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Online Review Helpfulness and Firms' Financial Performance: An Empirical Study in a Service Industry

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ABSTRACT

This study aims to bridge a significant research gap in the electronic word-of-mouth (eWOM) literature: measuring the effect of the degree of online review helpfulness (ORH) on firms' financial performance. As studies of the impact of ORH on firm performance in the context of service industries in general and more specifically in the hospitality sector are virtually nonexistent, this work intends to offer insights to eWOM researchers by analyzing if and to what extent ORH affects the financial performance of hospitality firms. Based on a re-visitation of the antecedents of ORH stemming from information adoption models, social influence theory and dual process theory, we analyze the moderating effects of the degree of ORH on the relationships between online review valence/volume and firms' financial performance. Based on the examination of 395,964 online reviews related to 261 higher-end hotels located in London, the third most visited destination worldwide, we find that the degree of ORH positively moderates the positive effect of the reviews' valence on financial performance, while it does not moderate significantly the positive effect of the reviews' volume on financial performance. Theoretical contributions to the nascent research stream taking an *outcome-oriented approach* to the study of eWOM helpfulness and managerial implications are discussed.

An increasing number of market intelligence companies have recently highlighted that the online search for durable and higher-priced categories, such as consumer electronics and travel and accommodation services, is gaining momentum among consumers [106]. Online reviews (ORs) have drastically modified the way that consumers gather information before their purchases and bookings [21, 84]. This is particularly relevant in the service industries and particularly in the hotel sector, where ORs are used by travelers to reduce the risks associated with accommodation choice [57].

Travelers trust online reviewers [12] and engage with other like-minded consumers to share their opinions and evaluations of products, services, and experiences in online travel communities [140, 142]. They gather ORs before their trips, to plan for their journeys [90], and ultimately to book and purchase travel and hospitality services [16, 105], also based on ORs.

Meanwhile, online travel review websites such as Tripadvisor.com and online travel agencies (OTAs) such as Booking.com and Expedia.com have literally inundated the Internet with online travel reviews, establishing themselves as the de facto travel

intermediaries and information brokers of the digital era in the focal industry. The multiplication of ORs has been found to generate information overload for consumers [110], who are increasingly facing the issue to understand which piece of information is helpful for them to better understand the quality of the services they can find online. To address this issue, sites such as TripAdvisor.com, Booking.com, and Expedia.com have developed mechanisms allowing customers to mark, vote, or like the helpfulness of the review, to signal to other consumers which ORs are most valuable in assessing travel services' quality and performance.

Several studies in marketing (e.g., [1, 11, 126]) and information systems and management (e.g., [52, 66, 67, 85, 104, 129]) have examined what makes an OR helpful. Also, the hospitality services literature has analyzed the drivers of online review helpfulness (ORH) (e.g., [39, 43]). However, there is a visible research gap, as extant studies have not yet analyzed the impact of ORH on company's financial performance. For instance, Baek et al. [11] point out that the relationship between ORH and product sales—and ultimately firms' performance—needs to be addressed in future studies. In the Future Research section of their study, Raguseo and Vitari [121, p. 265] emphasize that "further studies could evaluate the impact of this feature [online review helpfulness] on the financial performance that is achieved by hotels." The urgency of these calls for research on the commercial and financial effects of ORH in the hospitality sector is critical, as hotel customers increasingly use helpful ORs to make purchasing decisions [54], with some groups of consumers using them as a selective processing mechanism [55]. Moreover, while a few scholars have analyzed the direct effects of OR valence and volume on firm performance (e.g., [28, 95, 101, 103, 133, 151]), to the best of our knowledge no study has yet examined if and to what extent ORH interacts with other OR features such as OR valence and volume in affecting (hotel) financial performance, except for two studies conducted on the movie sector [86, 134] and examining products rather than services.

This study bridges the two aforementioned interrelated research gaps by addressing the following research question:

Research Question: To what extent does online review helpfulness influence firms' financial performance in the service industries and more specifically the hospitality industry?

To answer this question and to contribute to a better understanding of how electronic word-of-mouth (eWOM) helpfulness influences firms' performance, we conducted a longitudinal study on a large sample of higher-end hotels ($N = 261$) located in London over the period February 2015 to December 2016, for which 395,964 ORs were sourced from Booking.com and matched with financial performance data sourced from STRGlobal (STR), a leading research company in the provision of financial data in the hospitality industry. From a methodological point of view, we used hierarchical multivariate panel regression analyses to assess the effects of the information characteristics associated to eWOM (helpfulness as well as valence and volume) on the financial performance of hotel firms.

In addressing the overarching research question, this study makes several contributions to extant literature. First, from a conceptual point of view, it contributes to the eWOM body of literature by shifting the attention from the antecedents to the *outcomes—namely, financial performance—of helpful ORs.* As such it adopts an *outcome approach* to the study of ORH. Second, as studies of ORH outcomes in the context of service industries in

general and more specifically the hospitality sector are virtually non-existent, this study intends to offer insights to eWOM researchers by analyzing if and to what extent the degree of ORH moderates the relationships between eWOM valence/volume and financial performance of hospitality firms. By reflecting on the drivers and features of online consumer behavior through the theoretical lenses of information adoption models [116, 117], social influence theory [22, 23, 30], and dual process theory [36], we argue that exposure to others' helpful positive ORs can influence consumer behavior (both online and off-line) in different ways and ultimately consumers' purchasing decisions and firms' revenues. Third, in focusing on the moderating effects of ORH on the relationships between eWOM valence/volume and firms' financial performance, this study provides managerial insights that can assist digital marketers and OR platform managers operating in service industries.

The rest of the paper unfolds as follows. The next section reviews relevant literature on eWOM, with a focus on those studies investigating the relationship between eWOM and firm performance. This section also develops the three major hypotheses of the study. The following section describes the methodology deployed. The Findings and the Discussion sections respectively illustrate and discuss the research findings. The subsequent section elucidates the theoretical and managerial contribution and implications of the study, and the final section identifies the limitations and avenues for future research.

Literature Review and Hypotheses Development

The Value and Relevance of eWOM for Hospitality Firms

The rise and development of the Internet, social media, and multisided digital platforms have brought about a proliferation of user-generated content in the form of posts on social media and ORs. The latter ones enable potential, actual, or former consumers to articulate and share their opinions and perceptions about products, services, experiences, brands, and companies on the Internet [62]. In the marketing literature, they are part of eWOM [62], later termed *online word-of-mouth* [79], and more recently *digital word-of-mouth* [96], to include different types of WOM generated on the Internet [61].

Regardless of the changes in the actual naming of the phenomenon, an increasing number of marketing, information management, and computer science scholars are investigating its antecedents and consequences [40, 132], based on the empirical observation that eWOM is more powerful than WOM as a result of its one-to-many and many-to-many reach, convenience, speed, lack of face-to-face interaction, and potential anonymity [132].

The relationship between eWOM and financial/commercial performance has been studied by marketing management and information management scholars for consumer goods such as books [19], movies [29, 92], consumer electronics [95, 133], and to a lesser extent services [28, 149]. Within the service industries, the hospitality industry is heavily influenced by eWOM, with hotels seemingly the most affected [15] because of the development of OTAs such as Booking.com and Expedia.com and of other review sites such as TripAdvisor.

ORs constitute an irreplaceable information source for prospective buyers of travel services that are complex and difficult to evaluate prior to purchase and the quality of which is often unknown before consumption. For instance, in their early study, Gretzel and Yoo [57] found that ORs on TripAdvisor—the most noticeable independent online travel

review website—were used typically to inform accommodation decisions. Based on the literature review of eWOM in the hospitality sector conducted by Cantallops and Salvi [15], extant studies can be categorized in two main research lines: research on ORs generating factors (e.g., [76]) and the impact of the ORs on consumers (e.g., [131]) and companies (e.g., [94]). By triangulating the most updated literature reviews and meta-analyses on the topic of eWOM in hospitality management (viz., [15, 83, 148]), it seems that there is an abundance of studies related to ORs generating factors and their impact on consumers. However, the literature dealing with the impact of eWOM on hotel performance has gained momentum only recently [121, 148] and is reviewed in the next subsection.

ORs and Firms' Financial Performance in the Hospitality Sector

Several marketing management and information management scholars have examined the impact of several characteristics of ORs, such as valence, volume, and variance on sales and revenues for consumer goods (e.g., [2, 19, 24]). A few works have also attempted to systematize those studies by means of meta-analyses [47, 123, 152]. In their meta-analytic work on the effect of ORs on performance, both Floyd et al. [47] and You et al. [152] found that the effect of ORs valence on sales is generally positive.

In the service industries, and in particular in the hospitality sector, the relationship between eWOM and firms' commercial and financial performance has been analyzed only over the past decade [101, 118, 119, 144]. Recently OR ratings have been found to be a more significant predictor than traditional customer satisfaction measures to explain hotels' performance [78].

Three features of ORs that so far have been examined mostly in relation to firm performance in the hospitality sector are *valence* (i.e., the rating of the review), *volume* (i.e., the number of reviews), and *variance* (i.e., the standard deviation to the average rating).

Regarding valence, hotels displaying higher ratings have been found to generate higher sales [3, 77, 108, 149], higher average daily rates [3, 77], higher revenue per available room (RevPAR) [3, 119, 145], higher market shares [33], and higher perceived profitability from managers [107]. Of interest, the rating has been found to be more important for non-chain hotels than for chain ones [121]. Overall, there seems to be consensus across studies that there is a positive and significant relationship between the review valence and hospitality firm's performance. Accordingly, we formulate our first hypothesis:

Hypothesis 1: The higher the valence of online reviews, the higher the future hotel financial performance.

Regarding volume, a large amount of scholarly work has emphasized that OR volume (i.e., the number of ORs) is a relevant predictor of revenues (e.g., [4, 32, 58, 64, 92, 147]). Based on recent meta-analytical studies [123, 152], the relationship between the volume of ORs and sales is the most robust, statistically significant, and widespread across eWOM studies. Furthermore, in one of the meta-analyses [123], eWOM volume has been found to have a stronger impact on sales than valence. From a consumer perspective, it has been highlighted that more reviews could equate to higher levels of product popularity and awareness [39] and might therefore constitute a good signal for prospective customers.

In the hospitality sector, most of the studies have found a positive and significant relationship between the review volume and hospitality firm's performance (i.e., [145]). Hence, we formulate our second hypothesis:

Hypothesis 2: The higher the volume of online reviews, the higher the future hotel financial performance.

ORH and Financial Performance

In the information management and marketing literature focusing on the antecedents of ORH, the term *online review usefulness* seems to be used in a broad (and sometimes loose) way and relates to the extent to which an OR is perceived as useful by consumers, sometimes with perceived usefulness measured as one of the core constructs/variables of an acceptance or adoption model such as the technology acceptance model [25, 26] and its subsequent variations [139]. As such, usefulness pertains to online consumers' expectations that using ORs will enhance their performance in information seeking, which becomes a driver of consumers' attitude and intention to use ORs themselves [9, 10, 20, 31].

At closer inspection, it would seem that OR usefulness has to do with consumers' perceptions of ORs as a useful information source and therefore worthwhile of adoption, while helpfulness relates to the way consumers rate other consumers' ORs as more informative and therefore helpful. For instance, in their reference empirical study, Ghose and Ipeirotis [52] examine both review and reviewer-level features and find that informativeness, readability, subjectivity, and linguistic correctness influence sales and perceived usefulness. Furthermore, they observe that the OR that display a mix of highly subjective and objective sentences are rated as more informative (or helpful) by other consumers. Clearly, in their work the term *helpfulness* is used to indicate the degree of informativeness of ORs for other users, and they underline that "customers give 'helpful' votes to other reviews in order to signal their informativeness" [52, p. 1498]. In a more recent article, Felbermayr and Nanopoulos [42, p. 60] mention that "usefulness of online customer reviews . . . is evaluated by other customers through their helpfulness ratings." As such, in both studies [42, 52], helpfulness displays an intrinsic social nature [74], as it the by-product of other consumers' evaluations of the informativeness of the focal OR.

In our study, the term *helpfulness* is used and operationalized in terms of "helpful votes" (e.g., [42, 52, 134]) as a means through which online consumers evaluate the informativeness and information diagnosticity of others' ORs (e.g., [43, 44, 52]). As such, our focus is not on the individual utility that encourages a user to accept and adopt ORs (OR usefulness) but rather on the signaling effect that the helpful ratings have in inducing other reviewers to leverage ORs information for their decision-making processes [87].

In this work, ORH reflects the capability of a review to enable other consumers to better understand the performance and quality of a product or a service [71]. Perceived helpfulness relates to how potential customers perceive a peer-generated evaluation of a product, service, or brand as valuable and useful in their purchasing decision process [124]. The profusion and multiplication of ORs makes information about products and services easy to find but somehow difficult to process and judge, thus increasing cognitive costs [14]. To address, alleviate, and limit the issue of information overload for online

consumers [34, 48], most of the e-commerce websites (such as Amazon) have designed, devised, and activated mechanisms through which prospective online customers can give their votes for helpful reviews [114, 129]. Moreover, the majority of e-commerce platforms currently offer an option to OR readers to filter ORs based on their helpfulness. This should allow readers to make faster and more informed purchase decision [104] and enhance the effectiveness of the OR platform [68].

The aforementioned mechanisms not only help alleviate consumers' information overload [48, 72, 73] but also help online customers to immediately focus on those reviews that are perceived to have the higher diagnosticity [82, 150] as their information cues are more relevant [110]. Moreover, they help online consumers already familiar with ORs to carry out selective eWOM processing to deal with information overload [55].

Although a number of studies have focused on the antecedents of ORH in both the information management [18, 50, 51, 52, 53, 65, 66, 75] and marketing management [80, 88, 89, 127] fields looking at what makes an OR helpful, only two studies have tried to analyze the impact of helpfulness on commercial performance [86, 134]. Lee and Choeh [86] measure the interaction effects of OR volume and valence with ORH to observe the effects on movie box office and interestingly find that OR volume "does not interact with helpfulness to influence box office" [86, p. 860]. However, the explanation provided to interpret this finding looks not satisfactory, and we review it in more depth in the development of our hypotheses. Topaloglu and Dass [134] measure the moderating effect of ORH on the relationships between the type of content (affective or cognitive) on movie sales and the moderating effect of ORH on the relationships between the linguistic style of the OR and movie sales. Although these two studies look at different interaction and moderation variables, it might be argued that they constitute the first two seminal contributions of a nascent research stream revolving around an *outcome-oriented approach* to the study of eWOM helpfulness. To make a distinctive contribution to this nascent research stream, we observe that the two aforementioned studies are focused on goods rather than services. However, among the pioneers of the introduction of ORH helpful votes there are e-commerce websites selling travel, tourism, and hospitality services (e.g., Booking.com) and online travel review websites (e.g., TripAdvisor). As such, we need to bridge a clear gap identified in our focal research question: To what extent does online review helpfulness influence firms' financial performance in the service industries and more specifically the hospitality industry? This question addresses a critical research gap, as services sold online are extremely risky to evaluate before consumption, and ORH could help reduce uncertainties regarding travel and accommodation services quality and performance [43, 60].

As studies of the outcomes of ORH *in the context of service industries* in general and more specifically the hospitality sector are virtually nonexistent, this study intends to offer insights to eWOM researchers by analyzing how ORH moderates the relationships between OR valence/volume and the financial performance of hospitality firms. We develop our hypotheses in the ensuing subsections.

The Moderating Effect of the Degree of ORH on the Relationship Between OR Valence and Financial Performance

Building on social influence theory [22, 30], we argue that exposure to others' ORs can influence online consumer behavior because online review valence (under the guise of online ratings) represents a *normative* social influence that consumers conform to, as it

represents the opinion of the crowd in relation to the quality of the product/service reviewed [43]. In other terms, product ratings represent information cues that subsume the "wisdom of the crowd" [43], as average ratings equate to the average evaluation that reviewers have given to the various attributes of a product/service.

Before a real-world purchase, consumers will focus on products/services covered by positively valenced reviews rather than negatively valenced reviews. When deciding between two or more alternative products/services covered by ORs displaying the same positive ratings, the degree of ORH might work as a facilitating heuristic [36] allowing customers to enhance their selective eWOM processing [55] prior to choosing between two or more positively rated alternatives. As such, helpfulness votes work as a "decision-making cue" [134] that helps consumers that have already a proxy of the quality of the product/ service reviewed (i.e., the ratings) to opt for those alternatives whose positive reviews are voted as more helpful. This will strengthen the positive effect that valence has on financial performance. This phenomenon might seem particularly critical for services that unlike goods [86] involve risky decisions of intangible offerings. Accordingly, consumers of hospitality services would use OR valence as a signal of the quality of the service and adopt helpful reviews to choose among the high-quality alternatives (that are signaled by positively valenced ORs). As such we posit that in (hospitality) services settings, the information cues attached to ORH might amplify the positive effect of OR valence on hotels' financial performance. Relatedly, the higher the degree of ORH, the higher should be the consumers' purchasing attitude and intention to purchase online hospitality services covered by positive ORs. Therefore, we hypothesize the following:

Hypothesis 3: The degree of online review helpfulness moderates positively the positive influence of the valence of online reviews on future hotel financial performance.

The Moderating Effect of the Degree of ORH on the Relationship Between OR Volume and Financial Performance

According to the social influence theory [30], OR volume (under the guise of number and quantity of ORs) represents an *informative* social influence that consumers use, as it constitutes an indicator of product popularity that impacts consumer purchase intentions [111] and ultimately translates into higher product sales [149]. The only study analyzing the interaction of OR volume with the degree of ORH has been conducted in the movie sector [86] and found a very unstable interaction of ORH with volume, one that seems time-dependent and possibly sensitive to model specifications: indeed the authors found that ORH positively/negatively interacts with review volume on box office revenue for the first/ second week after a movie release, but the effect becomes not significant on the box office revenue for the third week after a movie release.

We argue that the ORs pertaining to services, and more specifically hospitality services, display a different nature. Indeed, based on impression formation research suggesting that extreme ratings are perceived as more diagnostic [130], research in hospitality and tourism services has found that extreme reviews are often associated with higher diagnosticity and helpfulness [39, 45, 113]. As such, the informational social influence driven by OR volume and the degree of ORH would not be enough to allow customer to make purchasing decisions: indeed, services consumers would still need a strong normative indicator such as valence (subsuming the *wisdom of the crowd*) to be persuaded to purchase even further

a product/service that is popular because covered by a high number of ORs. Given that previous research in hospitality indicates that high ORH can be associated also with low-valenced ORs [39, 45, 113], it is not clear how ORH will moderate the relationship between OR volume and financial performance in hospitality settings: the sign might be positive for very high-valenced reviews but negative for very negative-valenced reviews. As such, we argue that the degree of ORH is not likely to moderate significantly the positive influence of the volume of ORs on future hotel financial performance. Although we do not formulate a hypothesis, as it is not statistically correct to posit a null hypothesis that cannot be rejected, we still report the effect in our findings.

While in this paper we do not take intentionally in consideration interaction effects among volume and valence [137] or variance, additional factors can influence the financial performance in the hospitality industry. They are well known in the hospitality literature and include, for instance, location [125], seasonality [69], and educational systems; government support; and destination-related factors [8]. However, we control for all the time-invariant factors by deploying panel regression fixed-effects analyses. Moreover, we control for both seasonality and response volume that are relevant time-variant variables in the hospitality sector. As far as the first control is concerned, demand fluctuates significantly based on seasonality, and an increasing number of hotels today deploy revenue management systems to accommodate their pricing strategies and tactics [17, 59, 141]. Accordingly, controlling for seasonality allows us to control for revenue management strategies too. As far as the second control is concerned, as clarified by Raguseo and Vitari [121], the volume of hotel managers' responses to ORs' comments (i.e., response volume) can be considered as a hotel's managerial capability to manage its online reputation and visibility [146]. As the practice of responding to ORs has been evolving over time—with an increasing number of hotels replying to ORs—we embedded in our model specification the capability of managing eWOM effectively.

The overall research model, including dependent, independent, and control variables, is depicted in Figure 1.
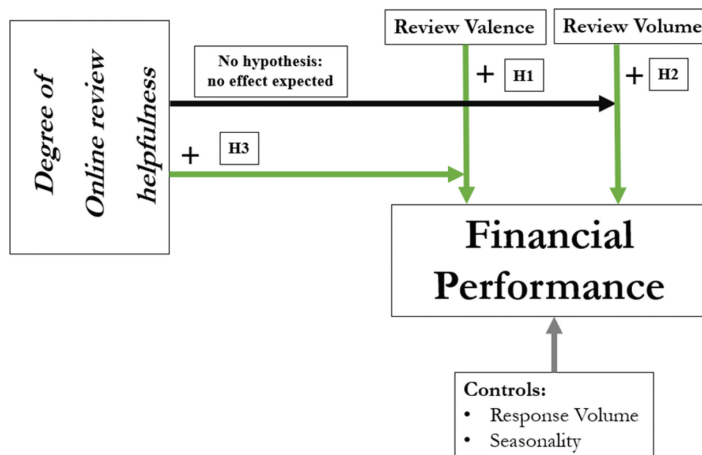

Figure 1. Research Model

Methodology

Data and Sample

This research gathered data over the period 2016–2017. We collected a large sample of granular data related to ORs and financial performance from two sources, respectively: Booking.com and STR. The former was chosen because it hosts the largest number (and share) of certified hotel reviews worldwide [122]; the latter was selected because it is a leading and internationally recognized research company in the provision and analysis of financial data to academic and industry researchers in the hospitality field.

As far as ORs are concerned, we developed a web crawler (consisting of different customized modules) in Python to retrieve data of Booking.com ORs for hotels based in London, UK, that ranks third among the top 100 city destinations worldwide with 19.2 arrivals in 2017 [35] and is the most visited city destination in Europe, with Europe being the leading continent for international tourist arrivals [138]. This data collection was not random but was based on the overall population of reviews published on the website over 23 months (February 2015 to December 2016), which resulted in 1,181,919 ORs. Booking.com was chosen, as it displays verified reviews (i.e., real opinions written by actual guests for real stays) and it is the leading OTA for the destination under analysis.

As far as financial data are concerned, we then obtained daily financial data such as RevPAR as well as hotel attributes information (e.g., size, age, location, class, scale, operations) from STR, a leading research company in the provision of data in the hospitality industry. Financial data were not available for the overall population of Booking.com hotels, and STR senior researchers matched our Booking.com dataset with their financial data on the ground that company-level financial data should be kept anonymous. We gave STR senior researchers instructions to get a representative sample of the hotels in London for which they had data, based on a number of dimensions (e.g., size, age, location, class, scale, type of operations).

After the matching, we retained only higher end hotels (four-star and five-star hotels) for a total of 261 firms covering 66.6% of the entire population of the four-star and five-star hotels available on Booking.com for the chosen city of London over the period under analysis. Of the 261 firms, 175 firms are four-star hotels covered by 334,265 ORs, and the remaining 86 firms are five-star hotels covered by 61,699 ORs (see Table A1 in the appendix). There are at least three relevant methodological reasons why we focused selectively on four-star and five-star hotels. First, we wanted to control for potential multiple and confounding effects, stemming from the different levels of customer expectations when taking into account different features of hospitality firms' marketing, reputational, and managerial practices [112]. Second, and related to the previous point, the Booking.com online ratings of four-star and five-star hotels are systematically higher if compared with online ratings of two-star and three-star hotels [98, 102] because there are objective differences in the quality of the services that they provide as detected by a number of studies in hospitality marketing literature (e.g., [7, 112, 113, 149]). Third, generally the coverage of one-star and two-star hotels as far as financial data are concerned is rather poor because of certain reasons such as absence of time and willingness of hotel managers and owners to share their financial data at a granular level [90, 119]. Indeed, most of the financial data that can be extracted by databases such as Bureau Van Dick do not include

fine-grained metrics such as RevPAR that instead is collected and monitored by companies with expertise in hotel performance such as STR.

After studying the frequency distributions of the variables (both the dependent and the independent ones), we assembled a dataset with variables aggregated on a monthly basis. Because the average number of days between the booking date and the check-in date ranges from 14 to 21 days [91], we chose to aggregate our daily data in 2 weeks, 3 weeks, and lastly 1 month. As all the analyses yielded consistent results, we opted for aggregating data on a monthly basis.

Consistently with recent literature [121, 144], as the structure of the data is longitudinal, we adopt a hierarchical multivariate panel regression model whereby revenue changes in period t are predicted and explained based on the ORs data in period $t - 1$. The underlying rationale is that our study aims at capturing the impact of ORs on firms' future financial performance, and therefore in our model specification the features of ORs are logically and chronologically drivers (or antecedents) of hotel performance.

Measures

Our dependent variable is a financial performance indicator very common in hospitality management studies: Revenue per Available Room (RevPAR) [121, 125]. We use it, as it typically provides a thorough picture of financial performance. Our independent variables include the valence, volume, and degree of ORH.

$$Cumulative\ Degree\ of\ ORH_{h,t} = \sum_{i=1}^{t} Degree\ of\ ORH_{h,i}$$

$$Cumulative\ Review\ Valence_{h,t} = \frac{\sum_{i=1}^{t} Review\ Valence_{h,i} * Review\ Volume_{h,i}}{\sum_{i=1}^{t} Review\ Volume_{h,i}}$$

$$Cumulative\ Review\ Volume_{h,t} = \sum_{i=1}^{t} Review\ Volume_{h,i}$$

$\forall\ h = 1, \ldots, N$ and $t = 1, \ldots, T$ with $N = 261$ hotels and $T = 23$ months

In the preceding formulas, the cumulative review volume is operationalized as the total amount of ORs available for each of the 261 hotels at a particular time t, with the maximum number of periods at 23 months. The cumulative review valence is operationalized as the ratio of the cumulative multiplication of review valence by review volume to the total number of ORs available for each of the 261 hotels at a particular time t with the maximum number of periods at 23 months.

Consistently with extant literature, the degree of ORH is defined as "the sum total number of viewers who rated a review helpful" [134, p. 10], and it is operationalized accordingly using the number of helpful votes received by an OR. Its cumulate value reflects the sum of previous values of the variable in time periods prior to the analyzed one.

In line with previous literature, besides the dependent variable and focal explanatory variables, we also embedded in our model two control variables: seasonality and the cumulated response volume. As far as the former variable is concerned, demand fluctuates significantly

Table 1. Variable Definition and Descriptive Statistics (Monthly Basis).

Dimensions	Variable	Description	Mean	SD	Skewness	Kurtosis	Min	Max
Financial performance	RevPAR	Average revenue per available room	162.16	103.16	2.65 (0.62)	12.60 (3.6)	26.44	892.08
Monthly review features	Review valence	Average online rating	8.54	0.62	-0.35	3.35	3.80	10
	Review volume	Number of reviews	66.91	70.27	2.80 (-0.57)	15.37 (3.49)	1	713
	Degree of ORH	Sum of the number of helpful votes	10.77	21.62	5.28 (0.49)	45.79 (2.47)	0	296
Cumulative review features	Cumulative review valence	Cumulative average online rating from the first observed period	8.55	0.55	-0.23	2.52	6.76	10
	Cumulative review volume	Cumulative number of ORs from the first observed period	761.28	973.5	3.26 (-0.60)	19.41 (3.38)	1	10,642
	Cumulative degree of ORH	Cumulative sum of the number of helpful votes from the first observed period	171.03	238.66	3.81 (-0.64)	25.12 (3.23)	0	2,438
Control variables	Cumulative response volume	Cumulative number of responses provided by the hotel management from the first observed period	81.6	235.39	5.62 (0.86)	46.95 (2.24)	0	3,617
	Seasonality	Set of 22 monthly dummy variables that denotes all the analyzed months except the first one for multicollinearity reasons	Categorical variables					

Note: There were 395,964 reviews for 261 hotels in London over 23 months (February 2015–December 2016). The values of skewness and kurtosis of the log transformation of the variables are in parentheses. The first observed period refers to February 2015. OR = online review; ORH = online review helpfulness; RevPAR = revenue per available room.

based on seasonality and an increasing number of hotels today deploy revenue management systems to accommodate their pricing strategies and tactics [17, 59, 141]. Accordingly, controlling for seasonality allows us also to control for revenue management strategies that can change very rapidly over time through dynamic pricing. As far as the latter control variable is concerned, as clarified by Raguseo and Vitari [121], the volume of hotel managers' responses to ORs' comments (i.e., response volume) can be considered as a hotel's managerial capability to manage its online reputation and visibility. As this response practice has been evolving over time —with an increasing number of hotels replying to ORs—it is important to proxy the capability of managing eWOM effectively through a variable capturing managerial responses: the cumulative response volume. The variable is computed as follows:

$$Cumulative\ Response\ Volume_{h,t} = \sum_{i=1}^{t} Response\ Volume_{h,i}$$

∀ h=1, …, N and t=1, …, T with N=261 hotels and T=23 months

The attributes related to the hotel firm such as hotel class and chain, being largely time-invariant over the period analyzed, were controlled by construction in the fixed effect model in line with Raguseo and Vitari [121]. This complies with the idea that fixed effect models offer reliable results even in presence of time-invariant omitted variables [143]. Table 1 shows the descriptive statistics of the variables under consideration. As RevPAR, review volume, and degree of ORH were skewed, we adopted a logarithmic transformation of the variables.

Finally, the cumulative review volume, the cumulative review valence, and the cumulative degree of ORH were standardized to make possible the evaluation of the moderation relationships in the model and compare the magnitude of the coefficients.

Model Specification

The model specification is presented in the following equation:

$$
\begin{aligned}
Log(\text{RevPAR})_{h,t+1} \ =\ & \beta_0 + \beta_1 (Cum\ Review\ Valence)_{h,t} \\
& + \beta_2 Log\ (Cum\ Review\ Volume)_{h,t} \\
& + \beta_3 Log\ (Cum\ Degree\ of\ ORH)_{h,t} \\
& * (Cum\ Review\ Valence)_{h,t} \\
& + \beta_4 Log\ (Cum\ Degree\ of\ ORH)_{h,t} \\
& * Log(Cum\ Review\ Volume)_{h,t} \\
& + \beta_5 Log\ (Cum\ Response\ Volume)_{h,t} \\
& + Month\ Dummies + \varepsilon_{h,t}
\end{aligned}
\tag{1}
$$

As is clear from the equation, the *Log (RevPAR)* was used as the dependent variable and it was regressed against the cumulative review valence and the cumulative review volume. Moreover, we measured the moderation effects of the degree of ORH on the relationships between OR valence/volume and the *Log (RevPAR)*. Additionally, we controlled for the cumulative response volume. The cumulative volume and cumulative response volume were log transformed.

The three hypotheses were validated using fixed effect panel regressions. The choice of the fitting model is the outcome of a number of diagnostic tests. First, we tested for the presence of

heteroskedasticity, controlling whether the variance of the error term is constant across observations. Accordingly, we employed the modified Wald test for groupwise heteroskedasticity in fixed effect regression models [56, p. 598], which signaled the presence of heteroskedasticity in the model. Second, because also cross-sectional dependence (also known as contemporaneous correlation) can lead to biased estimations, we employed Pesaran's [115] cross-sectional dependence test to assess whether the residuals were correlated across entities. The test failed to reject the null hypothesis, suggesting no cross-sectional dependence among the residuals.

As heteroscedasticity was detected, we followed the suggestion proposed by Wooldridge [143] for panel data where the number of periods T is small relative to the sample size N. Thus, we adjusted the asymptotic variance matrix estimator using the robust variance matrix estimator [5], which has been proved to be a valid technique to account for the presence of arbitrary heteroskedasticity [143]. Furthermore, to establish the suitability and consistency of the fixed effects estimator compared with a random effect estimator using robust standard errors, we employ the artificial regression approach described by Arellano [6] and Wooldridge [143]. This test of overidentifying restrictions was performed for all the models presented in the paper and revealed that the random effects estimation method was not preferable compared with the fixed effects estimation method.

One more reason why we adopted fixed effects panel regressions is that we are not interested in the influence of any time-invariant factors, but rather we wanted to focus on the impact of time-varying features of ORs. Opting for a fixed effect model allowed us to control for any biases caused by the omission of relevant individual characteristics and to rule out any time invariant features related to the unit of analysis [143], which in our case is hotels. Consequently, hotel star rating, whether or not the hotel belongs to a chain, and hotel location are omitted in the estimation of the model, as over the selected period they were not time variant.

Findings

We adopted a hierarchical multivariate panel regression analysis, measuring direct effects of OR valence and volume on firms' performance and, more important, the moderation effects of the degree of ORH on the relationships between OR valence and volume and firms' performance. Table 2 shows the results of the four fixed effects regression models fitted. The first model (Model 1) includes only the cumulative review valence and volume, whereas the second and third models include, respectively, the interaction of the degree of ORH with the cumulative review valence (Model 2) and the interaction of the degree of ORH with the cumulative review volume (Model 3). Model 4 encompasses both the direct effects of valence and volume and the two interaction effects.

At close inspection, all the models display a good fit explaining from 71.62% of the variance (Model 1 and Model 3) to 71.76% of the variance (Models 2 and 4). All the models display significant F-tests with a p value of less than 0.01 percent. In Model 1 (and consistently across all the models), the cumulative review valence and cumulative review volume have both a positive and significant influence ($p < 0.01$) on hotel firms' future financial performance. Accordingly, Hypotheses 1 and 2 are supported consistently with a part of the findings of several previous studies and meta-analyses [151]. However, the focus of this paper is on the moderating effects. The degree of ORH positively moderates the relationship between cumulative review valence and firms' future financial performance

Table 2. Main Hierarchical Regression Models.

Independent Variables		(1)	(2)	(3)	(4)
Cum review valence	H1	0.057***	0.072***	0.057***	0.074***
Cum review volume	H2	0.123***	0.128***	0.122***	0.137***
Cum Review Valence × Degree of ORH	H3		0.022***		0.025***
Cum Review Volume × Degree of ORH				−0.001	0.005
Cum response volume		−0.008	−0.006	−0.008	−0.007
March 2015		0.033	0.034	0.033	0.032
April 2015		0.219***	0.219***	0.219***	0.217***
May 2015		0.491***	0.489***	0.491***	0.487***
June 2015		0.360***	0.357***	0.360***	0.354***
July 2015		0.066	0.063	0.067	0.059
August 2015		0.522***	0.518***	0.522***	0.513***
September 2015		0.486***	0.483***	0.487***	0.477***
October 2015		0.155**	0.151**	0.155**	0.145**
November 2015		−0.160**	−0.164**	−0.160**	−0.171**
December 2015		−0.724***	−0.728***	−0.723***	−0.736***
January 2016		−0.384***	−0.389***	−0.384***	−0.398***
February 2016		−0.316***	−0.322***	−0.315***	−0.331***
March 2016		−0.128	−0.135	−0.127	−0.144*
April 2016		0.019	0.011	0.020	0.001
May 2016		0.254***	0.246***	0.255***	0.235**
June 2016		0.318***	0.310***	0.319***	0.298***
July 2016		−0.078	−0.086	−0.077	−0.098
August 2016		0.451***	0.442***	0.452***	0.430***
September 2016		0.174*	0.164	0.175*	0.152
October 2016		0.234**	0.225**	0.235**	0.212**
November 2016		0.045	0.036	0.046	0.022
December 2016		−0.535***	−0.545***	−0.534***	−0.559***
Constant		−0.064	−0.053	−0.064	−0.049
Observations		5,917	5,917	5,917	5,917
Number of hotels		261	261	261	261
R^2		71.62%	71.76%	71.62%	71.76%
F		265.85***	254.60***	257.57***	246.12***

Note: ORH = online review helpfulness.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

($p < 0.01$ for Models 2 and 4). As such, we find support for Hypothesis 3. This finding is at odds with the finding obtained by Lee and Choeh [86] in the context of the movie sector, wherein they instead found that the degree of ORH does not significantly moderate valence (in the first and second week after movie release), whereas it negatively moderates valence in the third week after release. Clearly this is a major difference, the possible motivations of which are discussed in the Discussion section.

Last, the degree of ORH does not moderate significantly the relationship between cumulative review volume and firms' future financial performance. Therefore, our argument related to the nonsignificant (or nonexistent) moderation effect seems well picked (see Models 3 and 4). Also this finding is only partially in line with what Lee and Choeh [86] observe in their study: more specifically, they find that the degree of ORH negatively moderates the effect of volume on box office revenues (in the second week after movie release), and in the third week the moderating effect becomes not significant.

The control variable related to the cumulative response volume is nonsignificant. In line with extant literature in the revenue management field (e.g., [17, 59, 141]), we detected demand changes over time as clearly indicated by the months variables that are mostly significant over the analyzed time span, with positive coefficients and the exception of a few months.

Furthermore, to test the reliability of our results, we conducted a series of robustness checks [38] (see supplementary material in the Appendix and models 5-7 in Table A.2) that consistently confirmed the findings just described.

Discussion

The effect of the *degree of ORH* as a *moderator* of the relationships between OR valence/volume and hotel firms' future financial performance constitutes an underexplored phenomenon, as evident from extant literature and the related meta-analyses [47, 123]. Furthermore, it represents an object of study relevant for a nascent research stream [86, 134] that we have termed as an *outcome-oriented approach* to the study of eWOM helpfulness.

The degree of ORH moderates positively the relationship between the OR valence and firms' performance. This finding is consistent with research showing that, based on social influence theory [22, 30], OR valence (under the guise of online ratings) represents a *normative* social influence that consumers conform to, as it represents the opinion of the crowd in relation to the quality of the product/service reviewed [43]. In other terms, product ratings represent information cues that subsume the "wisdom of the crowd" [43], as average ratings equate to the average evaluation that reviewers have given to the various attributes of a product/service.

Consumers use ratings to learn about product/service quality that is critical to make decisions before purchases. However, when they face decisions between two positively rated alternative products/services, the degree of ORH works as a facilitating heuristic—in line with dual process theory [36]—allowing them to obtain rapidly diagnostic information about different alternative products/services that are positively rated. Accordingly, helpfulness votes work as a critical "decision-making cue" [134] that help consumers to selectively process eWOM [55] and better interpret the information cues included in positively valanced ORs [49] that cover different product/service alternatives. This positive moderating effect might seem particularly relevant for services (especially hospitality and travel services) that unlike goods [86] involve risky decisions of intangible offerings. This finding offers a contribution to the outcome-oriented approach to the study of eWOM helpfulness that well complements drivers-oriented approaches that have found that consumers' perceived helpfulness of ORs positively influences their hotel online booking intentions [54].

Of interest, our finding—while complementing the findings of Topaloglu and Dass [134], who look at moderation effects on the affective content of ORs—is at odds with the results of Lee and Choeh [86, p. 860], who find that "review rating does not interact with helpfulness to influence box office. This indicates that users calibrate the review based on their assessment of the 'agreement' between their and reviewer's taste and make an independent judgment about the true quality of the movie." The explanation that the authors develop does not seem to be very convincing, as it recognizes neither the social mechanisms at play in online consumer behavior nor the way online consumers process information on online platforms. Our findings instead are well explained by a combination of normative social influences dictated by OR valence and cognitive heuristics adopted for faster and less expensive purchase decision-making processes.

In sum, while valence represents a major predictor and a leading indicator of firms' financial performance [152], our study reveals that it is reinforced by the degree of ORH, and not diminished by ORH as suggested by a previous empirical study [86] within the framework of the nascent outcome-oriented approach to the study of eWOM helpfulness.

The degree of ORH does not moderate significantly the relationship between the OR volume and firms' performance. According to the social influence theory [30], OR volume (under the guise of number and quantity of ORs) represents an informative social influence that consumers use, as it constitutes an indicator of product popularity that impacts consumer purchase intentions [111] and ultimately translates into higher product sales [149]. Our finding seems to be consistent with a previous study [86] that found a very unstable interaction of ORH with volume, one that seems time-dependent and possibly sensitive to model specifications. Furthermore, our finding is consistent with context-specific characteristics of services: indeed, extreme ratings/reviews are perceived as more diagnostic and helpful in hospitality settings [39, 45, 113]. Therefore, the informational social influence driven by OR volume and ORH would not be enough to allow customers to make purchasing decisions, as they would still miss a strong normative indicator such as valence, subsuming the wisdom of the crowd, to be persuaded to purchase a popular service. Accordingly, the moderation effect might work in opposite directions for extreme versus moderate reviews/ratings without any overall clear direction.

Arguably, while the degree of ORH might help consumers to attenuate cognitive over-load, since volume is only an informative social influence, consumers would still need a strong *normative* indicator such as valence to be persuaded to purchase a product/service that is popular because covered by a high number of ORs. This is a possible explanation that might need further external validation in future services marketing research revolving around both the antecedents and outcomes of ORH.

In sum, it seems that product popularity in eWOM (proxied by OR volume) does not provide a complete information cue, sufficient to persuade consumers of the quality of a product [43]. While ORH might help those consumer groups that make decisions based on time efficiency and helpfulness cues [55] to learn faster about the quality of products, it does not necessarily bridge per se the knowledge gap related to the quality of the service reviewed.

Conclusions and Implications

To date, both academic and industry research has emphasized that eWOM influences consumer decision-making and purchasing behaviors as ORs play a major role for online shoppers' information adoption, gathering, and deal seeking in both goods contexts (e.g., [11]) and services ones (e.g., [57]). Moreover, consumers increasingly adopt ORs to make informed purchasing decisions because they trust opinions posted online increasingly in travel and hospitality websites and online communities [105]. However, the proliferation of ORs stemming from third-party e-commerce websites and other travel review platforms is literally inundating the Internet, thus generating and overabundance of eWOM [44]. For instance, travelers using TripAdvisor for travel planning could have access to just over 1 million ORs at the beginning of 2005, and today they can access more than 760 million [135, 136], and this holds—with different figures but similar growth rates—also for OTAs such as Booking and Expedia. The hyperproduction of ORs is generating potentially

information overload for consumers [34, 70, 110] that might generate confusion [63] and increased cognitive processing costs [81]. This is the reason why many e-commerce websites such as Booking.com and Expedia.com have designed and introduced mechanisms through which prospective online customers can give their votes for helpful reviews [114, 129]. While several of the feature of ORs have been taken into account to explain hospitality firms' performance so far, to the best of our knowledge this is the first study explicitly measuring the moderating effects of the degree of ORH on the relationships between OR valence/volume and hotel financial performance. Accordingly, we contribute to advance the nascent stream of studies [86, 134] taking an outcome-oriented approach to the study of eWOM helpfulness, namely, an approach focused on the outcomes instead of the antecedents of eWOM helpfulness. Through a hierarchical multivariate panel regression analysis, we find that the cumulative review valence and volume have a positive impact on the financial performance of a large sample of higher-end hotels located in London. More importantly, we find that the degree of ORH can enhance the positive effect of cumulative OR valence on firm performance, whereas it does not moderate the positive influence of OR volume on firm performance.

Theoretical Implications

From a theoretical point of view, we make several contributions to both the services marketing and hospitality marketing bodies of literature and particularly the eWOM research stream. First, this study offers theoretical insights to eWOM researchers, with the overarching purpose of analyzing how ORH affects the financial performance of services firms, namely, hospitality firms. As such, it represents one of the first attempts to address the attention of services marketing scholars to the relevance of ORH in explaining firm performance by taking an outcome-oriented approach to the study of eWOM helpfulness, namely, an approach focused on the outcomes instead of the antecedents of eWOM helpfulness.

Second, we examine the moderating effect of the degree of ORH on the relationships between eWOM valence/volume and firms' performance by leveraging a combination of ORH-related studies relying on multiple theories including information adoption [117], social influence theory [22, 23, 30, 49], and dual process theory [36, 37]. Overall, relying on those theories is relevant to understand the "behind the scenes" of ORH and therefore provide more compelling explanations of the if, how, and to what extent eWOM helpfulness can work differently if associated with eWOM valence and/or eWOM volume. Third, we tease out the differentiated interaction effect of the degree of ORH with eWOM volume versus eWOM valence on firm performance. As far as eWOM valence is concerned, in line with social influence theory [22, 30], OR valence represents a normative social influence that consumers conform to, as it represents the opinion of the crowd in relation to the quality of the product/service reviewed [43]. Its positive effect on firms' financial performance is reinforced by the degree of ORH. Overall this finding contributes to a more nuanced and rounded theoretical development of eWOM research taking an outcome-oriented approach to the study of eWOM helpfulness, as it contradicts recent research [86] that found no significant interaction effect of the degree of ORH and OR valence.

As far as eWOM volume is concerned, based on social influence theory [30], OR volume represents an informative social influence that consumers use, as it constitutes an

informational cue of product popularity that impacts consumer purchase intentions [111] and ultimately translates into higher product sales [149]. Its positive effect on firms' financial performance is not affected significantly by the degree of ORH, as consumers would still need a strong normative indicator such as valence before being persuaded to purchase a popular product/service.

The detected *absence of symmetry* in the moderation effects of ORH on valence/volume might encourage the next generation of eWOM researchers interested in ORH to dig in depth about the type of social influence (weather normative of informative) behind each eWOM feature (valence or volume) and better understand how ORH might work differently (as an heuristics interacting with normative vs. informative social influence).

Fourth, our study reveals that the "quantitative" features of ORs traditionally examined in current eWOM research (e.g., valence and volume) are not sufficient to accurately explain firm performance anymore. We therefore offer a more comprehensive and theoretically informed explanation of the determinants leading to superior hotel firms' financial performance by combining different theories including information adoption [117], social influence theory [22, 30, 49] and dual process theory [36] to make sense of the underlying mechanisms affecting online consumer behaviors and ultimately translating into firms' revenues and performance.

Fifth, we suggest that research on the impact of eWOM on financial performance taking a company perspective [15, 121]—or better, an outcome-oriented approach to the study of eWOM helpfulness [134]—could significantly benefit from a closer look at those social features of an OR that can drive performance such as helpfulness [83], thus emphasizing qualitative aspects encompassing the diagnosticity of eWOM [82]. While complementing the findings of Topaloglu and Dass [134], who look at moderation effects on the affective content of ORs, we believe that social features of eWOM in general should play a more relevant role when explaining financial performance, as the degree of ORH moderates significantly the relationship between OR valence and firms' performance.

Managerial Implications

The study's findings bear important implications for managers of services firms in general (and more specifically for hospitality firms), as well as for OR platform managers. First, hospitality managers should keep on investing to improve the quality of their services, as this might ultimately translate into higher customer satisfaction and higher ORs' ratings that, consistent with previous research [3, 57, 90, 145, 152], have been found to influence positively firm financial performance. As eWOM valence represents by itself a sufficiently robust peripheral route used by consumers to learn about product quality, it is critical for managers to innovate and improve products and services constantly, as positively valanced ORs subsume the wisdom of the crowd that helps consumers to selectively process eWOM [55]. Second, with the exponential increase of eWOM in the travel and hospitality industries, social media strategists and digital reputation professionals working in or for hotel companies should increasingly cooperate with third-party e-commerce websites and OTAs, asking them to develop a set of digital analytics allowing them to cope with and monitor the expanding ocean of ORs. This implication seems to complement the results of a recent meta-analytical work on eWOM suggesting that "marketers should actively monitor eWOM, and it justifies the allocation of resources to eWOM management" [123, p. 314].

Third, our analysis suggests that online platform managers and e-commerce website administrators for OTAs such as Booking.com and Expedia.com should try to make extremely visible the most helpful reviews to (1) minimize the risk of customers' abandoning their website, (2) maximize the capability of attracting new customers [89], (3) allow extant customers to refine their selective eWOM processing heuristics [55], and (4) make the website more effective [68]. Indeed, as clearly emphasized in the empirical analysis, the degree of ORH reinforces the positive effect of OR valence on firm's performance in service settings. Last, there seems to be scarce collaboration between industry and academia to understand more about the antecedents that bring consumers to vote an OR as helpful and that contribute therefore to generate diagnostic and helpful eWOM from a company performance perspective. While scholars in different disciplines such as computer science and information systems [13, 67, 104, 129], marketing [19, 109] and travel and hospitality (e.g., [39, 43, 46, 82, 93, 127]) are trying to make sense of those antecedents, still there seems to be little use of the knowledge generated so far for business intelligence purposes and better decision-making in hospitality. Conversely, the triangulation of different techniques and types of data (big and small, structured and unstructured) might improve the business intelligence of many firms operating within the hospitality sector [97] and help managers gain some insights on the heuristics [128] and selective eWOM processing practices [55] that online consumers adopt to deal with eWOM to purchase hospitality and accommodation services in today's digital environment.

Limitations and Research Agenda

This study has some limitations that constitute opportunities for further research. First, we have confined our attention to a discrete and parsimonious set of explanatory variables with a major focus on helpfulness, valence, and volume, perhaps disregarding additional explanatory and control variables such as personality of reviewers [77] and promotional efforts and budget to improve visibility on third-party commercial websites [41] as moderating variables in the relationships between OR valence and volume and hotel performance. Although we took into account the degree of eWOM helpfulness as a critical moderator to explain the financial performance in a specific subsector of service industries, and tested how the extent of eWOM helpfulness can moderate the relationships between other eWOM characteristics (e.g., volume and valence) [86] and firms' performance, future research might seek more sophisticated specifications such as using more time variant variables (entailing competitors' sets proxies that are, however, missing in most if not all of eWOM studies) or even different techniques such as neural networks, despite their results are difficult to interpret as underlined by Phillips et al. [118]. Second, while we tried to control for unobservable managerial capabilities operationalizing them as the number of responses written by the hotel management (see [121]), we are aware that omitted time-varying variables, such as changes in hotels' management, cost structures, number of employees, and the like could have affected the estimation of our dependent variable. Through the use of fixed effects estimation method, we have removed the effects of time-invariant features and our robustness checks corroborate our main results; however, future research might also try to operationalize the aforementioned variables [144]. Third, the relative importance of some antecedents/predictors of financial performance could be potentially sensitive to econometric specifications (e.g., including log-log rather than level-level or log-level combinations) [27, 47] and a number

of factors such as research setting, and variable measurement (see [148]); thus further research in different settings (i.e., other destinations) and using different data (i.e., different online travel agencies and travel platforms) is needed to understand if the relative importance of eWOM helpfulness, valence, and volume is dependent on the type of product being reviewed and the platform [123, 152]. Fourth, we focused on higher-end hotels (i.e., four-star and five-star) for methodological reasons related to the need of controlling for potential confounding effects, stemming from the different levels of customer expectations when taking into account different features of hospitality firms' marketing, reputational, and managerial issues [112], which ultimately are mirrored in different levels of customer satisfaction [120] and online ratings on OTAs such as Booking.com. Further research might look at budget hotels (such as one-star and two-star) as well, provided that good quality financial data will become available. Fifth, our study did not control for reviewer-level factors such as reviewers' cultural background [100] and submission device used for the review [99]: these factors might be taken into account in future studies to understand if and to what extent they drive online reviewing behavior and ultimately eWOM and performance. Last, our study focuses on a single destination that, though relevant from a national and international point of view, is not necessarily representative of hotel populations in other destinations. This is the inevitable outcome of the availability of rare and granular ORs and performance data for that specific area. To generalize the results, additional research should be carried out in other destinations both nationally and internationally and include more recent data. Future research might also try to evaluate the impact on financial performance of private accommodation services intermediated by sharing economy platforms such as Airbnb, whose hosts and guests can vote the helpfulness of a review.

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Appendix

A.1 Distribution of ORs and firms by hotel class

Table A.1. shows the distribution of ORs analyzed in the study by hotel class.

Table A.1. Distribution of ORs and firms by hotel class, February 2015 - December 2016

Hotel Star Rating	Number of OR	Population of ORs on Booking.com	Number of Hotels	Population of hotels reviewed on Booking.com
4 Stars	334,265	451,828	175	280
5 Stars	61,699	87,608	86	112

A.2 Robustness checks

In order to rule out the possibility that our results might be affected by the specific time at which the cumulative variables are calculated, we ran robustness checks setting the time window at 3, 6 and 12 months in line with other business literature [38]. Accordingly, the data pertaining to the initial 3, 6 or 12 months was considered as the initial "memory" of the online system: this is consistent with the way Booking displays its ORs, namely on a rolling window of 24 months (unlike TripAdvisor that displays the entire history of ORs). For instance, in the robustness check using 3 months as memory in the system, we calculated the initial cumulative variables taking into account the first three months (from February to April 2015) as a proxy of the previous memory in the system and we ran our econometric models on the remaining 20 months. We applied the same procedure using historical time spans of 6 and 12 months, thus running all the models on 17 and 11 monthly time units, respectively. The findings are consistent with those commented above. The robustness analyses are shown in Table A.2.

Furthermore, and as part of the robustness checks, we also tested the direct effect of the degree of ORH on firm's performance and the effect was not significant while the rest of the four hypotheses were consistently supported.

Table A.2. Robustness Checks for Hierarchical Regression Models

Independent Variables		(5) Robust 3 Months	(6) Robust 6 Months	(7) Robust 12 Months
Cum Review Valence	H1	0.123***	0.162***	0.173**
Cum Review Volume	H2	0.190***	0.184***	0.258**
Cum Review Valence * Degree of ORH	H3	0.050***	0.055***	0.082**
Cum Review Volume * Degree of ORH		0.016	-0.005	-0.066
Cum Response Volume		-0.005	-0.005	-0.007
June 2015		-0.138***		
July 2015		-0.438***		
August 2015		0.010		
September 2015		-0.029	-0.039***	
October 2015		-0.365***	-0.372***	
November 2015		-0.685***	-0.690***	
December 2015		-1.255***	-1.260***	
January 2016		-0.921***	-0.927***	
February 2016		-0.860***	-0.866***	
March 2016		-0.678***	-0.684***	0.182***
April 2016		-0.537***	-0.543***	0.326***
May 2016		-0.307***	-0.312***	0.557***

(Continued)

Table A.2. (Continued).

Independent Variables	(5) Robust 3 Months	(6) Robust 6 Months	(7) Robust 12 Months
June 2016	-0.247***	-0.251***	0.617***
July 2016	-0.646***	-0.650***	0.219***
August 2016	-0.121*	-0.124**	0.746***
September 2016	-0.401***	-0.403***	0.467***
October 2016	-0.344***	-0.345***	0.526***
November 2016	-0.535***	-0.536***	0.336***
December 2016	-1.119***	-1.118***	-0.246***
Constant	0.469***	0.490***	-0.338***
Observations	5,160	4,398	2,864
Number of hotels	261	261	261
R-squared	73.41%	75.15%	66.80%
F	236.65***	260.28***	309.36***

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