quality of business or product because a product receiving positive reviews is more likely to be of high quality, and thus correlations between any reviews and product sales might be spurious. Having established that the impact of sentiment and moderation effects of reputation and status are consistent across various models, we next considered two identification strategies to further address the endogeneity issue: (1) we only used the sentiment of the most recent textual review and (2) we exploited a new instrumental variable, 'subjectivity', which is derived by natural language processing (NLP) and applied two-stage least squares (2SLS) method on our dataset.

4.3.1 Most recent single review

When average sentiment is taken from a large number of textual comments, the sentiment may partially reflect the product quality [7]. This, in return, may create a high correlation between the sentiment and any unobserved product quality left in the model's error term. In order to address this issue, since a single review may deviate from the average sentiment, when training the model, we only considered the sentiment of the most recent single review. As seen in Table 5, our main results still hold.

4.3.2 Instrument variable

Another common remedy to the plausible endogeneity issue is a panel two-stage least squares (2SLS) approach through identifying instrument variables (IV) [24, 27]. As an IV for our 2SLS model, we chose to use the subjectivity of the most recent textual comment, and introduce a new variable, $Subjectivity_{it}$, which denotes the subjectivity score for the latest text review on day t for hotel i.

A subjectivity of a textual review is a reflection of the user's sentiment toward the focal business, causing variation in the sentiment, but also the user's predisposition for posting, not directly related to the business quality. We applied machine learning-based text analysis at the review level to extract subjectivity score (= 1 - objectivity score), which ranges from 0.0 to 1.0. The value closer to 1.0 shows highly subjective (less objective) and that closer to 0.0 indicates less subjective (more objective). In Table 6, we provide sample sentences depending on their subjectivity extent. We provide in the Appendix the details of the machine learning

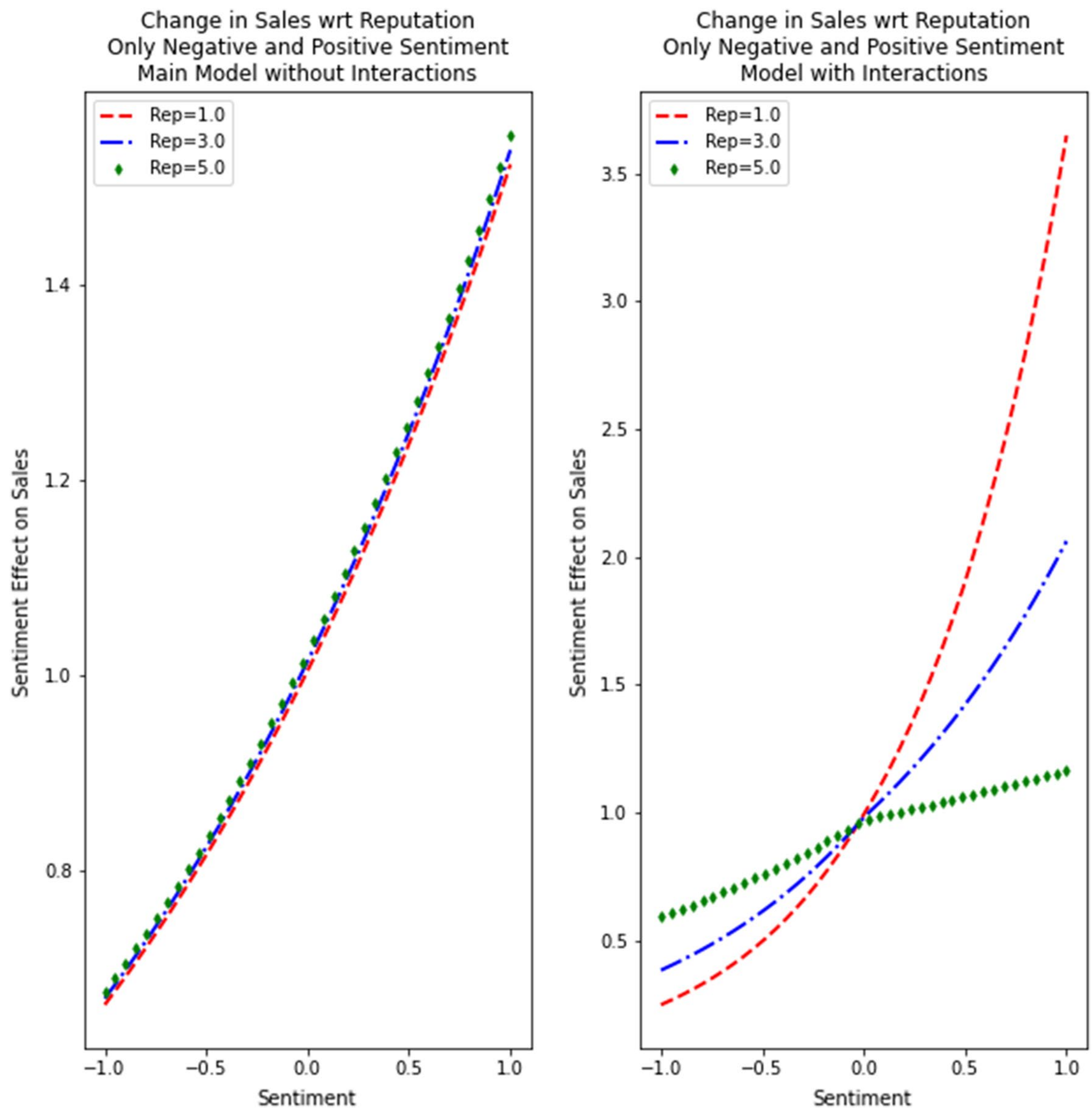

Fig. 7 Fragmented sentiment versus reputation

pipeline created for extracting the subjectivity score of reviews.

The results of the two-stage model are reported in Table 7, and all the results are qualitatively the same with our main findings. table:identification2

5 Conclusions

It has been a challenge for researchers to identify the individual impact of reputation and status on firm performance due to these two constructs being so intertwined with each other. As stated by [40], when reputation and status converge by time, they become increasingly indistinguishable from each other. Moreover, it is not so clear how these two assets interact with online reviews in terms of influencing customers' purchasing decisions. In this study, we used an online hotel reservation platform to investigate the moderating effects of reputation and status on the impact of sentiment of text reviews on daily hotel booking numbers. We used hotel's franchise affiliation as an indicator for that hotel's status whereas the hotel star ratings provided by the platform as a proxy to reputation. We found hotel reputation and status have distinct moderating effect on the overall positive effects of the online review sentiment on hotel booking numbers.

Both status and reputation carry a weight in terms of signaling product and service quality. Since reputation is based on evaluation of the past trajectory of product

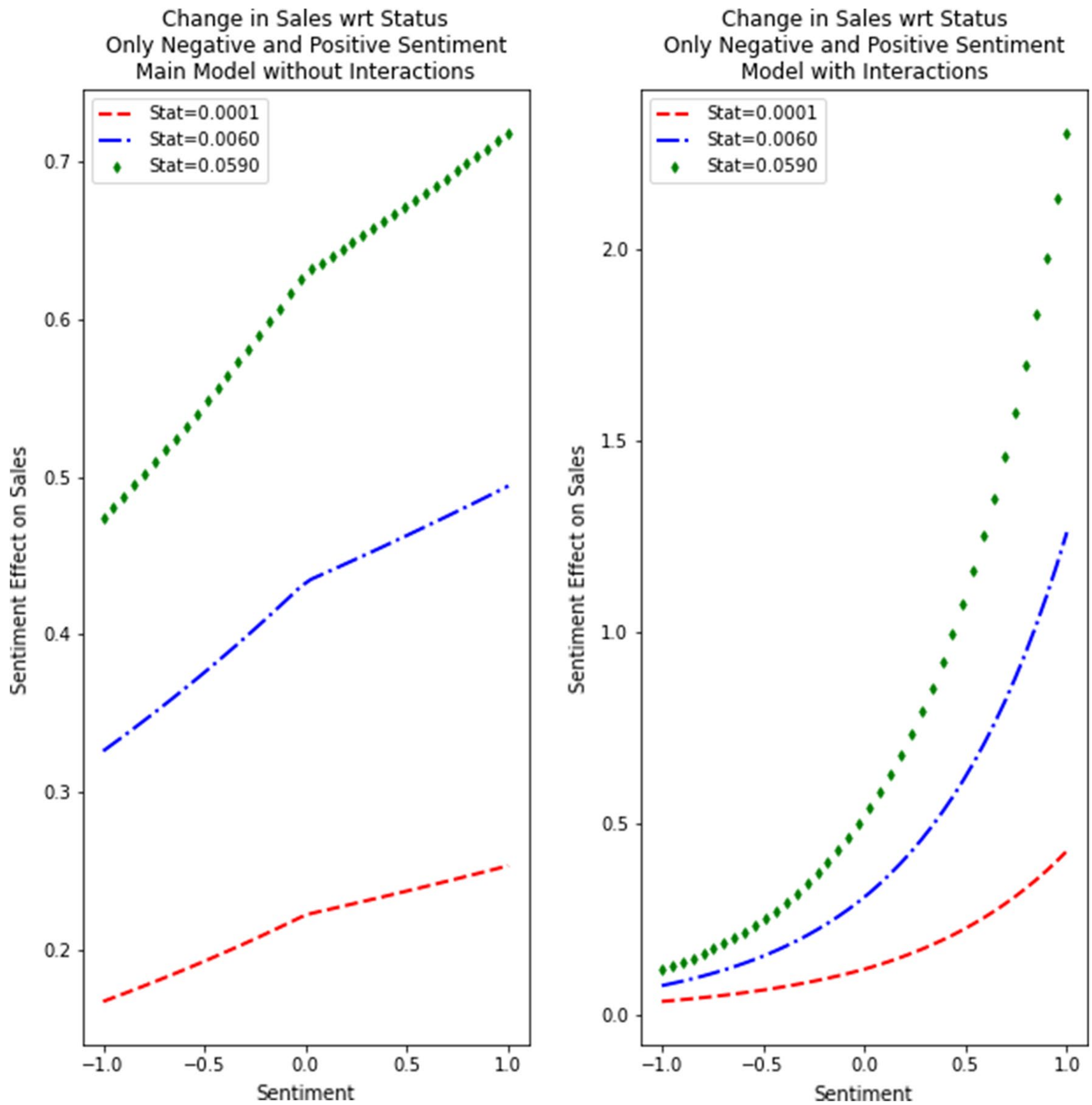

Fig. 8 Fragmented sentiment versus status

quality, it becomes effective in terms of removing any ambiguity for the prediction of the future quality trajectory. Thus, the effect of online reviews become less pronounced for hotels when their reputation increases. Consumers rely on an aggregate measure of the historical hotel achievement which may tone down the impact of reviews. On the other hand, even though status helps decreasing information asymmetry between the consumer and the firm, it is an indication of the hotel being considered as part of a group rather than how well the prior customers regarded the service of product they received from the same hotel. Thus, consumers need online reviews to verify the signal they receive for the focal hotel's status.

In addition to individual effects of reputation and status, it becomes interesting to observe the dominance of one variable over another under different circumstances. First of all, we note that these two assets work differently for their respective various levels as review sentiment changes. Reviews become less effective as reputation increases but stay still relevant for increased status. When both reputation and status are taking low or high values, the overall impact of the review sentiment on the sales is deflated. However, when we have high reputation but low status, customers become more eager to verify whether it is actually true for an independent hotel to attain a high star rating. Customers put more weight on reviews to verify this information. On the contrary, when a hotel is low reputation with a high status, customers do not consider much about what the reviews say, because the hotel reputation does not meet the customers'

Table 5 Identification startegy: the most recent review

	Poisson Regression		Negative Binomial	
Variables	Model 13	Model 14	Model 15	Model 16
$Senti_{it}$	0.491***	0.449***	0.462***	0.408***
	(0.033)	(0.031)	(0.074)	(0.067)
$Magni_{it}$	−0.011***	−0.007***	0.001	0.004
	(0.002)	(0.001)	(0.004)	(0.003)
$Reput_i$	0.332***	0.377***	0.230***	0.232***
	(0.005)	(0.005)	(0.011)	(0.011)
$RatioStat_i$	−0.006***	−0.002*	0.006**	0.004
	(0.001)	(0.001)	(0.003)	(0.003)
$Reput_i \times AvgSenti_{it}$	−0.080***	−0.074***	−0.110***	−0.095***
	(0.007)	(0.007)	(0.017)	(0.015)
$RatioStat_i \times AvgSenti_{it}$	0.028***	0.026***	0.008*	0.009**
	(0.002)	(0.002)	(0.004)	(0.004)
$Price_{it}$	−0.002***	−0.002***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{t-1}$	0.031***	0.032***	0.091***	0.091***
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.574***	0.669***	0.274***	0.088
	(0.022)	(0.034)	(0.022)	(0.070)
Month (LSDV)	Yes		Yes	
Day (LSDV)		Yes		Yes
Observation	23,561	26,547	23,561	26,547

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

increased high expectation due to hotel being a member of a hotel chain.

Our paper offers two primary academic contributions. First, this study proposes heterogeneous persuasive power of text reviews about a firm according to the reputation and the status of that firm. The previous literature considered both constructs substitutes of each other due to the the ambiguity of definitions or the difficulty of disentangling their moderating roles on the reviews. We provide in this paper empirical evidence that the reputation and status of a firm may have opposite moderating effects on the impact of textual review sentiment. Second, our paper joins the burgeoning scientific investigations to introduce new metrics to be utilized in text mining. We identify the subjectivity score from the textual comments and employ this measure as an instrument variable. The subjectivity of a textual comment is a reflection of that reviewer's feeling, thus it is strongly correlated with sentiment score while the subjectivity is not related to the quality of the product or service.

Our study has several implications for business and practitioners. First, our results verify that the information provided by online platforms decrease the value of being affiliated with a chain [31]. Becoming a franchise of a well known brand name may help a firm decrease information asymmetry between the firm and the buyer, but the additional information provided by the online platforms, in this case, the reputation, decreases the value of such affiliation. Second, our results make it very clear to any franchise that not providing adequate level of product quality will significantly reduce the impact of positive reviews. Third, the umbrella firm may not properly accrue the benefits of maintaining a chain if individual affiliated parties do not live up to the standards of the customer's quality expectation that is already established for the chain. Fourth, independent firms who take advantage of the online reputation mechanism that helps them cope with the disadvantage of lacking the status should be very careful about individual customer satisfaction and what these customers have to say online. Fifth, the online platforms should be aware of the moderating effect of reputation and status on the reviews and platforms may adopt firm-specific strategies when having their layout of the reviews designed regarding the selection and presentation order of the factors related to e-WoM on their sites [54], for instance, whether the reviews will be shown in chronological order in a linear manner or listed mixed in terms of reflecting the sentiment distribution of the overall reviews. Finally, our study sheds light on the question of why some

Table 6 Example sentence of subjectivity score

Extent	Category	Subjectivity Score	Examples
Max	High Subjective	0.9342	Great hotel, excellent location, most interesting points in Manhattan at less than 30 minutes walking.Breakfast is the only thing that could be better.
Average	Neutral	0.4634	This hotel was in a great location, clean, staff was friendly, overall we had an amazing weekend! The only issue was the lack of mirror (one in bathroom and one in closet which would be ok, but w/ three girls for a weekend trip it was a little difficult) Would definitely book this hotel again!.
Min	Low Subjective	0.0599	I travelled to NY with my husband for the weekend and because the hotel is so close to Trump Towers, a part of the street is closed and there is a lot of security, trucks, nypd, and reporters, also there was a protest on sunday and Trump was supposed to arrive on Monday. We didn't like that. I think the bed was too small for two.The hotel staff was very nice and helpful.

Table 7 Identification strategy II: IV estimation

	2sls Using Instrumental Variable			
	1st Stage	2nd Stage	1st Stage	2nd Stage
	$\overline{Sentiment_{it}}$	Sales	$\overline{Sentiment_{it}}$	Sales
Variables	Model 17	Model 18	Model 19	Model 20
$Subjectivity_{it}$	0.543***		0.535***	
	(0.0138)		(0.0126)	
$\overline{AvgSenti_{it}}$		19.43***		10.02***
		(3.189)		(2.871)
$AvgMagni_{it}$	0.053***	1.141***	0.053***	1.090***
	(0.002)	(0.150)	(0.002)	(0.140)
$Reput_i$		1.712***		1.872***
		(0.204)		(0.177)
$RatioStat_{it}$		−0.196***		0.022
		(0.055)		(0.047)
$Reput_i \times \overline{AvgSenti_{it}}$		−1.866***		−1.805***
		(0.705)		(0.625)
$RatioStat_{it} \times \overline{AvgSenti_{it}}$		0.460**		−0.274*
		(0.188)		(0.166)
$Rating_{it}$	0.152***	−1.812***	0.146***	−2.656***
	(0.003)	(0.211)	(0.003)	(0.266)
$Price_{it}$	8.24e−05***	−0.006***	0.000***	−0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{t-1}$	−0.001***		−0.001***	
	(0.000)		(0.268)	
Constant	−0.027***	−5.969***	−0.072***	2.132**
	(0.006)	(0.880)	(0.012)	(0.895)
Month (LSDV)	Yes	Yes		
Date (LSDV)			Yes	Yes
Observations	21,358	21,408	24,085	24,259

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

sellers or service providers do not openly respond to the negative text reviews, almost raising a concern of not taking the complaints seriously. Our findings suggest that as firm characteristics such as reputation and status interact with how customers interpret the sentiment of text reviews from other customers, firms may have non-uniform strategy to tackle the challenges of text reviews regarding their services and products on online platform.

Appendix A: N-recent textual comments

See Table 8.

Table 8 The interaction effect of price with average reviews' sentiment

Variables	Negative binominal							
	Average 5 recent reviews		Average 6 recent reviews		Average 7 recent reviews		Average 8 recent reviews	
	Model 21	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28
$AvgSenti_i$	1.396***	1.646***	1.355******	1.638***	1.840***	1.511***	1.947***	1.582***
	(0.149)	(0.137)	(0.159)	(0.146)	(0.166)	(0.153)	(0.173)	(0.159)
$AvgMagni_{it}$	0.093***	0.072***	0.117***	0.091***	0.138***	0.107***	0.165***	0.125***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
$Reput_i$	0.253***	0.248***	0.259***	0.252***	0.262***	0.254***	0.259***	0.249***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
$RatioStat_i$	−0.009**	−0.010***	−0.012***	−0.012***	−0.014***	−0.013***	−0.014***	−0.013***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$Reput_i \times AvgSenti_{it}$	−0.245***	−0.188***	−0.285***	−0.223***	−0.320***	−0.254***	−0.336***	−0.264***
	(0.033)	(0.030)	(0.035)	(0.032)	(0.036)	(0.033)	(0.038)	(0.035)
$RatioStat_i \times AvgSenti_{it}$	0.047***	0.048***	0.056***	0.054***	0.061***	0.056***	0.064***	0.058***
	(0.009)	(0.008)	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)	(0.010)
$Price_{it}$	−0.000***	−0.001***	−0.000***	−0.001***	−0.000***	−0.001***	−0.000***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{i(t-1)}$	0.090***	0.091***	0.090***	0.091***	0.090***	0.091***	0.089***	0.091***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−0.189***	0.129*	−0.301***	0.084	−0.384***	0.096	−0.447***	−0.120
	(0.066)	(0.078)	(0.067)	(0.077)	(0.068)	(0.078)	(0.068)	(0.079)
Month (LSDV)	Yes	N/A	Yes	N/A	Yes	N/A	Yes	N/A
Day (LSDV)	N/A	Yes	N/A	Yes	N/A	Yes	N/A	Yes
Observations	22,717	25,614	22,443	25,315	22,176	25,008	21,902	24,700

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix B: Machine learning pipeline for subjectivity score

We pre-processed a total of 62,000 reviews collected from Hotels.com. Before training a model, we pre-processed subjectivity training set data with a TF-IDF vector. Through tokenizing, lemmatization, and POS-tagging procedures, we first prepared the subjectivity training set using the movie review data. The training data set includes 5000 subjective review data from the Rotten Tomatoes pages and 5000 objective plot summary data from IMDb (Internet Movie Database). Then we prepared to predict

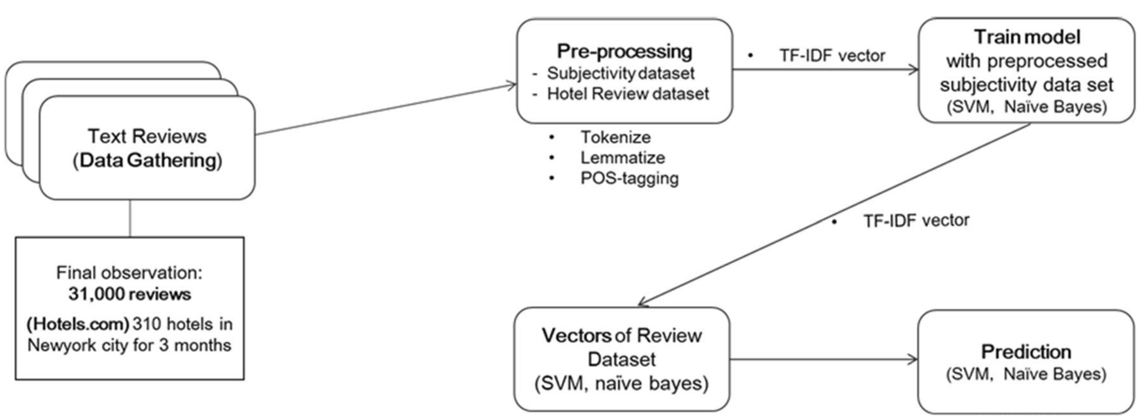

Fig. 9 Text-mining procedure of textual comments

the final subjectivity score by vectorizing the hotel review dataset with the same process. Using the Naïve Bayes classifier, we collected the subjectivity score at each review level. Our procedure of text-mining is graphically displayed in Fig. 9, and summarized statistics of text-mined variables are available with those of other hotel information in Table 1.

Appendix C: The detailed examples of magnitude and sentiment score

See Table 9.

Table 9 Example sentence of subjectivity score

No	Review	Sentiment	Magnitude
1	Thank God it was a very short stay. The hotel needs to be renovated	− 0.9	0.1
2	This is an old hotel. There were bad stains on the ceiling. No coffee maker or fridge or microwave. The view was inward and old and dirty. TV was antenna only. Therefore, no CNN or other all day news channels and weather. Lots of OLD movies. Would have been ok but our stay was during IRMA and we wanted to know how friends and family were faring in FL. Window air conditioner but we did not need so don't know if it worked or not. No paperwork about the stations or anything else either. One little desk light was the only lamp. Probably the worst hotel I've ever stayed in. For the ok attributes: The bathroom was clean. Sheets were clean. People were nice. It's a beautiful street right next to Central Park.	− 0.9	7.7
3	Overall 4 out of 5 all around. I would return	0.9	0.1
4	Great. Great. Great. Great. Great great. Great great. It was amazing very clean. The ambiance was amazing. The people at the front desk was helpful and professional. Great great great great great great great great great great great great great great great great great great great great	0.9	9.3

Appendix D: Price effect with reputation, status, and sentiment

In addition to the opposite moderating roles of reputation and status on the impact of the textual comments on the sales, we also included the moderation of price with organizational attributes (price*status, price*reputation) and sentiment (price*average sentiment) in our models. We found that, after controlling the confounding effects of the price, our main findings, i.e., review sentiment effect and the moderation effects of reputation and status on the same, are qualitatively identical and even more clearly identified. In other words, with the consideration of the price, it is confirmed that reputation and status take opposite roles in moderating the effect of text review on the sales. We present our findings in Table 10.

Table 10 Additional interaction of price with status, reputation, and average reviews' sentiment

	Poisson Regression		Negative Binominal	
Variables	Model 29	Model 30	Model 31	Model 32
$AvgSenti_{it}$	2.252***	1.821***	1.990***	1.645***
	(0.084)	(0.081)	(0.184)	(0.170)
$AvgMagni_{it}$	0.190***	0.135***	0.205***	0.151***
	(0.004)	(0.004)	(0.010)	(0.009)
$Reput_i$	0.517***	0.519***	0.270***	0.231***
	(0.010)	(0.009)	(0.019)	(0.018)
$RatioStat_i$	−0.077***	−0.059***	−0.009	−0.011**
	(0.003)	(0.003)	(0.006)	(0.005)
$Reput_i \times AvgSenti_{it}$	−0.345***	−0.377***	−0.312***	−0.258***
	(0.020)	(0.019)	(0.043)	(0.040)
$RatioStat_i \times AvgSenti_{it}$	0.159***	0.112***	0.072***	0.064***
	(0.005)	(0.005)	(0.012)	(0.011)
$Price_{it} \times AvgSenti_{it}$	0.002***	0.002***	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Reput_i \times Price_{it}$	−0.001***	−0.000***	−0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$RatioStat_i \times Price_{it}$	0.000***	0.000***	−0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Price_{it}$	0.002***	0.000*	0.000	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{i(t-1)}$	0.031***	0.032***	0.088***	0.090***
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	−1.154***	−0.013	−0.564***	0.218**
	(0.046)	(0.049)	(0.091)	(0.099)
Month (LSDV)	Yes	N/A	Yes	N/A
Day (LSDV)	N/A	Yes	N/A	Yes
Observations	21,358	24,085	21,358	24,085

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix E: Sub-sampled analysis for hotel groups

In this section, we conducted an additional two-by-two sub-sampled analysis by dividing the hotels into four groups depending on (1) whether a hotel belongs to a franchise or it is an independent hotel with a single brand and (2) whether the hotel's star (reputation) level is above and below a certain range (3.5). As a result of the sub-sample analysis, we presented our results in Table 11. We used negative binomial regression with the same control variables that we used in our main models. The result shows that, out of the four groups, the impact of the average sentiment on the sales is maximum for the group of franchised hotels with hotel reputation less than 3.5 stars. On the other hand, the impact of average sentiment on the sales becomes minimal for the group of franchised hotels with higher than 3.5 star ratings. For the group of hotels with an independent single brand, the average sentiment increases the sales for both low and high star groups, although the effect is stronger for the low-ranking group. The results indicate that the sentiment of textual reviews plays a critical role in increasing the sales for independent hotels with a single brand. However, for franchises, the sentiment in textual reviews plays a role for only the hotels with less than 3.5 stars.

Table 11 Sub-sampled groups depending on hotel star-rating and chain-affiliation

	Star-rating groups	
	Low star	High star
Chain_affiliated	1.112***	−0.078
	(0.160)	(0.049)
Independent_Hotel	0.312***	0.164***
	(0.090)	(0.057)

Low, high groups cut from 3.5 star

Independent hotel group includes a chain with an individual hotel

Table 12 The impact of rating with status and reputation

	Poisson Regression		Negative Binomial	
Variables	Model 33	Model 34	Model 35	Model 36
$ReviewRating_{it}$	1.233***	1.185***	0.788***	0.770***
	(0.024)	(0.024)	(0.053)	(0.052)
$Sentiment_{it}$	−0.000	0.000	−0.006	−0.007
	(0.005)	(0.005)	(0.013)	(0.013)
$Magnitude_{it}$	−0.005***	−0.005***	0.003	0.003
	(0.002)	(0.002)	(0.004)	(0.003)
$Reput_i$	1.984***	1.824***	1.326***	1.242***
	(0.033)	(0.033)	(0.076)	(0.074)
$RatioStat_i$	−0.604***	−0.614***	−0.320***	−0.327***
	(0.014)	(0.014)	(0.031)	(0.030)
$Reput_i \times ReviewRating_{it}$	−0.195***	−0.170***	−0.134***	−0.122***
	(0.004)	(0.004)	(0.009)	(0.009)
$RatioStat_i \times ReviewRating_{it}$	0.074***	0.075***	0.039***	0.040***
	(0.002)	(0.002)	(0.004)	(0.004)
$Price_{it}$	−0.001***	−0.002***	−0.000***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Sales_{i(t-1)}$	0.031***	0.031***	0.088***	0.088***
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	−9.739***	−9.314***	−6.177***	−6.290***
	(0.196)	(0.199)	(0.443)	(0.435)
Month (LSDV)	Yes	N/A	Yes	N/A
Day (LSDV)	N/A	Yes	N/A	Yes
Observations	23,551	23,551	23,551	23,551

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix F: Rating effect with reputation and status

In this section, we further examined how ratings independently work on sales in our dataset.The analysis results, which are presented in Table 12 show consistency as the effect of textual reviews. However, considering the ratings as static information accumulated and aggregated during certain periods of time, the rating information can not fully synchronize with the dynamics of the sales data which is changeable daily. In addition, the ratings are significantly correlated with reputation information(0.59), causing multicollinearity problems in the model. Therefore, we did not include ratings as a control variable in our main model for to prevent potential endogeneity issue. We further investigate the correlation between sentiment(average sentiment, the recent sentiment both) and reputation, and the correlation shows 0.25 and 0.14. As we examine the unique impact of reviews excluding rating information, we identify that both the base model and the moderation show more robust results.

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