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The role of electronic word of mouth in reducing information asymmetry: An empirical investigation of online hotel booking

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ABSTRACT

The hotel industry is plagued with asymmetric information, which may distort prices and reduce incentives to provide quality service. However, both branding and hotel star ratings play an important role in reducing information asymmetry. The question addressed here is whether electronic word-of-mouth (eWOM) - an increasingly popular form of online feedback -contributes to any further reduction in information asymmetry; and, if so, in what manner. Using a dataset of listed prices and guests' ratings extracted from Booking.com, including several covariates, we show that the price–reputation gradient is much steeper in lower star-rated hotels than in higher star-rated hotels. The gradient is also steeper in unbranded hotels than in branded hotels. As lower star-rated and unbranded hotels are laden with greater quality uncertainty, this finding lends support to the hypothesis that the greater the information asymmetry, the greater the role of eWOM in reducing that uncertainty. Managerial implications are discussed.

1. Introduction

Since the 1995 launch of Amazon, which first allowed online shoppers to post product feedback, online consumer reviews have become increasingly popular and widespread. Although electronic word of mouth (eWOM) is perceived as being less reliable than off-line world-of-mouth (Chatterjee, 2001), it is considered more credible than information created by the sellers themselves (Chen & Xie, 2008). Furthermore, eWOM has several advantages, including the ability to disseminate information more quickly and spontaneously than traditional world-of-mouth. Attesting to the popularity of eWOM, 90% of customers in the United States reported that their buying decisions are influenced by online reviews (Gesenhues, 2013) and 80% of British consumers were found to be influenced in the same way (Casaló, Flavián, Guinalíu, & Ekinci, 2015). In the hotel industry, Gretzel and Yoo (2008) estimated that 75% of travelers worldwide consider eWOM as an information source when planning their trips. Given the frequency with which eWOM is used, it is not surprising that the emerging literature has established a significant link between eWOM and the performance of companies.

The findings outlined above have been demonstrated in various industries which sell goods online, including books, movies, music and the hotel industry (Anderson, 2012; Litvin, Goldsmith, & Pan, 2008; Phillips, Zigan, Silva, & Schegg, 2015; Vermeulen & Seegers, 2009; Yacouel & Fleischer, 2012; Ye, Law, & Gu, 2009; Ye, Law, Gu, & Chen, 2011). This study focuses specifically on the hotel sector.

Most of the literature on eWOM is concerned with the effect of *volume* (i.e., the total number of online customer reviews posted) and *valence* (the average rating or the percentage of positive and negative opinions) on the performance of the firm. Numerous estimates of 'eWOM elasticity' have been suggested, a metric that quantifies the relationship between the volume/valence of eWOM and the firm's performance (e.g. its sales). You, Vadakkepatt, and Joshi (2015) performed a meta-analysis of 51 studies which estimated such elasticities. They found high levels of variance in the 610 reported eWOM elasticities even among studies that focused on the same product category. Moreover, they reported conflicting findings regarding the volume/valance metrics; for example, while Duan, Gu, and Whinston (2008) found that movie revenues are associated with the volume of eWOM and not with its valence, Chintagunta, Gopinath, and Venkataraman (2010) reported the opposite result. These conflicting, and sometimes puzzling results, suggest that the joint effect of the volume and valence of eWOM on firm performance is more complex than it might initially appear. Indeed, in their recommendations for future research, You et al. (2015) highlight the need to better understand how the volume and valence of eWOM interact with each other in affecting a firm's

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performance. Similarly, Moe and Schweidel (2012) note that the interpretation of volume and valence can be misleading when each metric is considered separately. As we discuss below, valence may be an important mediator of the relationship between volume and firm performance. Furthermore, the effect of both volume and valence on performance may vary substantially across the quality space, potentially playing a bigger role when quality uncertainty is greater.

A more discerning approach would be to acknowledge that the effect of eWOM is not monolithic - rather, it varies according to several factors such as:

(1) Product characteristics, e.g. new vs. mature goods (Cui, Lui, & Guo, 2012), experience- vs. search-goods (Cui et al., 2012; Park & Lee, 2009), high- vs. low-involvement goods (Gu, Park, & Konana, 2012), affiliation to strong vs. weak brand (Ho-Dac, Carson, & Moore, 2013), popular vs. non popular products (Zhu & Zhang, 2010), the presence/absence of sub-products within the same product type - in particular, graded vs. non-graded products (Dewally & Ederington, 2006) and product's durability, trialability and observability (You et al., 2015);
(2) Consumer characteristics, e.g., gender and income (Gopinath, Chintagunta, & Venkataraman, 2013), level of risk-aversion (Casaló et al., 2015), and susceptibility to reviewers' ratings (Bao & Chang, 2014).
(3) Platform characteristics, including the level of anonymity provided to online posters (Forman, Ghose, & Wiesenfeld, 2008) the reputation of the website (Park & Lee, 2009; Shamdasani, Stanaland, & Tan, 2001) and the trustworthiness of eWOM (You et al., 2015); and
(4) eWOM message configuration and distributional patterns, e.g., negative vs. positive eWOM (Park & Lee, 2009), extreme vs. moderate ratings (Park & Nicolau, 2015) and uneven vs. even prevalence of ratings (Chevalier & Mayzlin, 2006).
(5) Industry characteristics such as the state of growth and the intensity of competition (You et al., 2015).

Despite the significant volume of research into the effects of eWOM, we identify two gaps in the literature that this study aims to address. First, as noted above, the interaction between eWOM volume and valence may not be straightforward. Therefore, we examine the joint effect of the volume and valance of eWOM on firm performance. Second, as observed by Cui et al. (2012), existing research does not examine whether and how the effect of eWOM varies across product categories/sub-products. In the current study, we focus specifically on sub-categories of products that are defined by their degree of quality variation. In the industry under study here, quality variation is determined by an independent regulatory body that has divided the product into sub-categories that are characterized by different amounts of quality variation, and hence different amounts of information asymmetry. This allows us to address two questions: (1) whether and to what extent eWOM reduces information asymmetry. We look specifically at online market offering experience goods, namely online hotel bookings, and we examine whether eWOM removes asymmetry over and above that which is removed by star rating and branding; and (2) whether the joint effect of volume and valence of eWOM is influenced by information asymmetry.

As noted by Park and Lee (2009), one of the most important potential roles of eWOM is the reduction of the information asymmetry common in online markets for experience goods (e.g., hotel and hospitality services). As hotel bookings are generally made in advance and at a distance, problems of asymmetric information may arise due to the inability of customers to ascertain the true quality of the services they are about to purchase (Lewis & Chambers, 1999). Clearly, the hotel industry has taken considerable steps to mitigate asymmetric information by means of branding and the star rating scheme. The former is a form of reputation-based commitment, and the latter assures customers that a given hotel has met the multiple criteria associated with a particular star rating.

Given the important role already played by branding and star-rating in mitigating quality uncertainty, the question arises as to whether, and to what extent eWOM can contribute further to reducing the level of quality uncertainty. This is by no means a trivial question: while eWOM may accurately represent the preferences of consumers, it is potentially exposed to manipulation by sellers motivated to maximize profits at the expense of indulging in unethical behavior (Li & Hitt, 2008). In addition, as online reviewers are not a randomly drawn sample of the user population, eWOM is subject to 'noise' created by unsatisfied and vengeful customers.[2] Whether eWOM has informational content that can reduce information asymmetry in online markets for the hospitality and hotel industry is therefore an important empirical question, the relevance of which carries over to other business domains.

There are two papers directly related to the current study: Yacouel and Fleischer (2012) and Dewally and Ederington (2006). Yacouel and Fleischer (2012) studied the *qualitative* effect of hotels' online review scores on listed room prices and found that on average –and while controlling for a host of relevant covariates – the effect is positive, i.e. better review scores translate into higher prices, ceteris paribus. However, their paper did not study the *volume/valence* effect, which is at the heart of our analysis. Moreover, our paper examines not only the quantitative relationship between review scores and prices, but also explores how this relationship varies with quality uncertainty.

Dewally and Ederington (2006) studied the effect of different strategies to reduce information asymmetry in the online market for collectible items where professional grading of products is an option. They found that the prices of ungraded comics were more sensitive to eBay's feedback statistics, including eBay reputation, than were the prices of graded comics. Although there are some similarities, their paper differs substantially from ours in both scope and methodology. While Dewally and Ederington (2006) examined the differential effect of online reputation on the prices of certified and uncertified items, they did not explore (as we do) the joint effect of volume and valence, nor did they examine how this effect varies across the quality space. From a methodological perspective, several attributes of their data limit the extent to which the effect of eWOM on information asymmetry can be explored: (i) The authors only record whether the comics have a certification or not, while ignoring the actual certified grade (this is probably because only 27.9% of the items are certified). This prevents the quantification of the effect of review scores on prices. (ii) At the time of their study, eBay's reputation system allowed only three scoring options: negative, neutral and positive. This limits the sensitivity of the reputation measure and consequently the capacity to assess the reputation-price relationship. (iii) Unlike the Booking.com reputation mechanism, which assures reviewers' full anonymity and thereby enhances the perceived reliability of the reviews, eBay's feedback tends to be overwhelmingly positive, probably owing to the fact that buyers are reluctant to give sellers a negative rating for fear of retaliation (Resnick & Zeckhauser, 2002). It is for these reasons that we believe our methodology is more suited to the study of the relationship between reputation, quality uncertainty and performance.

The main contribution of this paper to the literature lies in its exploration of the hypothesis that the joint effect on performance of the volume and valence of eWOM is *non-uniform* across the quality space, changing quite substantially with the amount of quality uncertainty. However, testing this hypothesis runs into a natural difficulty, namely that it is hard to find industries in which products can be sub-categorized by levels of quality uncertainty. Fortunately, the hotel industry lends itself to this task; it constitutes an important and almost unique test case for reasons on which we elaborate below.

[2] See also the discussion in Chevalier and Mayzlin (2006) on the sample selection bias that is inherent in an amateur, rather than professional, review process.

The star-rating system is widely recognized as a mechanism to classify hotels into different quality standards. However, we argue that the system also sub-categorizes hotels by levels of quality uncertainty; specifically, the higher the star rating, the lower the level of quality uncertainty within it (i.e., quality uncertainty is lowest in 5-star hotels and highest in 1-star hotels). We base this claim on the fact that the number of criteria considered by rating organizations increases considerably with star rating. For example, according to the 2015–2020 classification criteria of the *Hotelstars* Union,[3] hotels must meet 121, 101, 80, 56, and 45 criteria to be eligible for a 5-star, 4-star, 3-star, 2-star, and 1-star rating, respectively.[4] This implies that 1- and 2-star hotels have much greater leeway in selecting the quality standards that they wish to adopt. We interpret this freedom of choice as one that translates into greater variation in quality standards and hence greater quality uncertainty.

We further argue that branded hotels convey less quality uncertainty than do their unbranded counterparts; a brand name is considered a form of credible commitment to quality service (Ingram, 1996; Schelling, 1960). Within hotels of a given brand, quality standards, service procedures, and inspection protocols are defined so as to align service standards in different hotel locations. Quality uncertainty is therefore expected to be lower in branded hotels than in unbranded hotels.

Our empirical results lend strong support to the view that eWOM has a more pronounced effect in sub-categories with greater quality uncertainty. In addition, they support the hypothesis that the effect of the volume of reviews is *non-uniform* across the quality space. We believe that our results help to shed new light on the non-trivial joint effect of volume and valence on firms' performance. Some of our results carry important policy implications, as presented in Section 5.1.

While our paper concerns the differential impact of eWOM across the quality space, we remain agnostic on the issue of the value of user ratings. De Langhe, Fernbach, and Lichtenstein (2015), among others, have pointed to several factors that might call into question the value of user ratings: (i) The sample of reviewers might not be representative of the user population. (ii) Reviews might be manipulated. (iii) There are cross-cultural and cross-linguistic differences in the approach towards writing reviews. (iv) The small sample size of reviews, which is common in the online marketplace, limits the reliability of the average user rating as a quality estimate. While the above arguments make a convincing case against the reliability and validity of user ratings, we believe that our research design minimizes these problems: (i) Unlike niche goods, where reviewer sample selection bias might be acute, hotel stay is a mainstream consumption good; (ii) Our choice of popular European tourist destinations, which attract guests from around the globe, reduces the risk of cultural bias in assessment (iii) We use Booking.com, which is well-known for its reliable review system (see Section 3); and (iv) As hotels do not have a typical product life cycle curve, they remain in business for relatively long periods. This means that hotels typically have large samples of reviewers, giving their average review scores greater reliability.

Alas, the decision to focus on hotels with relatively large numbers of reviews comes at a cost; with each review being an independent random draw, the law of large numbers implies that the average scores hardly change over time. This reduces the value of longitudinal analysis or other methodologies that exploit the time dimension of the data. It is mainly for this reason that we rely mostly on cross-sectional analysis.

A potential caveat of our study is the use of listed prices rather than realized prices, a cost we were forced to bear for using data drawn from Booking.com.[5] The use of listed prices poses some limitations on the interpretations of our results; this is discussed further in Section 5.2. For the sake of brevity we will use "price" and "listed price" interchangeably.

This paper is organized as follows: Section 2 lays down basic definitions and introduces the main hypotheses; Section 3 gives a detailed description of the data and discusses methodological issues; Section 4 presents the main empirical findings; and Section 5 offers some conclusions and recommendations for future research.

2. Basic concepts and hypotheses

The main hypothesis of this study is that eWOM plays a larger role in mitigating information asymmetry when quality uncertainty is greater. Testing this hypothesis requires the fulfillment of two preconditions. First, the chosen industry must present a coherent way of being sub-categorized by levels of quality uncertainty. Second, there must exist a performance-related measure (e.g. sales, prices, profits) that captures the differential effects of eWOM in different sub-categories. As explained above, the first condition is met if we define sub-categories as hotels with different star ratings. Similarly, unbranded hotels can be considered as being laden with more quality uncertainty than branded hotels. Therefore, a second appropriate classification of sub-categories is branded vs. unbranded hotels.

As for the second pre-condition, this study focuses on the effect of eWOM on the gradient of the price–reputation curve for each star category. Formally, let r stand for the measure of reputation generated by eWOM. For example, r may represent satisfaction level on a scale of 1 to 10.[6] Let $P(r)$ be the price (as listed by the hotel for a standard room) as a function of the reputation score for a group of hotels belonging to the same sub-category. We refer to $P(r)$ as *the price–reputation schedule*. If the reputation score, r, increases by an amount Δr, all else being equal, the resulting change in price (ΔP) is referred to as *the price–reputation gradient*, or simply as the slope of the price–reputation curve; it is denoted by $\frac{\Delta P}{\Delta r}$. Each sub-category would have its own price–reputation schedule, and, therefore, its own price–reputation gradient. If the reputation generated by eWOM has greater informational content in the sub-category i than in the sub-category j, the price–reputation gradient of i would be greater than that of j:

$$\left(\frac{\Delta P}{\Delta r}\right)_i \geq \left(\frac{\Delta P}{\Delta r}\right)_j \tag{1}$$

A price-normalized, continuous version of (1) would read

$$\left(\frac{\partial P}{\partial r}\frac{r}{P}\right)_i \geq \left(\frac{\partial P}{\partial r}\frac{r}{P}\right)_j \tag{2}$$

Note that (2) compares the *elasticity* of prices with respect to review scores in the two sub-categories– a more proper comparison given that 4- and 5-star hotels normally charge substantially higher prices than do their 1- and 2-star counterparts.

To understand how (2) is related to quality uncertainty (or put another way, how price responsiveness to changes in review scores is

[3] The hotel association of Austria, Czech Republic, Germany, Hungary, the Netherlands, Sweden and Switzerland.

[4] From a broader view, the relationship between the rigorousness of industry scrutiny and the perceived reduction of uncertainty is not entirely new to the literature. Numerous examples of such a relationship can be found in various fields such as industrial organization, corporate finance, public health and others. For example, an accounting-based regulation in the Chinese stock exchange (2002) — where only listed companies which achieve a minimum return on equity could apply for permission to issue additional shares through seasoned-equity offerings (SEO) — had a dramatic effect, as documented by Chen and Wang (2007). As such announcements are usually considered "bad news", the regulatory reform helped reduce information asymmetry and eventually reversed the negative response generated by external investors to companies announcing their intention to issue additional shares. As pointed out by Chen and Wang (2007, p. 221): …" The second benefit is that the regulation reduces adverse selection in SEO".

[5] Note, however, that the literature assumes that listed prices are good proxies for actual prices in the hotel industry (Rigall-I-Torrent et al., 2011; Rigall-I-Torrent & Fluvià, 2011).

[6] In our data, reviewers indeed give scores on a scale of 1 to 10. However, r is the average review score, and hence a continuous variable.

related to quality uncertainty), let us consider the case where each review score is subject to noise:

$$r = q + \varepsilon \tag{3}$$

Where q is the true quality (distributed normally with mean $\overline{q}$ and variance ${\sigma_q}^2$), and ε is an independent, identically distributed disturbance with zero mean and variance ${\sigma_\varepsilon}^2$. A standard result in the *signal extraction* literature establishes that[7]

$$E(q \mid r) = sr + (1 - s)\overline{q} \tag{4}$$

Here, $s \equiv \frac{\sigma_q^2}{\sigma_\varepsilon^2 + \sigma_q^2} \in [0, 1]$ is the signal's informativeness. In simple words, observing an average review score r, the conditional expected quality is simply a weighted average of the unconditional mean $\overline{q}$ and the review score r, with the weight attached to the signal (r) being the signal's informativeness, s.

Imagine now that sub-category i has greater variance in quality than does sub-category j, i.e. $({\sigma_q}^2)_i > ({\sigma_q}^2)_j$. Then clearly $s_i > s_j$(recall that the noise variance ${\sigma_\varepsilon}^2$ is assumed constant across all sub-categories) – the signal is more informative in sub-category i. Armed with that, it is plain to see why prices are more responsive to changes in the signal r in sub-category i: letting $P(r) = P(E(q|r))$, then.

$$\frac{\partial P}{\partial r} = a * s \tag{5}$$

where $a = \frac{\partial P}{\partial E(q \mid r)}$.[8] Clearly, as $s_i > s_j$then $\left(\frac{\partial P}{\partial r}\right)_i > \left(\frac{\partial P}{\partial r}\right)_j$.

This leads to the following hypothesis, which encapsulates the main research question of this study.

Hypothesis 1. *Steeper price-reputation schedules occur for unbranded and lower star-rated hotels.*

(i) Ceteris paribus*, hotels with lower star ratings have a steeper price–reputation schedule than do their counterparts with higher star ratings.*

(ii) Holding everything else equal, unbranded hotels have a steeper price–reputation schedule than do branded hotels.

We employ a rich dataset (see below) to test another important hypothesis. To the extent that the quantity of online reviews available for a given item is considered a measure of the reliability of its (online-generated) reputation, we expect to find a nontrivial joint effect between reputation (online average hotel rating) and the number of reviews. We also expect this effect to vary across star categories.

Hypothesis 2. *The mediation effect of valence on the volume-performance nexus and the double-edged sword effect of volume.*

(i) The effect of 'volume' (number of online reviews) on the listed price-reputation schedule will be positive for hotels with high average review scores, and non-positive for hotels with low average review scores.

(ii) The mediated effect of volume on the listed price-reputation schedule will be of greater magnitude in lower star-rated hotels than in higher star-rated hotels.

The main idea embedded in Hypothesis 2 is that the relationship between volume and price-reputation is *non-monotonic*, as it is mediated by valence. Intuitively, since having a greater number of reviews increases their perceived reliability, the direction of the effect on price of a rise in the volume of reviews depends on whether the average review score is relatively high or low. This has very important implications; as we discuss below, it implies that volume may turn into a double-edged sword once coupled with low review scores. Note that the second part of Hypothesis 2 is in the same spirit as Hypothesis 1: the mediated effect of volume on firms' performance is again expected to be more pronounced when quality uncertainty plays a bigger role.

3. Data and methods

The dataset used in this study was extracted from the online travel agency Booking.com. Based on estimated visits, time spent on site, and page views per visit, Booking.com has been proclaimed the "king of online travel, in all possible ways" (CNN, 2013; Skipf Take, 2014). We chose Booking.com as our data source for several reasons: (a) the site boasts a large number of guest-reviewed hotels with a large number of reviews per hotel; (b) information shared on this site is considered trustworthy, as only actual guests are entitled to write reviews[9]; (c) since Booking.com specializes in online hotel reservations, it has an interest in ensuring that the hotel descriptions published on its website match the actual hotel characteristics. (d) Booking.com's reputation mechanism assures reviewers' full anonymity, thereby enhancing the perceived reliability of their online reviews.

3.1. Data

This study focuses on the European hotel market, which is estimated to encompass 570,400 facilities (Eurostat, 2014) and represents half the global market. Two datasets were employed. Dataset 1 was collected in January 2012 with a search being conducted on the price of a standard double room in Paris, London, Barcelona, Vienna, Rome, and Berlin, for a one night stay in July (high season). Paris, London, and Rome were chosen because they had the largest number of hotels on Booking.com at the time this study was conducted. Barcelona, Vienna, and Berlin were randomly chosen from a set of medium-sized European tourist cities. Dataset 2 was collected at the same time as dataset 1 and examined the price for a one night stay in November (low season) for a standard double room in the same six cities. The relatively long interval between the collection of the price data and the requested dates of occupancy (six months for dataset 1 and ten months for dataset 2) was necessary to avoid issues of simultaneity. The long lead time also allowed us to gather data from as many hotels as possible; this is because hotels still had vacancies for the requested dates and so booking prices were more likely to be available than at a later date. To gather the data efficiently, we employed a web crawler.

In general, hotels that did not have a star-rating were eliminated from the dataset. We also excluded hotels that had no reviews – mainly those that were new to the site and labeled as such to customers. If such hotels had been included they might have caused a sample-selection bias. Our final dataset comprised 3222 eligible hotels for the high season (dataset 1) and 3145 eligible hotels for the low season (dataset 2).

The data collected from Booking.com included the number of reviews given to each hotel, the lowest listed price (in Euros) for a standard double room, the star-rating (provided by the hotel and set according to a national standard system), whether the hotel was affiliated to a hotel chain, and the average customer review score. The review score of each hotel is the arithmetic average of the scores given by individual guests after staying at the hotel, where each guest's score is itself an average of distinct item scores on a number of attributes. These distinct scores include ratings of staff performance, services provided at the hotel, cleanliness and comfort, as well as other features. The score for each item ranged from 1 to 10, with 10 denoting the highest standard. In addition, data on several control variables were collected, including the number of rooms in each hotel, whether or not breakfast is included in the price, and whether the listed price includes

[7] Equation (4) is a simple manifestation of the fact that when two variables are jointly normally distributed, the conditional expectation of one is a linear function of the observation of the other. A good reference is Romer, D. Advanced Macroeconomics, Fourth Edition (2012), McGraw Hill (see p. 295).

[8] More formally, $\frac{\partial P}{\partial r} = \frac{\partial P}{\partial E(q/r)} \frac{\partial E(q/r)}{\partial r}$. The assumption that $\frac{\partial P}{\partial E(q \mid r)}$ is constant is related to the fact that changes in prices due to changes in conditional expected quality are utility driven.

[9] As noted on Booking.com, "100% Verified Reviews. Real guests. Real stays. Real opinions."

Table 1
Descriptive statistics [mean (SD), or percentages for dichotomous variables] for the high- and low-season datasets.

Variable	Description	High season (n = 3222)	Low season (n = 3145)
Price	Listed price in € for a standard double room	122.8 (60.2)	126.1 (61.7)
Score	Total average score	7.4 (0.8)	7.5 (0.8)
Rooms	Number of rooms in the hotel	70.1 (85.6)	75.2 (88.7)
Reviews	Number of reviews of the hotel in 00′	2.6 (3.0)	2.5 (2.9)
Chain	= 1 if hotel is chain-affiliated	36%	34%
Breakfast	= 1 if breakfast is included in price	44%	41%
1 Stars	= 1 if 1-star hotel	3%	2%
2 Stars	= 1 if 2-star hotel	23%	23%
3 Stars	= 1 if 3-star hotel	47%	47%
4 Stars	= 1 if 4-star hotel	25%	26%
5 Stars	= 1 if 5-star hotel	2%	2%
Refundable	= 1 if price includes refunding options	76%	74%

a refund policy. Descriptive statistics for the variables are presented in Table 1.

3.2. Methods

A panel data estimator was used, with each of the six cities considered as a panel unit. Because a Hausman test indicated that the differences between the coefficients of the fixed- and random-effect models are systematic, a fixed-effects model with a clustered standard error (where the clusters are the cities) was employed for all regression analyses presented below. Stata 14.1 (StataCorp, 2015) was used for all econometric analyses.

To examine whether the effect of *Score* on the listed price (i.e. the slope of the price-reputation curve) varies across the different star-rating categories (Hypothesis 1.1), interaction terms between *Score* and the different star categories were generated; i.e., *1stars#score, 2stars#score, 3stars#score,* and *4stars#score,* with the omitted category being 5-stars.

There was clear evidence of right-skewness of the price distribution both throughout the sample and within each panel unit - the type 1 skewness measure ranged from 1.5 in Paris to 4.3 in Berlin. Consequently, a log-linear model was employed; i.e., the dependent variable (listed price in Euros for a double standard room) was transformed into its natural logarithm. However, employing a log-linear model poses some challenges when interpreting the effect of dummies and interaction variables on the dependent variable (unlike continuous variables which carry a straightforward interpretation). Therefore, to capture the effect of *Score* across the different star ratings, Stata's *margins* command was employed, which returns the different elasticities of *Score* for different values of the moderating variable (star-rating). Similarly, to capture the effect of the dummy variables, we followed the suggestion of Halvorsen and Palmquist (1980) and Kennedy (1981) to calculate the proportional impact of a binary variable in a semi-logarithmic regression.

Finally, to check the robustness of our findings, we also conducted analyses on four additional datasets: two datasets representing a standard *single* room in the same six cities during both high and low seasons, and two datasets representing a standard *triple* room in the same six cities during both high and low seasons. The results of those analyses were very similar to the ones reported here and therefore they have not been included in this paper.

4. Results

4.1. Hypothesis 1 part (i)

Hypothesis 1 states that the (listed) price-reputation schedule is steeper (a) for lower than for higher star-rated hotels (*Hypothesis 1 part (i)*), and (b) for unbranded than for branded hotels (*Hypothesis 1 part (ii)*). To test *Hypothesis 1 part (i)*, two regressions were estimated for each dataset: a regression with main effects only and a regression with the following interaction variables: *1stars#score, 2stars#score, 3stars#score*, and *4stars#score* (5-stars being the omitted category). Table 2 presents the regression results.

First, we see that the main effects (1a and 1b) and the interaction effects (2a and 2b) models are markedly similar for the high- and low-season datasets. Second, when compared with the omitted 5-star category, the coefficients of the dummy variables (*1-star*, *2-stars*, *3-stars*, and *4-stars*) are negative and highly significant in all specifications, as expected. Moreover, in all specifications, the values of these coefficients increase when moving from 1-star to 4-star hotels, indicating that prices increase with star-rating. Nevertheless, the difference between the coefficients of 1- and 2-star hotels is not statistically significant (5% confidence level), whereas the differences between the coefficients of 2- and 3-star hotels, and between 3- and 4-star hotels, are statistically significant, in all specifications examined (Table 2). Third, as expected, the impact of *Score* as a main effect (models 1a and 1b) is positive and significant; the regression coefficient implies that, on average, a 1-point increase in the average score given to hotels by online reviewers is associated with a listed price increase of 12.8% and 12.4% for a one-night stay in the high and low seasons, respectively. This finding confirms that the 'pooled' price–reputation schedule is upward-sloping.

Note, however, that it is the differential effect of *Score* on prices in the different star categories that is the focus of *Hypothesis 1 part (i)*. This is tested by an analysis of the *stars#score* interaction terms. These results are presented in columns 2a′ and 2b′ of Table 2, for the high- and low-season datasets, respectively. These analyses demonstrate that *Score* has the greatest elasticity in 1-star hotels, followed by 2-, 3-, and 4-star hotels. Nevertheless, the differences between *Score* elasticities of 1-star and 2-star hotels are not statistically significant in either the high (2a′) or low (2b′) season, whereas the differences between *Score* elasticities in 1-star and 3-star hotels are significant in the high season (2a′) and the differences between *Score* elasticities in 2-star and 3-star hotels are significant in the low season (2b′). Finally, in both the high and low season (2a′ and 2b′), the differences between the *Score* elasticities of 3- and 4-star hotels are statistically significant.

The insignificant differences between the impact of *Score* on prices in 1- and 2-star hotels, along with the finding that the main effects for 1- and 2-star hotels are not significantly different, warrant the merging of these two lowest star categories into a unified category: *1&2stars*.[10] Due to similarities in the coefficients of the high- and low-season datasets, the kernel density function of the dependent variable (price) was compared for the two datasets and was found to be similar (see Appendix A). Hence, the two datasets were merged into one in our subsequent analyses. However, as a precaution, a dummy variable, indicating whether an observation refers to the high season, was added to all subsequent regression analyses; it was found to be highly insignificant in all cases. A regression that includes the interaction terms (similar to 2a and 2b in Table 2) was re-run for the merged dataset, employing the unified *1&2stars* category. Due to space limitations, Table 3 reports only the results of the *stars#scores* interaction coefficients and the calculated elasticities.

The coefficients of *1&2stars*#score and *3stars*#score are statistically significant and are significantly different from each other. In terms of elasticities, all three interactions are statistically significant and

[10] In their research on European hotels, Abrate, Fraquelli, and Viglia's (2012) have also bundled together one and two stars.

Table 2
Fixed-effects regressions, dependent variable: ln(Price), clustered standard errors.

	High season (1a)	Low season (1b)	High season		Low season	
			(2a)	(2a′)	(2b)	(2b′)
	Main effects[a]	Main effects[a]	Interactions[a]	Elasticities[b,c]	Interactions[a]	Elasticities[b,c]
Score	0.128*** (0.007)	0.124*** (0.014)	0.010 (0.053)		0.048 (1.42)	
1stars#score			0.156** (0.058)	1.636*** (0.509)	0.140* (0.051)	2.012*** (0.273)
2stars#score			0.125* (0.050)	1.497*** (0.161)	0.078* (0.025)	1.409*** (0.305)
3stars#score			0.116* (0.055)	1.165*** (0.128)	0.074 (0.012)	1.055*** (0.120)
4stars#score			0.085 (0.064)	0.714*** (0.181)	0.050 (0.022)	0.598*** (0.143)
1-stars	− 1.067*** (0.127)	− 1.215*** (0.078)	− 2.280*** (0.463)		− 2.205*** (0.423)	
2-stars	− 1.040*** (0.111)	− 1.121*** (0.093)	− 2.046*** (0.455)		− 1.764*** (0.234)	
3-stars	− 0.800*** (0.081)	− 0.857*** (0.072)	− 1.761** (0.507)		− 1.468** (0.155)	
4-stars	− 0.481*** (0.088)	− 0.547*** (0.079)	− 1.249* (0.582)		− 0.969* (0.240)	
Refundable	0.117** (0.035)	0.094** (0.032)	0.118** (0.034)		0.097** (0.031)	
ln(Rooms)	− 0.008 (0.029)	0.009 (0.029)	− 0.009 (0.029)		0.009 (0.029)	
Chain	0.016 (0.039)	− 0.009 (0.012)	0.012 (0.037)		− 0.011 (0.012)	
Breakfast	0.089* (0.041)	0.087 (0.045)	0.089* (0.041)		0.087 (0.012)	
Reviews	− 0.011*** (0.002)	− 0.012*** (0.001)	− 0.035 (0.002)		− 0.031 (0.001)	
Cons	4.454*** (0.163)	4.532*** (0.118)	5.436*** (0.541)		5.075*** (0.153)	
Adjusted R^2	0.472	0.480	0.473		0.481	
N	3222	3145	3222		3145	

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
[a] Clustered standard errors in parentheses.
[b] Delta-method Std. errors are in parentheses.
[c] Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

Table 3
Fixed effects regressions, dependent variable: ln(Price).

Variable	Coefficients[a]	Elasticities[b,c]
Score	0.029 (0.72)	
1&2stars#score	0.110** (2.99)	1.495*** (0.164)
3stars$#score	0.094* (2.03)	1.103*** (0.112)
4stars#score	0.067 (1.31)	0.647*** (0.158)
Cons	5.296*** (11.79)	
Adjusted R^2	0.473	
N	6367	

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
[a] *Clustered standard errors in* parentheses.
[b] *Delta-method Std. err are in* parentheses.
[c] Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

significantly different from each other, implying that the effect of *Score* on the listed price is more pronounced in the lowest than in the highest star category. This finding lends support to *Hypothesis 1 part (i)*, namely, that *lower star-rated hotels have a steeper price–reputation schedule than do higher star-rated hotels.* Fig. 1 shows the different *Score* elasticities across different star categories based on the results shown in Table 3.

The higher price-reputation premium found in lower star-rated hotels may reflect customers' greater delight in the realized quality (as reflected in *Score*) compared to what was expected on the basis of the star rating. Put another way, customers may reward low star-rated hotels whose quality exceeds expectations more generously than would be normal, and punish high star-rated hotels more severely where quality standards fail to meet expectations. The same logic applies to the differences between branded and unbranded hotels (see Section 4.2).

To capture these effects – the delight and negative disconfirmation effects, respectively - we measure the effect (on listed price) of high *Scores* in *lower starred hotels* vs. the effect of low *Scores* in *higher starred hotels.* To this end, we divided the *Score* variable into quartiles and calculated the elasticities for the intersection of the highest *Score* quartile with *lower starred hotels* and the lowest *Score* quartile with the *higher starred hotels.* Fig. 2 illustrates these results.

As Fig. 2 demonstrates, the elasticity of the highest *Score* quartile (dashed line) is highest for 1- and 2-star hotels, while the impact in 5-star hotels is not significantly different from zero. This represents the delight effect. Interestingly for the lowest *Score* quartile (solid line), while the effect is minor in 1- and 2-star hotels, it is negative (though not significant) in 5-star hotels. The solid line in Fig. 2 serves therefore to demonstrate the disconfirmation effect.[11]

Note that since we only have access to listed, rather than actual prices, our finding that higher price-reputation premiums are found in lower star-rated hotels may carry a different explanation. Since strategic pricing practices, aimed at ensuring that hotel prices match guests' willingness to pay (Cetin, Demirçiftçi, & Bilgihan, 2016), are not as prominent in unbranded hotels as they are in branded ones (Carlbäck, 2016; Ruetz & Marvel, 2011; Ivanova & Ivanov, 2015 and Altin, Schwartz, & Uysal, 2017), our results might reflect greater responsiveness of hotel managers in lower rated and unbranded hotels to eWOM (see Section 5.2 for detailed discussion and further interpretations). As 20% of our sample's 1- and 2-star hotels are branded as well as 42% of our 3-star hotels, in an attempt to add validity to our interpretation of the results, we conducted an additional regression analysis, identical to the regression in Table 3, which included branded hotels only. The results (provided in Appendix B) reveal the same phenomenon; the effect of *Score* on the listed price is more pronounced in the lowest than in the highest star category. Nevertheless, as discussed in Section 5.2, we cannot rule out other interpretations based on the fact that managers in different star categories may adopt different approaches to strategic pricing.

4.2. *Hypothesis 1 part (ii)*

To test the second part of Hypothesis 1, namely that unbranded

[11] We are indebted to an anonymous reviewer for pointing this out to us.

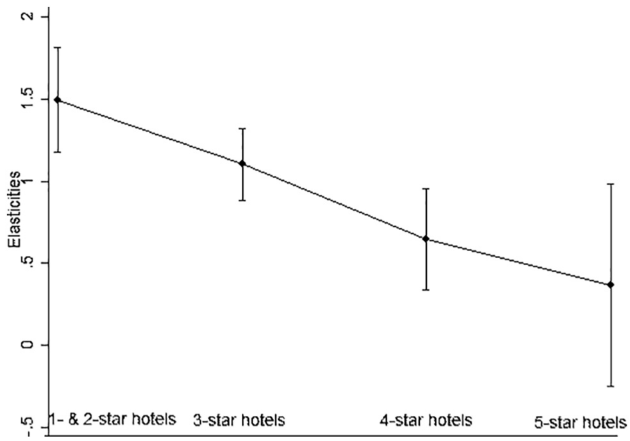

Fig. 1. *Score* elasticity[1] as a function of star category (showing 95% confidence intervals). [1]Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

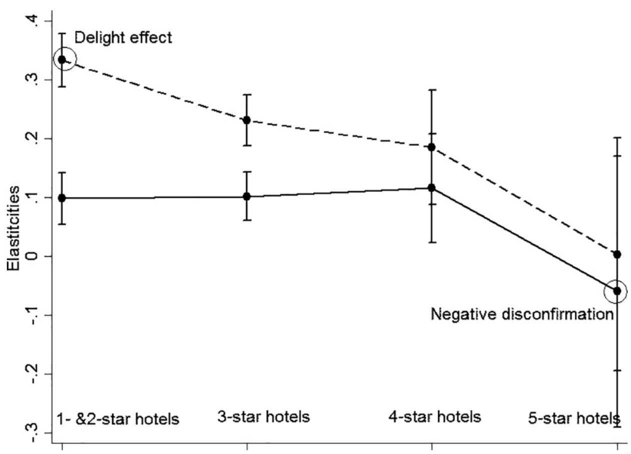

Fig. 2. Elasticities[1] of lowest vs. highest *Score* quartile as a function of star category (showing 95% confidence intervals). The solid line represents the elasticities of the lowest Score quartile, the dashed line represents the elasticities of the highest Score quartile. [1]Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

hotels have steeper price–reputation schedules than do branded hotels, an interaction term was created between the variables *Chain* and *Score* (Table 4). Since 82% of the 1- and 2-star hotels examined in our data are not branded, in order to avoid collinearity bias, 1- and 2-star hotels were omitted from the regression reported in Table 4.

As expected, the coefficient of *Chain* is positive and significant. Applying the calculation of Halvorsen and Palmquist (1980) and of Kennedy (1981) of the proportional impact of a binary variable in a semi-logarithmic regression, the coefficient of *Chain* implies that being a branded hotel is associated with a 5% average listed price increase, compared with being an unbranded hotel (all else being equal). While this finding is not surprising and was demonstrated in previous studies of the hotel industry (e.g., Yacouel & Fleischer, 2012), the interaction term is negative and significant. This finding implies that, on average, a one-point increase in the *Score* of unbranded hotels has a stronger effect on the listed price than a one-point increase in the *Score* of branded hotels, all else being equal. Thus, the reputation premium for branded hotels appears to be smaller than that for non-branded hotels, supporting *Hypothesis 1 part (ii)*.

A higher level of interaction – *stars#chain#score* – was introduced to compare the impact of *Score* for the different star categories (3-, 4-, and 5-star hotels) in branded vs. unbranded hotels. Due to space limitations, Table 5 presents only the *Score* elasticities for the different star categories with and without chain affiliation.

Table 4
Fixed-effects regression. Dependent variable: ln(Price).

Variable	Coefficient[a]	Clustered standard errors
Chain	0.405***	− 0.108
Chain#score	− 0.053***	− 0.014
Breakfast	0.078***	− 0.009
3 stars	− 1.545***	− 0.351
4 stars	− 1.132***	− 0.356
Score	0.066	− 0.043
3stars#score	0.084**	− 0.042
4stars#score	0.072*	− 0.041
ln(Rooms)	0.011*	− 0.006
Refundable	0.122***	− 0.009
Reviews	− 0.007***	− 0.002
Cons	4.944***	− 0.355
Adjusted R^2	0.555	
N	4758	

[a] *Clustered standard errors* in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
Score elasticities[a] by star category for branded vs. unbranded hotels.**

	Branded hotels elasticity	Non-branded hotels elasticity
3 stars	0.653*** (0.114)	1.160*** (0.066)
4 stars	0.739*** (0.135)	0.945*** (0.136)
5 stars	0.559* (0.327)	− 0.207 (0.557)

Delta-method Std. errors are in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
[a] Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

It appears that in non-branded hotels, the impact of *Score* on prices in 3- and 4-star hotels is significantly stronger than in 5-star hotels, with the highest impact being found in non-branded 3-star hotels. *Score* elasticities are significantly smaller for 3- and 4-star hotels in branded than in non-branded hotels; however, within branded hotels, the differences in *Score* elasticities between 3-, 4-, and 5-star hotels are not statistically significant. Thus, not only does *Score* have a stronger effect in non-branded hotels than in branded hotels, but this effect also varies across star categories, with the greatest effect on the listed price being seen in the lowest non-branded star category (in this case, 3 stars, which carries here the highest level of quality uncertainty). This result confirms *Hypothesis 1 part (ii)*.

4.3. Hypothesis 2

The results in Tables 2 and 4 reveal that the main effect of the variable *Reviews* (denoting the number of reviews) is negative and highly significant. This counterintuitive result cannot be easily reconciled with the results of previous similar studies and calls for deeper analysis. We believe that the relationship between *volume* and *price* is complex in nature, possibly owing to the intervention of moderators and/or mediators. Thus, we have hypothesized (*Hypothesis 2, part (i)*) that the effect of the number of reviews on prices is mediated by *Score*. Accordingly, a model that accounts for the interaction between *Score* (valence) and the number of *Reviews* (volume) is employed.[12] Part (*ii*) of

[12] Note that the potential collinearity concern is dismissed here since the correlation between *Score* and *Reviews* in the data is zero for all star categories, except 4-star hotels, for which this correlation is extremely low ($r = 0.06$).

Table 6
Reviews elasticities[a] by star category and *Score* quartile.

	(1)	(2)	(3)	(4)
	stars 1,2	stars 3	stars 4	stars 5
1st quartile	− 0.082** (0.020)	− 0.015 (0.011)	− 0.040*** (0.007)	− 0.048 (0.073)
2nd quartile	− 0.054** (0.021(	− 0.014 (0.021)	− 0.046** (0.018)	− 0.040** (0.061)
3rd quartile	− 0.019 (0.017)	0.016 (0.015)	− 0.013 (0.011)	− 0.202 (0.159)
4th quartile	0.034* (0.018)	0.034*** (0.011)	0.010 (0.027)	− 0.067 (0.076)

Delta-method Std. err are in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
[a] Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

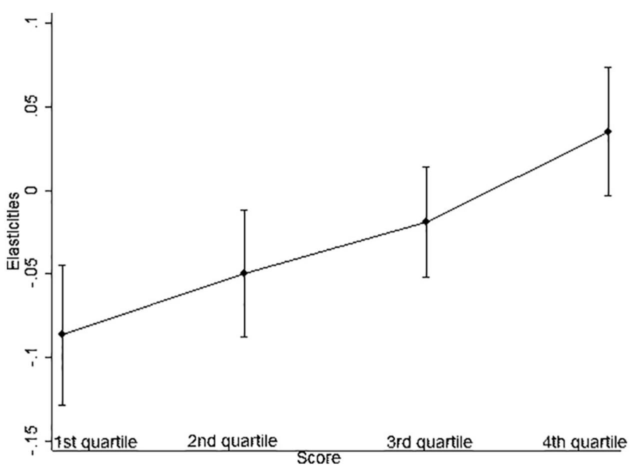

Fig. 3. *Volume* elasticities[1] in 1&2-star hotel category as a function of *Score* quartile, (showing 95% confidence intervals)
[1]Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

Hypothesis 2 maintains also that the effect of *volume* on price in lower star-rated hotels is stronger than in higher star-rated hotels; this requires a third-degree interaction term. Since both *Reviews* and *Score* are continuous variables, interpreting their interaction effects would be challenging. Hence, we divided the *Score* variable into quartiles for each star category (1- and 2-star hotels are combined). Accordingly, four separate regressions were analyzed, one for each of the star categories: 1&2 stars, 3 stars, 4 stars, and 5 stars. In each regression, three interaction terms were included: *quartile2#reviews, quartile3#reviews,* and *quartile4#reviews,* where *quartile2, quartile3,* and *quartile4* indicate whether the *Score* of the hotel lies in the 2nd, 3rd or 4th quartile, respectively. Due to space limitations, Table 6 presents, for each *Score* quartile, only the calculated elasticities of the variable *Reviews* in each star category.

Reviews elasticity is negative for all hotels in all star categories in which the *Score* lies in the first and second quartiles, and it becomes positive and significant only for 1&2 and 3-star hotels at the highest (4th) *Score* quartile. Thus, when *Score* lies in the lowest two quartiles,

Table 7
Nonparametric resampled residual bootstrap of mediation[a] with 1000 replications to test whether *Score* mediates the effect of *Reviews* on listed price.

	Coef.	Bias	Bootstrap Std. Err	[95% conf. interval]		
ind(eff)	0.115	− 0.001	0.053	0.014	0.220	(P)
				− 0.110	0.070	(BC)
dir(eff)	− 1.160	0.006	0.228	− 1.583	− 0.685	(P)
				− 1.889	− 1.360	(BC)
tot(eff)	− 1.045	0.005	0.236	− 1.482	− 0.543	(P)
				− 1.821	− 1.247	(BC)

(P) percentile confidence interval. (BC) bias-corrected confidence interval.
[a] Stata command "resboot_mediation" was employed.

Table 8
Fixed-effects (within) regression. Dependent variable: ln(Price).*

ln(Price)	Coefficients	Robust standard errors
Dummy_2012	0.252***	0.041
Dummy_2017	0.091	0.061
Reviews	− 0.084***	0.022
ln(Rooms)	0.182	0.372
Refundable	0.0891**	0.033
Breakfast	0.092	0.059
3stars	1.099	0.495
4&5stars	1.789	0.601
Score	0.303***	0.066
3stars#score	− 0.131**	0.067
4&5stars#score	− 0.218**	0.073
Cons.	2.248**	1.400
Number of observations = 420		
R^2: within = 0.31, between = 0.61, overall = 0.52		

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

the number of reviews seems to have a negative effect on listed price. This effect is greatest for the lowest star category (1&2-stars). As the *Score* rises in the 1&2-star category, the negative effect of volume of reviews on price decreases, and the effect turns positive only for the highest scored hotels, such that *Score* and *Reviews* synergize each other. Fig. 3 demonstrates the *volume* elasticities in the 1&2-star category for different levels of *Score*, representing the results shown in column 1 of Table 6. In 4- and 5-star hotels, it appears that the number of reviews has a significant effect only when the *Score* is relatively low. This effect is negative, but still of smaller magnitude than is the case in 1&2-star hotels. These results support Hypothesis 2 and add additional insights into the moderating effect of *Score* (valence) on the effect of *Reviews* (volume) across different star categories.

Finally, we conducted a nonparametric re-sampled residual bootstrap test of mediation with 1000 replications to test whether *Score* mediates the effect of *Reviews* (volume) on the listed price. The results are highly significant indicating an indirect effect of approximately 12%. The results of the test are reported in Table 7.

4.4. Further empirical analyses

In this section we report the results of additional tests that exploit the time dimension of our data. We conducted both a panel data fixed-effects analysis and a "difference-in-differences" regression. To this end,

Table 9
Score elasticities by star category.

Score	Elasticities[a]	Delta-method Std. err
1&2 stars	2.239***	0.488
3 Stars	1.271***	0.346
4&5 Stars	0.626*	0.354

* $p < 0.10$.
*** $p < 0.01$.
[a] Note that the elasticities reported are not price elasticities per-se, rather they refer to the listed price.

Table 10
"Difference-in-differences" estimation results.[a,*,**,***]

Before	After			
Control: 119	119	238		
Treated: 108	108	216		
	227	227		
Outcome var.	Outcome	Std. Err	|t|	P > |t|
Before				
Control	− 0.163			
Treated	− 0.17			
Diff (T-C)	− 0.007	0.024	− 0.3	0.763
After				
Control	− 0.065			
Treated	0.067			
Diff (T-C)	0.131	0.024	5.56	0.000***
Diff-in-Diff	0.139	0.033	4.19	0.000***
$R^2 = 0.24$				

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.
[a] Means and Standard Errors are estimated by linear regression.

we employed two additional datasets collected from Booking.com in 2008 and 2017 for Paris. Paris was chosen as it is the city with the largest number of hotels featured on Booking.com. In addition, it contains the largest number of hotels which appeared in all three periods and includes the largest number of hotels that have not undergone structural changes (such as adding room capacity or becoming affiliated with a chain). This last point is important to ensure that the "difference-in-differences" method can be properly applied. We integrated the three data sources, resulting in the generation of panel data with three points in time (2008, 2012 and 2017) for each hotel in the sample.

We first conducted a panel data fixed-effects regression. The results, as can be seen in Table 8, are essentially the same as in the cross-sectional analysis discussed earlier (see Table 2).

Table 9 reports the different *Score* elasticities across different star categories using the same regression analysis as that shown in Table 8.

The results show that the effect of *Score* on the listed price is most pronounced in the lowest star category and least pronounced in the highest star category.

Second, we conducted a "difference-in-differences" analysis, with our "treatment group" being hotels with improved review scores between 2008 and 2012 and our "control group" being hotels with identical or poorer review scores. The "effect" of the treatment is assessed by computing the change in a hotel's price expressed as a percentage. We also included a number of control variables such as star rating, chain affiliation and whether or not breakfast is included. Our purpose in this analysis is twofold: first, we examine whether the treatment effect is significant and positive; second, we look at whether and how this effect varies across low star-rated and high star-rated hotels. The overall main effect is positive and significant indicating a treatment effect, as demonstrated in Table 10. The calculated elasticity of the *Diff-in-Diff* variable is 0.15 and highly significant ($P < 0.0001$).

Running the "difference-in-differences" regression on low-starred hotels only yields an elasticity of 0.17 ($P < 0.0001$), which is significantly higher than the overall elasticity calculated for all star categories. In the case of higher-starred hotels, the treatment's coefficient and elasticity are insignificant. These results lend support to our finding that an improved online rating has a positive and significant effect on hotels, at least in terms of the listed prices, and that this effect is more significant in lower-starred hotels than in their higher-starred counterparts.

5. Discussion

The main purpose of this study was to test empirically whether eWOM plays a significant role in alleviating information asymmetry in online hotel booking, beyond the reduction occasioned by branding and the star-rating system. Following the comments of Cui et al. (2012) that there is a lack of evidence as to whether the effect of eWOM varies across product categories, this study adds an important dimension to the literature by making a distinction between product sub-categories based on the level of quality uncertainty. The results provide firm evidence of the power of eWOM to reduce information asymmetry differentially as a function of uncertainty: the elasticities of online-generated reputation score on listed price were found to be significantly larger in low star-rated hotels and in unbranded hotels, where uncertainty with respect to quality is likely to be a more significant issue.

With respect to the volume of eWOM, our results reaffirm the view that a proper understanding of the effect of volume on performance must take account of key moderating/mediating variables. The joint effect of volume and valence was demonstrated and was shown to vary across star categories. Moreover, the finding that the effect of volume changes sign when moving from low to high review scores lends further support to the view that the reliability of online customers reviews goes hand in hand with the volume of reviews.

A previous study by Vermeulen and Seegers (2009) indicated that the volume of a hotel's eWOM is positively correlated with the probability that potential guests will book this hotel. The results of the current study reveal a more complex picture: all things held constant, when the hotel's *Score* lies within the three lowest (star category-adjusted) quartiles, volume has a negative effect on listed price. This effect was observed in all star categories, but it is strongest for the lowest star categories. Conversely, when *Score* lies at the highest quartile (again, star category-adjusted), volume has a positive effect on listed price, and this effect is stronger for the lowest star categories. These findings suggest that when quality variation is substantial (as in the case of 1-, 2-, and even 3-star hotels), a large number of reviews combined with low/medium scores potentially carry the largest negative effect on the price-reputation schedule, and vice versa. The explanation for this is straightforward: in low star categories, in which quality uncertainty is high, a larger number of reviews carries greater informational content and grants higher credibility to the given score. In other words, *volume* can turn into a double-edged sword; if high volume is paired with low/medium valence, then the elasticity of listed price with respect to volume is negative and is the highest in absolute terms. Conversely, when high volume is paired with *high* valence, the elasticity, although positive, is smaller in absolute terms than in the case of low/medium valance. The findings also suggest that, in general: (i) the listed price elasticities with respect to *Score* are bigger than those with respect to *volume*, a result which is supported by Filieri (2015) who examined the effect of online consumer reviews on consumers' stated purchase intentions; and (ii) the effect of eWOM is weaker in the presence of brands – a finding that is in line with the results of Ho-Dac et al. (2013).

5.1. Managerial implications

With the constant expansion of online commerce and the problem of opaque quality standards faced by many industries, the findings of this study may well apply to online businesses far beyond the hotel sector. The effect of eWOM on the survival prospects and profitability of businesses makes it a crucial feature of the modern business environment. This is particularly so for small, new businesses which often lack the reputational advantages that go with a brand. However, reliance on eWOM in such cases, exposes the business to the risk of reputation cascades, with the possibility that the opinions formed by the first few customers could mean life or death to the business.

Furthermore, as many online commerce websites report only *average* review scores, and with the *law of large numbers* implying that pronounced variations in average scores are possible only when the number of independent draws is relatively small,[13] young businesses (with a small number of customer reviews) have only a limited time to achieve a good 'first impression'. Thus, such businesses should pay careful attention to how their online reputation evolves, before it becomes relatively fixed. Such a "no second chance to make a first impression" effect – a mere product of the use of average scores and the law of large numbers – could again mean life or death to young businesses.

You et al. (2015) concluded that managers need to take account of product- and industry-specific factors in understanding the impact of eWOM volume and valence. In line with that view, and bearing in mind the competitive environment of the hotel industry and the fact that a hotel stay is an experience-good, our results demonstrate the critical importance of eWOM for the performance of non-branded 1- and 2-star hotels. More precisely, the worst situation for such hotels is a low/medium *Score* paired with a high *volume* of reviews; therefore, managers of such hotels should employ eWOM as a key tool in their overall marketing and promotional strategy. Sites such as Booking.com, in which hotels have very little control over user-generated content and have negligible, if any, ability to manipulate that content, pose a greater challenge to these managers. In such cases, efforts could be made to (i) identify satisfied hotel guests and proactively induce them to post a review online and (ii) identify guests who are likely to post a review and ensure that they receive the best possible service (the identification of such customers has received some attention in the literature, e.g. Bronner & de Hoog, 2011). Finally, affiliation with a chain can alleviate the crucial dependence of 1- and 2-star hotels on eWOM. In contrast to hotels in a low-star rated category, the impact of eWOM on branded 4- and 5-star hotels (which are business entities with solid and well-established reputations) appears to be much smaller.

5.2. Limitations and suggestions for future research

A possible limitation on the interpretation of our results is the fact that we used listed prices rather than actual prices as our dependent variable. For obvious reasons, hotels which operate in a highly competitive environment are disinclined to voluntarily disclose information on realized prices. This is why other studies have also employed listed prices in studying the effects of eWOM.[14] Indeed, listed room prices may eventually differ from realized prices. However, these differences in listed prices in the cross section of sellers, reflect variation in a host of possible factors, including the favorability of online customer reviews; hotels armed with better review scores are in more favorable position to list higher prices than those listed by rival hotels. For this reason, we believe that listed prices are a good proxy for realized prices.

That said, the reliance on listed prices, along with differences in yield management practices (which are discussed in Section 4.1) open the door for other interpretations of our results.[15] Such interpretations include the possibility that ill-informed managers (in terms of market intelligence) in lower rated/non branded hotels are more responsive to online consumer ratings. Another possibility is that managers of lower rated, unbranded hotels depend more heavily on leisure guests than on corporate contracts and are therefore driven to make larger adjustments to their listed prices. Thus, future research should focus on actual prices, as much as possible, along with other performance measures.

Second, this study focused on the hotel industry in Continental Europe. Our results indicate that average review scores do not change significantly over time, specifically after a certain threshold of reviews is reached. The results, however, may not be representative of other areas and may be specific to the case of Europe; similar studies in other regions of the world would therefore be worthwhile.

Third, this study accounts for the effect of *Score,* which is a single-key metric. However, many sites (including Booking.com) provide an option to give textual feedback; this carries more information than a single metric and could be usefully incorporated in future studies. Fourth, data were collected from only one online travel agency, which is known for its source credibility. Future studies should gather data from other agencies (e.g., TripAdvisor) and explore the effect of the characteristics of each platform on the results.

A fifth issue arises from the finding that the effect of eWOM is less significant in the presence of brand names. This study addresses the effect of brand affiliation on a dichotomous level: branded vs. unbranded hotels. In line with the findings of Ho-Dac et al. (2013), an important extension would be to further distinguish between branded hotels according to the brand equity, and analyze the effect of eWOM across both star-rating and brand strength. The hotel industry enables such an analysis, as many brands have hotels at several star categories. Sixth, a significant question is whether and how the *variation* in *Score* changes across star categories and, in particular, how it interacts with eWOM to relieve information asymmetry across different star categories. In that regard, it would be relevant to study whether the different levels of information asymmetry embedded in each star category are reflected in the number of page views by potential guests when evaluating hotels. It is reasonable to assume that, for low star-rated hotels, potential guests will view more pages and, thus, will be exposed to a greater variation in eWOM *Score.* Hence the *Score* variation is expected to exert more influence in low star categories.

Finally, many online forums (including Booking.com) allow users to indicate the perceived helpfulness of online reviews. Future studies should incorporate this aspect and examine its effect on the overall impact of eWOM across different star categories.

[13] In order to demonstrate this point, we extracted a sub-sample of 330 hotels in Paris for which we have average review scores for two points in time, 2008 and 2012. From this sub-sample we omitted hotels that did not have at least 100 review scores in 2008 (the earlier period), leaving us with 109 hotels. We conducted a simple statistical test in order to test the hypothesis that the average score (once above a threshold number of reviews) changes only slightly. The results confirm this view. In fact, our results confirm that the entire distribution remained almost the same with the mean score changing from 7.17 to 7.20, and the standard deviation changing from 0.06 to 0.07 between 2008 and 2012. A simple *t*-test did not support the rejection of the null that the means of the *Score* variable are equal. For the full results of this analysis, please contact the authors.

[14] E.g., Yacouel & Fleischer, 2012; Koçaş & Akkan, 2016; Öğüt & Onur Taş, 2012 and Rigall-I-Torrent et al., 2011.

[15] We are indebted to an anonymous reviewer for pointing that out to us.

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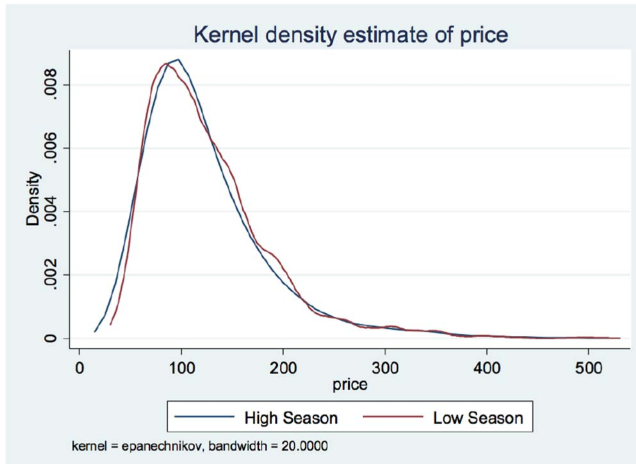
Appendix A. Kernel density of the variable *Price* in the high- and low-season datasets



Appendix B. Fixed-effects (within) regression including branded hotel only. Dependent variable: ln(Price)

ln(Price)	Coef.	Robust Std. Err
Reviews	− 0.012**	0.003
ln(Rooms)	0.001	0.016
Breakfast	0.102*	0.048
3 stars	0.672*	0.322
4 stars	0.804*	0.441
5 stars	1.559**	0.620
1&2stars#score	0.138**	0.035
3stars#score	0.077*	0.043
4stars#score	0.099**	0.036
5stars#score	0.069	0.045
Refundable	0.131**	0.042
Constant	3.262***	0.290
Number of observations = 2206		
R^2 within = 0.415		

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

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