ELECTRONIC WORD OF MOUTH AND HOTEL PERFORMANCE:

A META-ANALYSIS

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Abstract: This study synthesizes existing empirical results about the relationship between electronic word of mouth (eWOM) and hotel performance via meta-analysis. Based on estimates from 25 articles, the average eWOM valence-based elasticity is estimated to be 0.888, whereas the average volume-based elasticity is 0.055. A hierarchical linear model is applied to uncover five aspects that explain variations in eWOM elasticities: research setting, data structure, variable measurement, model specification, and research outlet. The estimation results highlight several significant aspects affecting elasticity, such as year of study, geographic setting, panel data structure, data frequency, performance measurement, control of price variable, and function form. Finally, implications are provided for researchers and hoteliers.

Keywords: meta-analysis; eWOM effect; hotel performance; hierarchical linear model (HLM)

1. Introduction

It is well known that the intangible, perishable nature of tourism and hospitality products makes it difficult for consumers to gauge their quality prior to purchase. This phenomenon underscores the perceived uncertainty in consumers' decision-making process as it relates to travel, which fosters a fundamental need to obtain reliable, useful information when considering travel options (Liu & Park, 2015). With the recent proliferation of social media websites that facilitate the sharing of travel experiences with others, the role of online consumer reviews has become increasingly pertinent for the tourism and hospitality industry. A recent report by Mintel (2016) revealed that consumer review websites have been identified as the second most frequently used information source apart from search engines (e.g., Google) when travelers are researching a trip. Service providers have therefore begun to leverage online consumer reviews, also known as electronic word of mouth (eWOM), as marketing tools by inviting consumers to post their personal experiences for others (Litvin & Dowling, 2016).

In the same vein, the relationship between online consumer reviews and hotel performance has gained considerable attention from tourism and hospitality scholars (Schuckert, Liu, & Law, 2015). Importantly, however, existing research remains largely inconclusive. For example, while some studies suggest positive effects of eWOM on predicting hotel performance (e.g., Ogut & Tas, 2012; Ye, Law, Gu, & Chen, 2011), others have found that the influence is negligible or context dependent (Lu, Ye, & Law, 2014). Although prior research has provided essential insight into the role of eWOM, a consensus about its utility vis-à-vis the tourism and hospitality industry is elusive. Thus, the present study argues that the range of research approaches, settings, designs, data sources, and estimation methods used in earlier analyses may hinder generalizability (Floyd, Freling, Alhoqail, Cho, & Freling, 2014). For instance, eWOM's influence on hotel performance has been found to vary across different hotel classes (Blal & Sturman, 2014). Using panel data to facilitate sound analyses, Duverger (2013) demonstrated a non-linear (i.e., inverted U-shaped) relationship between eWOM and hotel performance. Therefore, the aim of this research is to assess eWOM's elasticity relevant to hotel performance by considering five aspects as contextual variables: research setting, data structure, variable measurement, model specification, and research output.

To fill this theoretical gap in the current literature, this study employs a meta-analysis method, reviewing 25 research articles related to the tourism and hospitality industry. Meta-analysis enables the authors to synthesize the literature stream quantitatively and therefore assess eWOM elasticity as it corresponds to hotel performance (You, Vadakkepatt, & Joshi, 2015). More specifically, this paper takes into account two separate metrics in measuring eWOM elasticity—valence- and volume-based approaches—to identify contributing factors to the sizable variation among estimated eWOM elasticities. In this vein, eWOM elasticity refers to percentage changes of firm performance against percent changes of eWOM consisting of valances and volumes of review ratings (Floyd et al., 2014; You et al., 2015). This research considers eWOM as numerical review ratings provided by consumers on travel review/booking websites (Park & Nicolau, 2015). By doing so, this research represents a pioneering effort to synchronize the eWOM–performance relationship in the tourism and hospitality literature. Use of regression-based meta-analysis makes it possible to accommodate and correct potential biases in previous econometric results objectively (Stanley & Doucouliagos, 2012).

2. Literature Review and Conceptual Framework

2.1 Theoretical background

Online consumer reviews have long been considered important sources of information; they allow potential customers to assess the quality of a product or service and develop an associated image (Filieri, 2016). Online reviews play a particularly central role in the hospitality and tourism industry due to the services' inherent intangibility and perishability. Indeed, consumers find it difficult to evaluate the quality of services before actually consuming them (O'Connor, 2010; Yang, Mueller, & Croes, 2016). This unique characteristic implies that people experience significant uncertainty over their choices and, thus, require substantial information in order to reduce perceived risks and make informed decisions. Dickinger (2011) found that online reviews posted by other travelers are often thought of as more up-to-date, informative, enjoyable, and reliable than information from travel service providers.

The prevalence of social media websites has created an environment where people face information overload when confronted with numerous online consumer reviews. As such, in an effort to reduce decision-making costs, they tend to rely more on review ratings than textual comments. In other words, consumers who peruse multiple reviews are likely to focus on the reviews' valence and volume, which serve as proxies for underlying product quality (Chaiken & Maheswaran, 1994) and hotel reputation (Anderson & Lawrence, 2014). Previous studies have indicated that the valence and volume of online reviews indeed influence tourists' decision-making process (Liu & Park, 2015), along with organizations' pricing strategies and performance (Xie, Chen, & Wu, 2016). Signaling theory posits that people rely on signals when tasked with making a judgment that requires balancing uncertainties. Given that most travelers today use online channels to purchase tourism products, information asymmetry about product quality has become widespread (Lu et al., 2014). Abrate, Capriello, and Fraquelli (2011) discussed the importance of quality signals associated with hotel reputation as indicated by star rating and brand affiliation. Online consumer reviews that reflect and justify users' attitudes toward products help readers reduce information asymmetry about product quality and, as a result, increase their likelihood of purchasing relevant products (Park & Nicolau, 2015). In addition, online reviews' perceived effectiveness and reliability reduce search costs for consumers and enhance sellers' trustworthiness, which persuades people to pay more for products and ultimately increases sales (Pavlou & Dimoka, 2006).

The valence of online reviews—that is, the evaluative direction (positive or negative) of the review in terms of service experience—is more effective than the midpoint of an individual's attitude toward the product (Mudambi & Schuff, 2010). Put another way, one-sided reviews that clearly indicate the direction of a consumer's opinion generate more diagnosticity and greater salience than moderate reviews. The accessibility-diagnosticity model suggests that a piece of information is perceived as diagnostic when it assists consumers in deeming an alternative worthy of further consideration (Feldman & Lynch, 1988). In contrast, online comments that do not help consumers determine whether a product warrants deliberation are not considered diagnostic (Herr, Kardes, & Kim, 1991). Park and Nicolau (2015) demonstrated that consumers consistently consider extreme ratings (whether positive or negative) to be more useful and enjoyable than moderate ratings. Furthermore, people find negative reviews more helpful than positive comments, as the guidance they receive is likely to reduce loss rather than increase gain (c.f. Kahneman & Tversky, 1979).

The volume of online consumer reviews underpins the bandwagon effect (see Van den Bulte & Lilien, 2001). A greater volume of opinions provided by other consumers positively affects customers' judgment, regardless of whether the opinions are positive or negative (Babić Rosario, Sotgiu, De Valck, & Bijmolt, 2016). This phenomenon is tied to herding behavior, otherwise known as social contagion, where people are likely to mimic others' situational behavior in order to reduce their own risk (Banerjee, 1992; Iyengar, Van den Bulte, & Choi, 2011). For purposes of this paper, the greater the number of opinions shared online by existing consumers, the greater the chance that other customers will become aware of the product; message repetition attracts consumers' attention (Duan, Gu, & Whinston, 2008).

2.2 The effects of online consumer reviews on hotel performance in the hospitality and tourism industry

Numerous studies have empirically examined the relationship between online consumer reviews and hotel performance. Ogut and Tas (2012) discovered that customer ratings boost hotel performance and affect hotel room prices (Nieto et al., 2014). Several studies measured hotel performance by the proxy variable of number of reviews for a property (see Ogut & Tas, 2012; Ye, Law, & Gu, 2009). Ye et al. (2011) found that a 10% increase in review ratings posted on a major Chinese online travel agency (OTA) increased online hotel bookings (measured by number of consumer reviews on hotels) by more than 5%. In a more comprehensive study investigating 10 major cities (five in Europe and five in the United States), Anderson and Lawrence (2014) assessed hotel-level word of mouth (WOM) by using ReviewPro's Global Review Index. The index is an aggregate of millions of social media reviews in more than 35 languages, from OTAs, review websites, and social media platforms. Results revealed that the review index positively influenced not only the elasticity of hotel performance but also room rates.

Consistent with the above literature, two elements comprise consumers' online reviews of hotels—valence (i.e., review ratings) and volume (i.e., review number)—each of which plays a distinct role in shaping business performance. For example, a positive valence affects revenue per available room (RevPAR) in luxury hotels, whereas review volume influences low-tier hotels' performance (Blal & Sturman, 2014). However, these results are inconsistent across studies: Kim, Lim, and Brymer (2015) determined that only valence, not volume, affects hotel performance.

Different from other research, Duverger (2013) focused on a longitudinal panel data sample (138 hotels with monthly performance) in evaluating the temporal dynamic nature of market share via online reviews collected from three major OTAs (TripAdvisor, Orbitz, and Expedia). A positive relationship was identified between average hotel property ratings and the ratio of a property's RevPAR to that of the market. Interestingly, the study revealed a quadratic (i.e., inverted U-shaped) relationship, implying that the effect of review ratings has diminishing returns.

From a methodological perspective, caution must be exercised around the endogeneity of eWOM. In the hotel industry, managerial expertise contributes to performance in several ways: hotels with more effective operational management tend to receive high consumer ratings, and customers will likely prefer to stay in hotels that are operating well. Taken together, these factors encourage increased bookings compared to hotels with poorer management. To account for endogeneity in the statistical model, Lu et al. (2014) applied a difference-in-difference approach by using large panel data (more than 40,000 observations) to eliminate unobservable factors along with the endogenous effect. They also discussed the importance of considering a moderation effect associated with hotel scales, which interacts with the relationship between consumer ratings and hotel performance (see Blal & Sturman, 2014). Several scholars have also considered other contextual variables involved in review patterns, such as rating variations (Xie, Zhang, & Zhang, 2014) and hotel features, including operational strategy (e.g., management response to consumer reviews) and dates of demand between weekends and weekdays (Schamel, 2012). Phillips, Barnes, Zigan, and Schegg (2017) investigated textual review and rating datasets from 68 online platforms to assess their effects on performance for 442 hotels. Based on the results of sentiment analysis, they concluded that positive hotel experiences in general have the greatest impact on hotel demand and revenue.

These research efforts provide valuable information. To develop a better understanding of the effects of online consumer reviews, however, it is necessary to address the systematic variation resulting from diverse contextual factors (Blal & Sturman, 2014). It is also plausible that the multiple research approaches, settings, and data sources utilized in analyses of online consumer reviews may render generalizable conclusions nearly impossible (Floyd et al., 2014). Even when studies focus on similar empirical contexts, there are conflicting findings about eWOM volume and valence. Given the importance of these metrics to the topic at hand, this study attempts to synthesize extant research on eWOM and compare the elasticities of eWOM volume and valence to uncover their effects on hotel performance.

2.3 Conceptual framework of meta-analysis

The conceptual model of meta-analysis addresses the following factors related to the varied effects of online consumer reviews (i.e., eWOM elasticity) on hotel performance: research setting (i.e., research time, geographic setting, and hotel class); data structure (i.e., panel data, sample size, and data frequency); variable measurement (i.e., eWOM platform, performance measures, and elasticity type); model specifications (e.g., omitted variables such as price and other eWOM, dynamic specifications, functional form, and model complexity); and research outlet (i.e., journal article; Babić Rosario et al., 2016; De Maeyer, 2012; Floyd et al., 2014; Purnawirawan, Eisend, De Pelsmacker, & Dens, 2015; You et al., 2015; see Figure 1). The following section discusses these factors in greater detail.

(Please insert Figure 1 about here)

2.3.1 Research setting

Research time

In line with the expansion of IT technology, more and more travelers have come to embrace eWOM platforms to familiarize themselves with hotels prior to booking. In previous years, when eWOM platforms were less popular, eWOM elasticity was small and even negligible. Lewis and Zervas (2016) found that ratings posted on review platforms became more influential over time in determining hotel demand, a fact that is explained by these platforms' growing popularity. Therefore, the eWOM elasticity of hotel performance is expected to increase over time. Formally, this research proposes that

H1: eWOM elasticities increase over time.

Geographic setting

Consumers' cultural background is generally considered an important factor in dictating information-seeking and purchasing behaviors. Hofstede's cultural dimensions theory (2010) suggests that national cultures vary based on the six dimensions of power distance, individualism/collectivism, uncertainty avoidance, masculinity/femininity, long-term orientation, and indulgence/self-restraint. This theory has been well applied in the tourism industry, unveiling that Chinese travelers' behavior is largely shaped by relatively higher levels of power distance, collectivism, femininity, and long-term orientation compared to other cultures (Reisinger & Crotts, 2010). In exploring differences in web communication behaviors between American and Chinese travelers, Park and Reisinger (2012) discovered heterogeneous behaviors across information seeking, communication, and transactions. More specifically, Chinese travelers from highly collectivistic societies tend to use the Internet for social purposes and entertainment, and they generally perceive higher risks when shopping online. Thus, it is important to assess geographical context—in this case, whether the hotels investigated are located in China or elsewhere. These arguments lead to the following hypothesis:

H2: eWOM elasticities are lower with hotels in China than elsewhere.

Hotel classes

Consumers' online review habits appear to vary by hotel class. Indeed, consumers are more likely to leave comments when they stay in higher-end hotels versus lower-end accommodations (Miguens, Baggio, & Costa, 2008). Blal and Sturman (2014) found that eWOM volume appears to exert positive effects on economy, midscale, and upper-midscale hotels, whereas effects are negative for upscale and luxury hotels. Furthermore, the star ratings reflecting hotel classes serve as another signaling factor (Lu et al., 2014). A five-star hotel is thought to provide guests with high-quality facilities and services, which affects customers' expectations for service consumption. Indeed, although a five-star hotel may have negative reviews, consumers are still confident in anticipating better quality compared to lower hotel classes with higher consumer ratings. Thus, the following is hypothesized:

H3: eWOM elasticities are higher with low-class hotels than mid- and high-class hotels.

2.3.2 Data structure

Panel data

Longitudinal panel data provide researchers clearer insights into causality while controlling for potential confounds (Rindfleisch, Malter, Ganesan, & Moorman, 2008). For example, because panel data generally contain a greater degree of freedom and within-in-unit variation than cross-sectional data, more meaningful model parameters are likely to be obtained (Baltagi, 2008). As a result, findings derived from panel data are often considered more informative when inferring a factual relationship between the variables being analyzed (Floyd et al., 2014). Therefore, the following is proposed:

H4: eWOM elasticities are different between those studies analyzing panel and cross-sectional data.

Sample size

There is substantial evidence that a sufficient sample size is essential to achieving acceptable error in model estimates and to determining error in the parameters being estimated, which is associated with coefficient variation (Beaman, Huan, & Beaman, 2004). Sample size ultimately reflects the accuracy and reliability of findings. Therefore, this study argues that an appropriate sample size is necessary to ensure the accuracy of empirical findings delineating the eWOM–performance relationship. Additionally, sample size can influence the magnitude of estimated eWOM elasticities. Thus, the following is hypothesized:

H5: eWOM elasticities vary across models using different sample sizes.

Data frequency

A finer level of temporal aggregation of the variable (e.g., a daily rather than monthly, quarterly, or yearly level of data) used in the empirical model influences eWOM volume and valence elasticities. Essentially, data aggregation at a coarser level is more likely to dilute variations of performance as an outcome variable (You et al., 2015). Thus, the following hypothesis is proposed:

H6: eWOM elasticities are different across levels of data aggregations across weekly, quarterly, and yearly formats.

2.3.3 Variable measurement

eWOM platform

It is important to address whether all eWOM communication channels generate equal or disparate effects (Ya et al., 2015). A large number of studies in tourism and hospitality have focused on specific eWOM platforms, such as TripAdvisor, booking.com, ctrip.com, or Yelp (e.g., Park & Nicolau, 2015; Xie et al., 2014). Research has also found that disclosure of a reviewer's identity increases the perceived usefulness and trustworthiness of online reviews (Liu & Park, 2015). Comments posted on platforms that offer structured fields for user information and encourage reviewers to reveal their true identities (e.g., TripAdvisor) are more valuable to other consumers than information provided on platforms that allow reviewers to remain anonymous. In this respect, Ya et al. (2015) found that platforms such as community-based sites, blogs, and online review websites play an important role in eWOM valence elasticities. In particular, because TripAdvisor is the largest online community for travelers and has a well-developed eWOM metric system (Levy, Duan, & Boo, 2013), and because many OTA websites share TripAdvisor's hotel eWOM metrics, TripAdvisor as a platform can be expected to provide the largest eWOM effect. These arguments lead to the following hypothesis:

H7: eWOM elasticities are different depending on types of review platforms.

Performance measures

There are two main approaches to measuring hotel performance in studies investigating eWOM effects in tourism: direct performance measures and proxy measures of performance. The former (e.g., room nights sold, room revenue, occupancy rate, and RevPAR) is relatively straightforward when interpreting performance elasticities (see Anderson & Lawrence, 2014). However, due to restricted access to actual performance data, numerous studies have utilized proxy measures of performance, such as the number of reviews written on review websites, based on the assumption that review volume reflects the number of consumers who have experienced a specific product or service (see Ogut & Tas, 2012; Ye et al., 2009, 2011). Thus, it is important to understand the influence of different performance measures on eWOM elasticity.

H8: eWOM elasticities are different depending on the type of hotel performance measurement.

Elasticity type

As discussed in Section 2.1, online consumer reviews vary in volume (i.e., the total number of eWOM units regarding a specific product or service) and valence (i.e., the idea that eWOM can be positive, negative, or neutral; Liu, 2006). Volume refers to the number of consumers who have experienced a level of popularity about a product in the market. Hence, it can be expected that eWOM volume enhances consumers' awareness of a given product and reduces their uncertainty about it, which ultimately encourages sales (Chintagunta, Gopinath, & Venkataraman, 2010).

eWOM valence captures the favorability, sentiment, or polarity of consumer reviews related to evaluations and reputation of a product or firm. Consumers' attitudes toward and/or preferences for a product can be formed, reinforced, or changed by directional consumer reviews (Kim & Gupta, 2012). Thus, discerning two metrics of eWOM— valence and volume—makes it possible to test the heterogeneity of sales elasticities. Therefore, the following is hypothesized:

H9: eWOM elasticities are different according to the types of elasticities estimated.

2.3.4 Model specification

Price control

Tourism and hospitality services have long been regarded as high-involvement products that present significant risk, complexity, and price (McKercher, 2016). In addition, people do not purchase these types of service products as often as they do routine products (i.e., low-involvement products). As a result, consumers who buy high-involvement products engage in an extensive problem-solving process that requires significant time and effort as they search for and review relevant information (Mathwick & Rigdon, 2004). This implies that when consumers purchase expensive (i.e., high-involvement) products, they are likely to look for reliable and useful information by depending more on eWOM compared to those who buy inexpensive products. Moreover, because price is closely associated with other unobservable characteristics that may influence hotel performance (e.g., location), excluding a price variable can lead to an omitted variable bias of estimates. Therefore, estimated eWOM elasticities can be expected to depend on an empirical model's specifications, including the inclusion or lack of a price measure. These arguments lead to the following hypothesis:

H10: eWOM elasticities are different between those studies controlling and overlooking room rates.

Because different eWOM metrics (i.e., valence, volume, and valence) capture different aspects of eWOM effect, disregarding other eWOM metrics in the model may lead to some omitted variable bias as well. Therefore, the following is hypothesized:

H11: eWOM elasticities are different between those studies controlling and overlooking other eWOM metrics.

Dynamic specification

It may take time for hotels to internalize the benefits resulting from a positive online reputation; therefore, some studies specify lagged independent variables in the empirical model (Blal & Sturman, 2014; Lu, Xiao, & Ye, 2012; Xie, Zhang, Zhang, Singh, & Lee, 2016), especially for weekly or monthly data. In general, specifying lagged eWOM independent variables can be expected to result in greater eWOM elasticity of hotel performance.

H12: eWOM elasticities are different between those studies stipulating and overlooking lag of independent variables and others.

Functional form

There are four typical functional forms in econometric models that estimate eWOM effects on hotel performance. A log-log form includes the dependent variable (i.e., performance) and the independent variable (i.e., eWOM valence or volume) in the estimated model as the natural log of the original variable. A log-lev form refers to the specification that log-transformed only the dependent variable while leaving the independent variable untransformed, whereas a lev-log form suggests the opposite. Lastly, a lev-lev form includes untransformed dependent and independent variables of interest (Floyd et al., 2014). As suggested by previous literature, the functional form can influence eWOM elasticity (Floyd et al., 2014; You et al., 2015). Formally, the following hypothesis is proposed:

H13: eWOM elasticities are different according to different functional forms in estimating eWOM effects.

Model complexity

The number of independent variables indicates an empirical model's complexity. Because eWOM valence and volume also reflect some hotel characteristics that shape hotel performance, omitting these key factors may lead to an "omitted variable bias" (Greene, 2007) associated with the eWOM elasticity estimate. Therefore, eWOM elasticity can be expected to depend on model complexity as measured by the number of independent variables in the empirical model. Thus, the following is hypothesized:

H14: eWOM elasticities are influenced by the number of independent variables being estimated in research.

2.3.5. Research outlet

Journal article

This research analyzed whether articles were published in research journals and how the research outlet influences the estimated eWOM elasticities. If such influences exist, they can be explained by the issue of publication bias, which refers to "the selective publication of studies with a particular outcome, generally those which are statistically significant, at the expense of null studies" (Ferguson & Brannick, 2012, p. 120). Publication bias may result in reduced inter-study variability and inflation of biased mean estimates (Dickersin, 2005), which may potentially affect estimated eWOM elasticities (Floyd et al., 2014). More specifically for journal publication bias, this bias indicates that researchers are less motivated to submit manuscripts with non-significant eWOM effect to journals because editors and reviewers are less likely to accept such manuscripts (Card, 2015, p. 257). As a result, less significant and non-significant eWOM effects are more likely to be seen in research from other outlets, such as conference papers and working papers, which receive less pressure from editors and reviewers. These arguments lead to the following hypothesis:

H15: eWOM elasticities are less in journal articles than other resources.

3. Coding and Empirical Models

3.1 Data collection and coding

A search was conducted for relevant empirical literature investigating the relationship between hotel performance and eWOM in online reviews by using the Google Scholar search engine, EBSCO Hospitality & Tourism Complete database, SSRN's eLibrary, and the ProQuest Dissertations & Theses database. The final search was completed on Dec. 11, 2016. The keywords used in the literature search included "online rating", "hotel sales", "hotel performance", "online reviews", "hotel demand", and "TripAdvisor". The references in identified papers were consulted in a search for further studies. The search was restricted to English-language materials but was not limited to journal articles.

After the papers were collected, they were screened according to the following criteria: (1) valence and/or volume metrics of online reviews were used as independent variables, and hotel performance measures (e.g., revenue, RevPAR, occupancy rate, room nights sold, review volume as sales proxy) as dependent variables; (2) the studies' empirical models had no latent variable with which to measure hotel performance or eWOM metrics; and (3) elasticities were either provided in each paper or could be clearly derived from the estimated coefficients and other information. Room rate was not considered as a performance measure; therefore, estimates using room rate as the dependent variable were excluded. Elasticity was chosen as the effect size in the meta-analysis for several reasons. First, elasticity has an inherent economic meaning and has been widely used in meta-analyses of marketing literature (Floyd et al., 2014; You et al., 2015). Second, many studies in the sample reported elasticity estimates directly without providing other necessary information to calculate alternative effect sizes, such as *t* statistics and partial correlations (Stanley & Doucouliagos, 2012). Third, some elasticity estimates were obtained from the interactions between eWOM metrics and dummy/categorical variables, which compounded the challenges of obtaining standard errors and *t* statistics.

The literature search resulted in a total of 25 papers comprising the meta-sample. This sample covered a variety of article types, including journal articles (19), dissertations and theses (2), an academic report (1), a book chapter (1), a conference paper (1), and a working paper (1). eWOM elasticities that used metrics of variance and ranking were excluded; very few studies reported them, and the ranking metric is a function of review valence and volume (Rianthong, Dumrongsiri, & Kohda, 2016). Because studies in the sample used different functional forms in their empirical models, regression coefficients were transformed into elasticities by using formulas suggested by Floyd et al. (2014) and You et al. (2015). For the log-log function, the elasticity is the regression coefficient β itself; for the lev-lev function, the elasticity is $\beta\bar{x}/\bar{y}$ ($\bar{y}$ and $\bar{x}$ are the mean values of the dependent and independent variables, respectively); for the log-lev function, the elasticity is $\beta\bar{x}$; and for the lev-log function, the elasticity is $\beta/\bar{y}$. If some studies failed to report information necessary for the meta-analysis, every effort was made to contact the authors.

Most studies in the sample presented multiple estimations using different model specifications and/or different sub-samples. Moreover, they sometimes presented multiple elasticity estimates based on different eWOM metrics in a single estimation. Therefore, multiple elasticity estimates were coded from different estimations in a single study. By doing so, efficiency was improved from the expanded sample size and additional within-study variation across elasticity estimates (Melo, Graham, & Noland, 2009). The final sample was composed of a total of 161 valence- and volume-based estimates taken from 25 studies. Apart from elasticities, 15 independent variables discussed previously were also coded to explain variations in eWOM elasticities. Table 1 presents the coding schemes and descriptions of these variables. In the research team, two coders recorded and calculated elasticities and the abovementioned independent variables. After independent coding, the coders verified the consistency of results and resolved any disagreements by discussion.

(Please insert Table 1 about here)

3.2 Empirical models

Hierarchical linear modelling (HLM) was used to uncover the impacts of various factors on eWOM elasticities. HLM is particularly suited to modelling data with a nested structure, as in the case of this dataset: an elasticity estimate is nested in a study. The traditional ordinary least squares (OLS) regression assumes each observation to be independent from the others; however, in this data set, different elasticities from the same paper can be correlated with one another. In this research context, the HLM model can effectively account for within-study error correlations stemming from unobserved study-specific factors (Edeling & Fischer, 2016), providing more reliable estimation results. An HLM model is specified as follows:

$$y_{ij} = \mathbf{X}_{ij}\beta + \mu_i + \varepsilon_{ij}, \tag{1}$$

where *i* indexes each study, and *j* indexes each elasticity estimate in study *i*. In the model, y_{ij} denotes the *j*th elasticity estimate in study *i*, and $\mathbf{X}_{ij}$ represents a set of independent variables.

Moreover, ε_{ij} is the normal error term (as in OLS regression), and μ_i denotes the study-specific effect that captures unobserved characteristics of the study that remained unchanged across estimates within the study; ε_{ij} and μ_i follow an independent normal distribution with a mean of zero and a variance of σ_{ε}^2 and σ_{μ}^2, respectively. The HLM model was estimated by using the maximum likelihood estimation with the expectation-maximization algorithm, which is expected to generate asymptotically efficient and consistent estimates (Hox, Moerbeek, & van de Schoot, 2010).

4. Results

4.1 Coding results

First, all 161 eWOM elasticities from 25 studies were coded. Most of these studies reported a positive and significant effect of eWOM on hotel performance. However, some studies found insignificant effects based on model estimation results. For example, Blal and Sturman (2014) obtained an insignificant effect of eWOM volume on hotel performance based on 319 hotels in London, and similar results on this insignificant effect were identified by Kim et al. (2015) from 128 U.S. hotels in a hotel chain. Furthermore, some studies investigated the eWOM effect for hotels in different classes; therefore, different eWOM elasticities were extracted for them. More specifically, Anderson (2012) and Anderson and Lawrence (2014) found larger eWOM elasticities for mid-scale hotels compared to high-end ones; however, Duverger (2013) and Blal and Sturman (2014) showed that eWOM elasticities are larger for high-end hotels.

Figure 2 shows the distributions of reported elasticity estimates in the data. For all elasticities (in the upper panel), the mean value is 0.722 with a standard deviation of 0.965. As shown in the histogram, the majority (92.55%) of elasticity estimates are positive. For valence-based elasticities (N = 129), the mean value is 0.888 and the standard deviation is 0.999; both are larger than their volume-based elasticity counterparts (N = 32), which are 0.055 and 0.329, respectively. These results suggest that a 1% increase in eWOM valence would lead to a 0.722% increase in hotel performance, whereas a 1% increase in eWOM volume would lead to a 0.055% increase in hotel performance. As shown in the middle- and lower-panel histograms, compared to valence-based elasticity, volume-based elasticity covers a narrower range of positive values. Note that there is an apparent outlier, as indicated in the left tail of the distribution of volume-based estimates. Further empirical investigation showed that the results would not change if this estimate was removed; these results are available upon request.

(Please insert Figure 2 about here)

Table 2 presents the descriptive statistics of continuous independent variables in the specified HLM model. The average data year of the sample was around 2011, and the year ranged from 2007 to 2014. Out of all elasticity estimates, 12.4% were based on Chinese hotel data, and 59.0% used panel data covering hotel properties over time. A large proportion (58.4%) of the estimated elasticity stemmed from TripAdvisor-based metrics. Notably, 16.8% of estimates were estimated by using review volume as a proxy of hotel performance, which may introduce significant measurement errors. As for variables related to the empirical model specification, 17.4% of estimates were obtained from a model incorporating a price variable, 23.6% from models using the lagged value of eWOM metrics as independent variables, 53.4% from models covering other eWOM metrics, and 39.1% from models in a linear functional form (lev-lev) without log-transformation of variables. Moreover, the average number of independent variables specified in the empirical model was around nine. Lastly, 68.9% of elasticity estimates were collected from journal articles. Table 3 presents the descriptive statistics of categorical independent variables. Across the sample, 71.43% of estimates were based on a sample of hotels across different classes. In this research, the sample included a variety of observation frequencies, with month-based estimates outnumbering quarter-, year-, and week-based ones. As stated earlier, the sample was dominated by valence-based elasticity estimates, which accounted for 80.12% of all estimates. The correlation matrix of independent variables was also calculated. Most coefficients were below 0.5, suggesting the absence of multi-collinearity (Gujarati & Porter, 2010).

(Please insert Table 2 about here)

(Please insert Table 3 about here)

4.2 HLM results

Table 4 presents the estimation results of the HLM models. A series of models was estimated depending on the type of eWOM elasticities (i.e., the general eWOM elasticity, the eWOM valence elasticity, and the eWOM volume elasticity). Moreover, because some studies used the review number to proxy hotel sales, which may yield problematic results, different HLM specifications were run with and without elasticities from these studies. In Model 1, only a few estimated coefficients were statistically different from zero. First, *proxy_perf* had the largest significant estimated coefficient across independent variables, and using review volume as a performance proxy substantially inflated the estimated elasticity by 1.343 points. H8 is therefore supported. Second, this result suggests that volume-based elasticity (*elasticity_type* = volume) is 0.751 point less than valence-based after controlling for other factors. H9 is therefore supported.

Third, elasticity estimates from the linear function without log-transformation of any variables were 0.524 point less than estimates from other function forms. H13 is therefore supported. Fourth, sample size appeared to be negatively associated with estimated eWOM elasticity, and a larger sample size tended to generate a smaller elasticity estimate. H14 is therefore supported.

(Please insert Table 4 about here)

As shown in Model 1, using review volume as a performance proxy would substantially inflate the elasticity estimate; therefore, Model 2 was run using the same specification after excluding 27 estimates from relevant studies. In Model 2, the insignificant estimate of *year* provides little support to H1. The coefficient of *China* was negative and significant, suggesting that hotels in China derive considerably fewer benefits from eWOM valence and volume compared to their American and European counterparts. This result lends support to H2. For categorical variables, a positive coefficient indicates a more elastic effect of eWOM in this category compared to the reference category, and a negative coefficient indicates the opposite. Therefore, a positive coefficient of *class* = low indicates that the eWOM elasticity of low-class hotels is significantly lower than that obtained for the reference category: all types of hotels. H3 is therefore supported. Moreover, *panel_data* was estimated to be negative and significant, and the use of panel data substantially reduced the elasticity estimate by 0.908 point. H4 is therefore supported. Similarly, as suggested by the results, a larger sample size used in the empirical model was associated with a smaller calibrated elasticity estimate. H5 is therefore supported. As for data observation frequency, compared to monthly data (the reference category *freq* = monthly), weekly data generated a larger elasticity estimate by 0.306 point. However, the insignificant coefficients of *freq* = quarterly and *freq* = yearly indicated that quarterly and yearly data produced no statistical difference in the size of eWOM elasticities compared to monthly data. H6 is therefore partly confirmed. In addition, no empirical evidence was found to support a larger elasticity from TripAdvisor-based reviews. H7 is not supported by the result. Like Model 1, Model 2 highlights a smaller size for volume-based elasticity and is 0.776 point less than a valence-based elasticity, ceteris paribus.

Regarding variables related to model specification, the Model 2 results highlight the important role of price measures as a control variable in estimating eWOM elasticity. More specifically, controlling the price measure increased the size of eWOM elasticity by 0.130 point, suggesting that omitting the price measure leads to a significant downward bias. This result corroborates H10. However, the use of a lagged eWOM variable and inclusion of other eWOM variables did not explain the variation of eWOM elasticity in the sample, leaving H12 unsupported. The negative and significant coefficients of *linear_function* and *indep_vars* indicate that the use of a linear functional form (lev-lev) and more independent variables leads to a smaller elasticity estimate, lending support to H13 and H14. Lastly, the coefficient of *journal_article* was insignificant but positive, demonstrating that the magnitude of eWOM elasticity from journal articles is not statistically different from that of other types of studies. Therefore, H15 is rejected.

Because valence-based elasticity estimates dominated the sample, Model 3 presents the HLM results for valence-based elasticities only. Similar to the results of Model 1, online review volume was found to be a very poor proxy of hotel performance because of the significant and sizable estimated coefficient of *proxy_perf*. Therefore, in Model 4, those elasticity estimates that used review volume to proxy performance were excluded. Model 4 provided similar results to

Model 2, such as negative and significant estimated coefficients of *year*, *China*, *class* = low, *panel_data*, ln*sample_size*, and *linear_function*. However, some differences were noted. For example, using weekly data (*freq* = weekly), omitting price controls (*price_control*), and including more independent variables (*indep_vars*) did not necessarily induce a statistically different valence-based elasticity estimate.

Model 5 presents the estimation results of volume-based elasticities exclusively. Because only 32 observations were included, some categorical independent variables had to be omitted, such as *freq* and *class*, to provide more reliable statistical inference of the results. Note that no studies adopted review volume as a performance proxy in any of the 32 observations. As suggested by the significant coefficients of *year* and *TripAdvisor*, volume-based elasticity was also found to decrease over time, and volume-based elasticities from TripAdvisor reviews were significantly larger than others, revealing the central role of hotels' visibility on TripAdvisor in spurring performance. Therefore, H1 and H7 are supported for the valence-based eWOM elasticities. Furthermore, the model specification largely explained variation in volume-based elasticities across studies. More specifically, including price controls (*price_control*) and using lagged eWOM variables in the model (*lagged_indep*) often led to a larger volume-based elasticity estimate, whereas incorporating other eWOM independent variables (*other_eWOM*) decreased estimates. Another model specification variable, *indep_vars*, was also estimated to be significant, and its negative coefficient indicates that including more independent variables would reduce the size of volume-based elasticity.

5. Conclusion and Discussion

In light of the proliferation of online consumer review websites and the nature of tourism and hospitality products, eWOM has been recognized as one of the most important information sources in the industry. It not only affects consumers' decision-making process but also influences hotel performance. Hence, several scholars have attempted to estimate the effects of eWOM on hotel performance (e.g., Xie et al., 2014). Interestingly, their findings have been inconsistent and inconclusive. This study provides generalizable evidence, demonstrating the effects of online consumer reviews on eWOM elasticity according to volume- and valence-based metrics. Specifically, a meta-analysis using an HLM model was applied by synthesizing 25 studies on eWOM elasticity in the tourism and hospitality fields to identify factors explaining elasticity variation. This research thus offers important and insightful contributions to academics and practitioners in the tourism and hospitality industry.

This study resolves existing conflicts in the literature and sheds lights on generalized effects of eWOM volume and valence metrics by accounting for research setting, data structure, variable measurement, model specification, and research output as five aspects that influence eWOM elasticity of hotel performance. As a result, this research synthesizes extant research on eWOM elasticity. To the authors' knowledge, this is the first systematic attempt to compare the degree to which eWOM elasticities are different between different measurements. Indeed, the results of this study revealed that mean eWOM valence elasticity (0.888) is twice as large as its counterpart (0.417) in the general marketing field as reported by You et al. (2015), highlighting how necessary it is for hotels to maintain a high eWOM valence level to attract customers. This result can be explained by the experiential nature of hotel products: no one knows the quality of the product until consuming it. Customers therefore require supplemental independent reviews to make a decision and reduce the risks associated with purchase. However, the mean eWOM volume elasticity (0.055) is lower than its counterpart (0.236) in the general marketing field (You et al., 2015). One possible explanation is that, as one of the first industries to embrace online review platforms (Ong, 2012), eWOM valence elasticity is more substantial in the tourism and hospitality industries than in others. Therefore, effective reputation management may be especially rewarding for the tourism and hospitality business.

Second, these results underscored higher eWOM elasticity for mid-scale and high-end hotels, suggesting that these hotels should place high priority on monitoring and managing eWOM on various platforms in a timely manner. This finding falls into line with Blal and Sturman's (2014) and Lu et al.'s (2014) studies. Third, because TripAdvisor-based volume elasticity was found to be more pronounced than others, hoteliers should motivate their guests to post reviews on TripAdvisor over other platforms. Hotel managers' engagement with consumers' feedback on TripAdvisor is therefore of paramount importance. As shown in Table 2, approximately 60% of the sample have investigated TripAdvisor as a key platform for their research. Xiang, Du, Ma, and Fan (2017) have indicated a consistent conclusion that TripAdvisor has been widely perceived as a premier data source in the hotel industry due to the number of reviews available, wide distribution of review sentiment, adequate length of consumer reviews, credibility, and helpfulness. Finally, the results from this regression-based meta-analysis provide flexible estimates of eWOM elasticity-based, context-specific circumstances. Therefore, hotel chains and groups can calibrate property-specific eWOM returns based on the characteristics of each hotel and propose more effective strategies to prioritize reputation management in some of them.

This study provides some methodological implications and guidelines for researchers when investigating the eWOM–performance relationship in tourism and hospitality. First and foremost, it is inappropriate to use review volume to proxy hotel performance/sales in the empirical model because this results in a biased estimate of eWOM effect, based on this study's meta-analysis results. Checking Appendix A, around 30% of articles have considered the number of consumer reviews to measure hotel performance. Use of indicators that allow researchers to estimate actual performance, rather than proxy measurements, is suggested. Second, it is highly recommended that researchers collect panel data to understand the eWOM–performance relationship, if available. The estimates from panel data (60% of the sample) were found to be significantly different from others (40% of the sample used cross-section data). Due to several inherent advantages of panel data, this type of data is particularly useful to understand a causal relationship. Third, model specification is important to ensure a reliable estimate of eWOM effect. More relevant independent variables—in particular, the price variable—should be incorporated into the empirical model to alleviate the potential omitted variable bias. Lastly, since the results suggested that models using the lagged independent variables do not yield different results, use of the unlagged independent variables in empirical models is recommended to keep more observations in the sample. This finding is partially consistent with You et al.'s (2015) study concluding that the omission of a lagged term did not have significant influence on valence elasticities.

Some limitations of this study should be noted. First, due to sample size concerns, other eWOM metrics were not included, such as eWOM variance and online ranking. The estimated elasticities based on these metrics may present different patterns from those identified here. Second, eWOM elasticities in non-hotel hospitality settings were not considered. Lastly, since the standard error of elasticities was not coded due to data limitation, it was not possible to conduct some formal statistical procedures (e.g., funnel plot, fail-safe N, and standard error control in regression) to test the issue of publication bias rigorously (Orwin, 1983; Stanley & Doucouliagos, 2012). Therefore, it is recommended that future studies investigate alternative eWOM metrics and elasticities in other tourism and hospitality sectors, such as restaurants.

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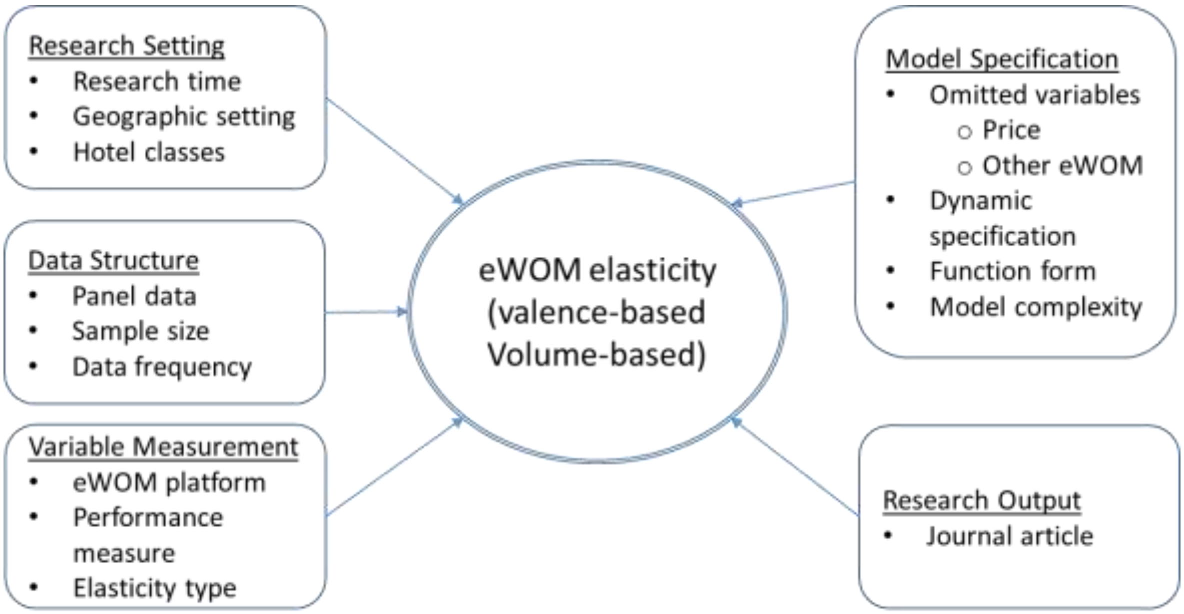

Figure 1. Conceptual framework of determinants of eWOM elasticity on hotel performance.

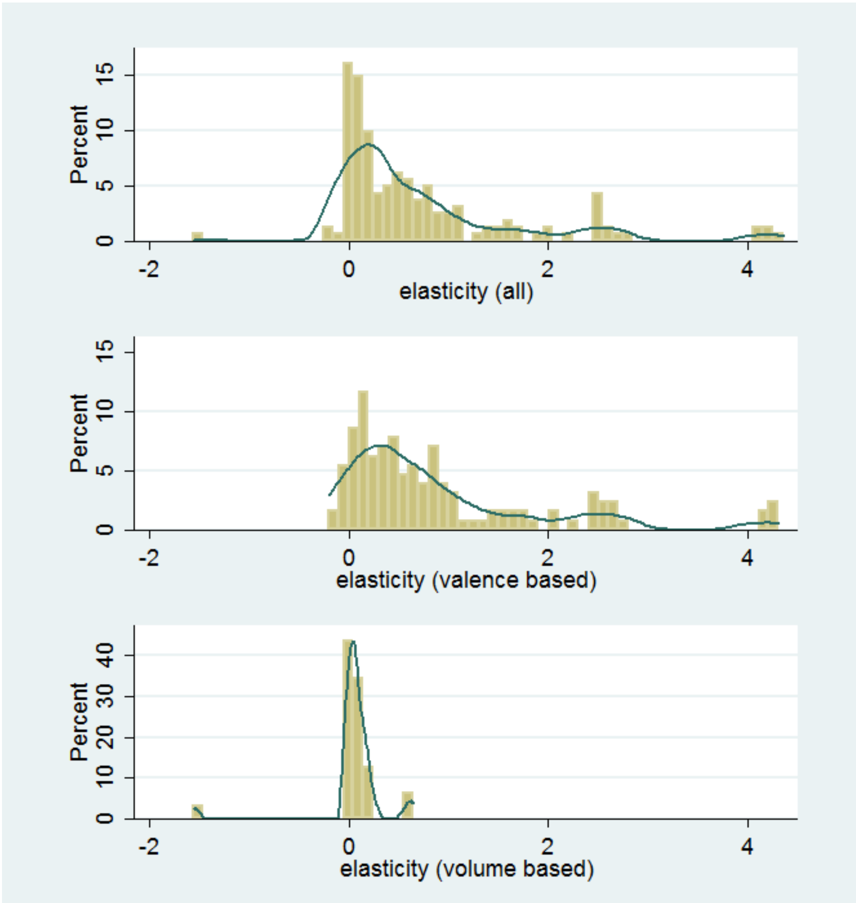

Figure 2. Histogram and kernel density of calibrated elasticity from extant literature.

Table 1. Coding scheme and description of independent variables.

Variable	Coding scheme	Description
Research setting		
year	midpoint of research period (in year)	time of study
China	1 = hotel properties in China; 0 = other	geographic setting
class	1= all types, 2 = low, 3 = mid, 4 = high	classes of hotels sampled
Data structure		
panel_data	1 = panel data; 0 = other	whether data cover multiple time periods
ln*sample_size*	log of sample size in the model	size of data sample
freq	1= weekly, 2 = monthly (reference category), 3 = quarterly, 4 = yearly	frequency of data observations
Variable measurement		
TripAdvisor	1 = TripAdvisor-based eWOM metric; 0 = other	platform effect of eWOM
proxy_perf	1 = number of reviews to proxy hotel sales as a performance measure; 0 = other	measurement of sales
elasticity_type	1= valence-based, 2 = volume-based	type of eWOM elasticity
Model specification		
price_control	1 = including price or average room rate as a control variable; 0 = other	omitted variable problem associated with price measures
lagged_indep	1 = specifying lag of independent variables; 0 = other	dynamic specification of independent variables
other_eWOM	1 = including other online eWOM measures in the empirical model; 0 = other	omitted variable problem associated with other eWOM metrics
linear_function	1 = linear function form (lev-lev); 0 = other	functional form of the model
indep_vars	number of independent variables in the empirical model	complexity of the model
Research outlet		
journal_article	1 = published in a research journal with ISSN; 0 = other	

Table 2. Descriptive statistics of continuous independent variables.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
year	161	2010.702	1.900	2007	2014
China	161	0.124	0.331	0	1
panel_data	161	0.590	0.493	0	1
ln*sample_size*	161	8.570	2.384	4.779	12.593
TripAdvisor	161	0.584	0.494	0	1
proxy_perf	161	0.168	0.375	0	1
price_control	161	0.174	0.380	0	1
lagged_indep	161	0.236	0.426	0	1
other_eWOM	161	0.534	0.500	0	1
linear_function	161	0.391	0.490	0	1
indep_vars	161	8.602	6.201	1	43
journal_article	161	0.689	0.464	0	1

Table 3. Descriptive statistics of categorical independent variables.

Variable (category)	**Freq.**	**Percent**
class = all	115	71.43
class = low	6	3.73
class = mid	17	10.56
class = high	23	14.29
freq = weekly	22	13.66
freq = monthly	75	46.58
freq = quarterly	42	26.09
freq = yearly	22	13.66
elasticity_type = valence	129	80.12
elasticity_type = volume	32	19.88

Table 4. Estimation results of HLM meta-analysis.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Elasticity type	All	All†	Valence	Valence†	Volume
year	-0.0761	-0.212***	-0.103	-0.267***	-0.0936**
	(0.074)	(0.054)	(0.089)	(0.083)	(0.046)
China	-0.517	-0.631***	-0.535	-0.714***	
	(0.523)	(0.178)	(0.602)	(0.240)	
class = low	0.458	-0.402***	0.417	-0.715***	
	(0.399)	(0.083)	(0.429)	(0.185)	
class = mid	0.397	-0.167	0.392	-0.337*	
	(0.262)	(0.126)	(0.275)	(0.197)	
class = high	0.466	-0.210	0.468	-0.382**	
	(0.381)	(0.130)	(0.423)	(0.156)	
panel_data	0.0464	-0.908***	-0.0268	-1.185***	0.0275
	(0.453)	(0.182)	(0.503)	(0.254)	(0.115)
ln*sample_size*	-0.199***	-0.236***	-0.192***	-0.289***	-0.0212
	(0.059)	(0.043)	(0.072)	(0.067)	(0.038)
freq = weekly	-1.076*	0.306**	-1.325***	0.265	
	(0.571)	(0.137)	(0.504)	(0.161)	
freq = quarterly	-0.143	0.154	-0.432	-0.244	
	(0.323)	(0.167)	(0.364)	(0.207)	
freq = yearly	0.0298	0.00583	-0.254	-0.310	
	(0.433)	(0.138)	(0.498)	(0.206)	
TripAdvisor	0.0765	0.113	0.0514	0.260	1.196***
	(0.453)	(0.125)	(0.567)	(0.180)	(0.095)
proxy_perf	1.343**		1.598***		
	(0.561)		(0.553)		
elasticity_type = volume	-0.751***	-0.776***			
	(0.161)	(0.145)			
price_control	-0.0463	0.130**	-0.129	0.0469	0.480***
	(0.353)	(0.065)	(0.409)	(0.129)	(0.033)
lagged_indep	-0.0603	0.130	-0.208	0.172	0.0735**
	(0.252)	(0.125)	(0.395)	(0.155)	(0.027)
other_eWOM	0.0534	-0.0259	0.0521	-0.108	-0.189***
	(0.137)	(0.086)	(0.158)	(0.117)	(0.043)
linear_function	-0.524**	-0.484***	0.0348	-0.410**	-0.0492
	(0.231)	(0.179)	(0.527)	(0.202)	(0.097)
indep_vars	-0.0116	-0.0188**	-0.00597	-0.00359	-0.0638***
	(0.011)	(0.007)	(0.008)	(0.010)	(0.009)
journal_article	0.395	0.0861	0.307	-0.108	-0.0731*
	(0.378)	(0.103)	(0.392)	(0.165)	(0.041)
constant	155.4	429.8***	210.2	541.8***	188.0**
	(150.234)	(108.872)	(180.474)	(167.747)	(92.439)

$\ln\sigma_{\mu}$	-0.655**	-16.37	-0.561**	-22.67	-22.92
	(0.284)	(46.347)	(0.284)	(51.009)	(81.500)
$\ln\sigma_{\varepsilon}$	-0.647**	-1.085***	-0.621**	-1.138***	-2.011***
	(0.263)	(0.105)	(0.299)	(0.132)	(0.137)
# of observations	161	134	129	102	32
# of studies	25	19	25	19	10
AIC	336.7	127.4	289.6	95.36	-17.87
BIC	404.5	182.5	349.7	145.2	-3.2
ll	-146.3	-44.71	-123.8	-28.68	19.93

(Notes: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, * indicates significance at the 0.1 level. Robust standard errors are presented in parentheses. † indicates that the sample excludes elasticities using review counts as hotel performance proxy.)