LEVERAGING HOTEL PERFORMANCE BY CONSUMER REVIEWS

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ABSTRACT

This study quantifies the business value of consumer reviews and discusses its wider implications to hotel performance, specifically to delineate the unique effects of the User-Generated Content (UGC) components on room sales. In contrast to earlier studies that take consumer reviews as an exogenous factor, this study finds empirical evidence that consumer reviews both influence and are influenced by room sales through a dynamic framework. In consideration of the endogeneity in consumer reviews, this study uses a dynamic generalized method of moments (GMM) model to address the reviews/sales relation and illustrates why other commonly used estimation that ignore the dynamic relationship between current reviews and room sales may be biased. A longitudinal panel-data sample of 56,284 hotel reviews on a daily basis, along with quarterly hotel performance over a ten-quarter observation window, is used for the empirical modeling.

This study finds that room sales are significantly influenced by the review volume, suggesting the importance of awareness effect. Specifically, a 1% increase in the average quarterly number of reviews received would result in a 0.10 units increase in the average revenue per available room. Compared to paid or owned traditional marketing channels, the earned consumer reviews' business value can be justified by the marginal costs of producing extra copies of reviews by consumers and providing social media service by hotel managers. Nevertheless, this study shows that the rating of consumer reviews and its variation does not have effect on hotel room sales after accounting for the endogeneity, indicating that online reviews have little persuasion effect on consumer purchase

decisions. Thus, this study considers the awareness effect of Word-of-Mouth (WOM) as the primary effect in the dynamic mechanism between consumer reviews and room sales.

From the theoretical perspective, this study represents a comprehensive understanding of consumer reviews by integrating both awareness and persuasion effects. By identifying strategically important review components and their effects, the study adds to the prior literature by providing a positive reconciliation of the mixed findings about the effect of consumer reviews. From the managerial perspective, the awareness effect of consumer reviews suggests that businesses should embrace and facilitate WOM activities. However, consumers are not influenced by the persuasion effect of online WOM, thus presenting a challenge to businesses that try to influence sales through "planting" positive product reviews. Hotel managers shall therefore focus more on the mechanisms that facilitate dispersion of underlying word-of- mouth exchange rather than try to influence online ratings. From the methodology perspective, this study contributes to the hospitality literature by providing econometric justifications for the use of dynamic panel data estimation, discussing the conditions under which it improves inference beyond the traditional pooled OLS and traditional fixed- effects estimates. This study shows that dynamic effect is likely to be particularly important in hospitality research since much of our research seeks to determine the effect of different stimulating variables (e.g., consumer reviews, pricing strategy, customer relationship management, etc.) on hotel performance, an aspect of research that is particularly susceptible to biases that may arise by ignoring the effect of historical performance on current stimulating variables. The empirical attempt initiated in this study welcomes replications of future research.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Technological advances over the past decades have led to the proliferation of User-Generated Content (UGC) on social media platforms where consumers shop for goods (Ghose et al., 2012). Ever since Amazon.com published its first consumer book review in 1995, an estimated 43% of online retailers now offer consumer reviews or ratings on their websites (Gogoi, 2007), enabling consumers to access word-of-mouth (WOM) and inform one another on a variety of products. Consumer reviews are now posted on a wide range of products and services and have become important part of the decision-making process for many consumers (Calveras & Orfila, 2009; Chevalier & Mayzlin, 2006; Vermeulen & Seegers, 2009).

Specific to the hospitality industry, WOM has been recognized as one of the most influential resources of information transmission, especially for experience goods such as hotel rooms, restaurant meals, and travel packages, whose product characteristics are difficult to observe until consumption (Nelson, 1970; Pine & Gilmore, 1998). This leads to a burgeoning group of hotel review websites such as TripAdvisor.com, Travelocity.com, and Expedia.com, in which consumers could reduce the level of perceived risk and uncertainty in purchasing hospitality products by referring to reviews posted by past consumers (Klein, 1998). Reports indicate that each year hundreds of millions of potential hotel guests consult review sites, 84% making their hotel choices affected by consumer reviews they have read (travelindustrywire.com, 2007). In total, online reviews influence over $10 billion a year in online travel purchases (etcnewmedia.com, 2010).

Aware of this opportunity, hotel managers are embracing online consumer reviews as a new media to boost room sales (Duverger, 2013). We use hotels in Texas as an example to illustrate this trend. There were 62 hotels in Texas Sate enlisted on TripAdvisor.com within its first year of operation. By 2011, the number has been close to 830, representing an impressive growth in a ten-year's time (See Figure 1). From 2008 to 2010, business scenario accompanied by the economic recession in Texas and the US has drastically affected the operations and business of the hotel industry, but the consumer review activities follow an upward growth trajectory. Social media are a viable channel to crank up hotel business in difficult times (Zelasko, 2010), and the momentum has remained strong nowadays.

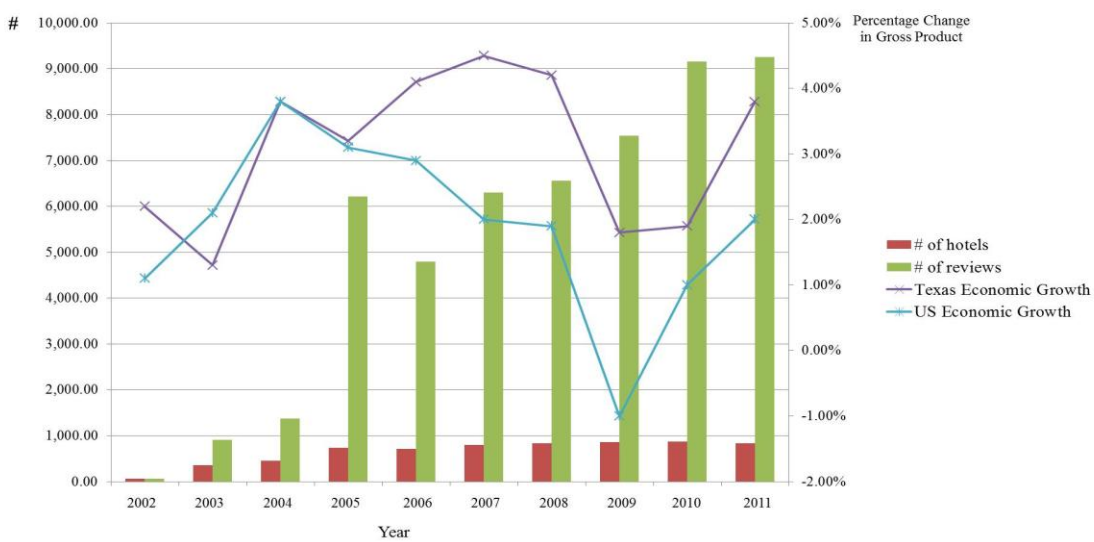

Figure 1. Growth of Consumer Reviews against the Economic Downturn in Texas Hotel Market, Fiscal Year 2002 – 2011.

Source: (a) TripAdvisor.com (2012). Texas Hotels (http://www.tripadvisor.com/Hotels-g28964-Texas-Hotels.html); (b) Texas Comptroller of Public Accounts (2012). Biennial Revenue Estimate (2010 – 2011) (http://www.window.state.tx.us/taxbud/bre2010/outlook.html).

At the same time, however, consumer reviews may represent a challenge for hoteliers. The transparency of social media can highlight any inconsistencies between the brand pledge and its execution across geographic boundaries (Deloitte Hospitality, 2010). Social media sites as highly public feedback platforms may generate unsolicited or bogus opinions. Negative experiences or fake reviews can be communicated quickly to a large audience. Consumers see through these reviews and any resulting negative publicity can make a potentially bad situation even worse, damaging the hotel brand.

So the picture is not clear. Is the proliferation of consumer reviews simply an increasingly mixed industry phenomenon? Or can consumer reviews play a truly useful economic role? The area emerged in recent year as one of utmost importance for hospitality management but despite its undisputed significance, few literature have provided empirical evidence of the value of consumer reviews to hotel business. There have been a number of recent studies investigating the effect of online reviews on hotel performance using panel data in a time-series structure (e.g., Duverger, 2013; Ye et al. 2010; Zhang et al. 2009). The results, however, are mixed and the strategic importance of different consumer components (e.g., valence, variation, and volume) remains inconclusive. This can be quite disconcerting for hospitality marketers who seek outcome-based implications.

The confusion and challenges mainly come from three aspects. First, there are fragmented views of the influence of consumer reviews. Some studies focus on review rating or valence that signal a consumer's assessment of product quality (Chatterjee, 2001; Chen et al. 2004; Forman, 2008; Liu, 2006); some investigate the variation of review ratings that measure the degree of disagreement among consumers (Godes & Mayzlin, 2004; Sun, 2012); while others focus on review volume that increase product awareness among consumers through dispersion (Dellarocas et al. 2007; Godes & Mayzline, 2004). Second, many studies treat consumer reviews as exogenous (Chen et al. 2004; Dellarocas et al. 2007; Forman et al. 2008; Liu 2006). Consumer reviews, however, is not only the driving forces of consumer purchase but also the outcome of product sales. The causality between product sales and reviews works in both directions. Ignoring the dual influencer and indicator roles of consumer reviews is one of the main causes of the confusion (Duan et al. 2008). Third, many researchers conduct their analyses in a cross-sectional context (Chen et al. 2004; Dellarocas et al. 2007; Liu, 2006; Ye et al. 2010). A cross-sectional setting, however, cannot control for the intrinsic product heterogeneity. In particular, it cannot explain whether the difference in sales is due to the unobserved differences in product quality or the effect of consumer reviews.

This study is interested in quantifying the business value of consumer reviews to hotel performance. The research question is whether and how do consumer reviews affect room sales. Given previous limitations and challenges, we assess both the persuasion effect and the awareness effect of consumer reviews components (i.e., valence, variation, and volume) in this study using a dynamic panel model to fully capture the dual nature of consumer reviews and individual hotel heterogeneities that have not been fully accounted for in prior literature that reply on static models (i.e., the pooled ordinary least squares (POLS) and fixed-effects). We draw upon a unique torrent daily review data auto-parsed from TripAdvisor.com, supplemented by quarterly observations of hotel transactions that are matched to the Texas Comptroller's Office database. Our empirical findings point to strategically important review components that are able to drive hotel business and how hotel room sales can be generated by these review components. Useful implications on how hoteliers could utilize consumer reviews to leverage the hotel performance are discussed.

This study advances our knowledge body of consumer reviews in four ways. First, some consume review research focuses on the effect of review rating or variation that influence a consumer's assessment of product quality (Chen et al. 2004; Forman et al. 2008; Liu, 2006; Sun, 2012) while others focus on the volume of consumer reviews that increase product awareness among consumers through dispersion (Dellarocas et al. 2007; Godes & Mayzlin, 2004). We assess both the persuasion effect and the awareness effect of consumer review components (i.e., valence, variation, and volume) in this study. First, our analyses show that the number of reviews is significantly associated with room sales after taking into account of the causality issue, indicating the presence of significant awareness effect. Second, our findings challenge conventional thinking by showing that review ratings and their variation do not affect hotel sales after controlling for endogeneity, suggesting little persuasion effect for online reviews. Review valence or variation may reflect hotel quality or service satisfaction, but they do not influence room sales. This result indicates that consumers are fully capable of inferring the true quality of a hotel from online reviews without being influenced by the ratings of the reviews *per se*. Our empirical findings point to strategically important review components that should be incorporated in hotels' online business strategy. Our results reconcile some of the inconsistencies of previous studies with respect to which review components is good proxy of room sales.

Second, we use dynamic system GMM panel modeling to capture the dual nature of online reviews and dynamic sales/review relationship (i.e., endogeneity). Our system GMM dynamic panel model takes full advantage of the panel data structure and addresses endogeneity in several ways. First, unlike POLS estimation, we can include firm-fixed-effects to account for (fixed) unobservable heterogeneity. Second, unlike traditional fixed-effects estimates, it allows current consumer reviews to be influenced by previous realizations of, or shocks to, past performance. Third, unlike either POLS or traditional fixed-effects estimates, a key insight of the dynamic panel GMM estimator is that if the underlying economic process itself is dynamic – in our case, if current reviews are related to past performance – then it may be possible to use some combination of variables from the hotel's history as valid instruments to account for simultaneity. Thus, an important aspect of the methodology is that it relies on a set of ''internal'' instruments contained within the panel itself: past values of performance can be used as instruments for current realizations of reviews. This eliminates the need for external instruments. Our empirical findings point to an accurate and comprehensive understanding of how room sales of hotels are generated by consumer reviews by mitigating the endogeneity problem.[1] The results reconcile some of the inconsistencies of previous studies with respect to which review components is good proxy of room sales.

Third, the product category examined in our data is also worth mentioning. Previous researchers have typically focused on short life cycle products such as movies and books, likely due to the available of data in these categories. However, books and movies are unique in that they have product life cycles that are both short and follow

[1]We should note there is no way to statistically ensure that an endogeneity problem has been solved. What we are able to do is to mitigate the endogeneity issue but not eliminate it.

predictable exponential patterns (Moe & Fader 2001; Sawhney & Eliashberg 1996). These products experience the greatest level of sales (and review activity) immediately after launch. Very quickly after that, sales (and review activity) taper off dramatically. The danger of using such product categories is that results can be very sensitive to when in the product life cycle the researcher collects the data. In this study, we use sales and review data for products in a mature product category (i.e., hotel rooms) with relatively stable sales. As a result, the sales changes observed can be more easily attributed to changes in the consumer review environment and are less likely to be a result of changes due to the natural progression of the product life cycle. In addition, both online reviews and hotel sales are high-frequency data that can be collected on a daily basis. This provides sufficient observations for empirical analysis.

Finally, we position our study as interdisciplinary research in which research perspectives and scientific methodologies from marketing, management science, and hospitality are integrated and synergized. We stay focused on the relevance of consumer review research to the hospitality industry. Instead of simply applying multi-disciplinary theories or methodologies in the hospitality context, we consider the industry priorities the motivation of conducting this research. We argue why consumer reviews are so unique to the hospitality industry is because they serve as the major channel for consumers to learning experience goods (Nelson, 1970) that are predominately available in the hospitality industry. The purpose of using multi-disciplinary lens is to look at the hospitality issues rather than simply contextualizing the research in hospitality. Our theoretical arguments and empirical methodologies can be generalized to marketing and management domains. Our managerial implications might shed light to the practice of social media marketing in hospitality and the wider service industries.

The dissertation proceeds as follows. In Chapter 2, we review the prior literature on consumer reviews and explain how this study adds to the knowledge body. In Chapter 3, we develop hypotheses and present the conceptual framework. In Chapter 4, we describe the sample and data. In Chapter 5, we discuss the advantages of dynamic panel models compared to other traditional models and present model specifications. In Chapter 6, we present a series of estimations of the review/performance relation. We conclude the dissertation with a summary of results and implications in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

Social media frenzy has taken the world by storm in the last few years (Deloitte Hospitality, 2010). Consumer reviews become the subject of extensive research (Cunningham et al., 2010). A burgeoning academic literature has sprung up to study how online reviews affect consumers' decision-making and what is their impact on firm performance (Moe & Trusov, 2011). These studies can be primarily divided into two streams: (1) investigating the mechanisms of online reviews in facilitating consumer behavior and (2) examining the strategically important components of online reviews that can influence firm performance. Most of the extant studies are written from a marketing or information systems perspective but there are also contributions from psychology, management and computer science (De Maeyer, 2012). Methodologies encompass lab studies, empirical studies, survey studies and conceptual work (Cheung & Thadani, 2010).

Much of the earliest work focuses on the effect of eBay reputation feedback scores on prices and quantity sold; for example, Melnik and Alm (2002) and Resnick et al. (2006). Widespread adoption of social media and advanced development of information technology have revolutionized the industry. Increasingly, many later studies examines the role of consumer reviews primarily on product sales online at Amazon.com (e.g., Chen et al. 2004), BarnesNoble.com (Chevalier & Mayzlin, 2006), GameSpot.com (Zhu & Zhang, 2010), Travelocity.com (Ghose et al. 2012), Yelp.com (Luca, 2010), and other social media platforms. The literature on consumer reviews is now at a point where it would be useful to take stock of what is already known, identify sub-areas and tie them together into an overall picture, and use this understanding to identify gaps in our knowledge. For academic researchers, this comprehensive review hopefully will be helpful in identifying interesting areas for further research. Practitioners will hopefully come away with a more detailed understanding of the different facets of online reviews and related constructs, allowing for a deeper insight in how to harness these reviews to their advantage.

The purpose of this chapter, therefore, is to provide a broad overview of what has been documented on the impact of consumer reviews with implications on firm performance and consumer behavior. Reviewing these landmark papers on consumer reviews are important as a prelude to developing a theory-based model that we test in the subsequent sections. This chapter is organized in accordance with two streams of the literature. Each section in this chapter follows a similar format of a mini-literature review citing representative studies in each sub-area, with a discussion of their mixed findings. The goal is to be reasonably comprehensive in substance, not to include every single study on the subject. Note that these two sub-research areas represent different aspects of the same phenomenon of online reviews, and are therefore by necessity somewhat intertwined. Nearly all of the reviewed papers address multiple sub-areas, and some are cited multiple times if they have something important to add to different headings.

2.1 Mechanisms of Consumer Reviews

Many studies agree that reviews play a role similar to what WOM plays in a more traditional setting and are sources of information in the consumer decision-making process (Brown et al. 2007). Online consumer reviews can be associated with eWOM behavior (Chen & Xie, 2008), and thus are used as a proxy of actual consumer behavior (Dellarocas et al. 2007). For example, there is empirical evidence that consumers who consult product reviews to select recommended products twice as often as those who do not consult review recommendations (Senecal & Nantel, 2004). In addition, consumer reviews as a form of earned WOM produce a substantially higher and longer market response than traditional owned marketing actions such as promotion events and media appearance (Trusov et al. 2009). Although majority studies acknowledge the importance of reviews in facilitating subsequent consumer behavior, how review information would affect consumers' choices and purchasing decisions is critical (Vermeulen & Seegers, 2009). A group of literature focuses on the behavior-facilitating mechanism of consumer reviews and three primarily mechanisms are discussed: credible persuasion, uncertainty mitigation, and social contagion. Table 1 presents these studies that are synthesized according to their topic relevance.

Table 1. Review of the Mechanisms of Consumer Reviews

Focal Area	Author(s)	Year	Setting	Finding
Credible Persuasion	Chevalier and Mayzlin	2006	Book	Consumers are more likely to trust brands that offer user ratings and reviews and view reviews from fellow independent consumers as credible information sources of decision-making.
	Bickart and Schindler	2001	Sports equipment, health supplements, photography, and stereo equipment	Consumers rely on online reviews to make purchase decisions because they are more user-oriented and credible than content posted by business providers.
	Campanell	2006	Retailing	Consumers trust online reviews more than other firm-controlled marketing communications such as newspapers, TV commercials, or promotional emails.
	Senecal and Nantel	2004	Calculator and wine	Consumers tend to rely more on non-expert sources because expert reviews may amplify reviewer impact.
	Dellarocas	2006	Movie	Firms hire professional experts to write consumer reviews that may inflate the product ratings.
	Forman et al.	2008	Book	The prevalence of reviewer disclosure of identity information is associated with increases in helpfulness rating of the review and the subsequent online product purchase.
Uncertainty Mitigation	Gretzel and Yoo	2008	Travel	Online reviews offer quality information to reduce risk in purchasing experience goods.
	Chen and Xie	2008	Electronics	Consumer reviews help consumers identify the products that best match their idiosyncratic usage conditions.
	Ghose et al.	2012	Hotel	Consumer reviews can be useful in reducing the risk of purchasing uncertain products and services.
	Zhu and Zhang	2010	Video Game	Consumer reviews may merely represent individual consumers' preferences and these reviews have little influence on consumers' decisions.

Table 1. Review of the Mechanisms of Consumer Reviews, continued

	Eliashberg and Shugan	1997	Movie	Consumer reviews serve as predictors rather than influencers of consumers’ decision making.
	Li and Hitt	2008	Book	The self-selection bias of online product reviews in early buyers and late buyers that consumer reviews may not accurately communicate a fair evaluation of product quality.
	Ghose and Ipeirotis	2007	Book, DVD, and video	Reviews are influenced by reviewers’ subjectivity and may thus be biased.
Social Contagion	Chu	2009	Advertising	As consumers post their recommendations and opinions about a product or service in social networking sites, they attempt to persuade their peer consumers to see their point of view and, thus, influence their decision-making.
	Zhang et al.	2009	Restaurant	Consumers are likely to follow the opinions of other reviewers as a result of pressure to conform to a peer group.
	Moe and Trusov	2011	Skin care and beauty products	Reviewer rating behavior is significantly affected by previous ratings. Product reviews not only reflect the customers' experience with the product, but they also affect the ratings of later reviews as well.
	Schlosser	2005	fast-food restaurant and sports car	Consumers who have decided to post their opinions tend to negatively adjust their product evaluations after reading negative reviews; when individuals facing a heterogeneous audience, they adjust the message to offer a more balanced opinion.
	Godes and Mayzlin	2009	Advertising and restaurant	Although "opinion leadership" is useful in identifying potentially effective spreaders of WOM among very loyal customers, it is less useful for the sample of less loyal customers.

2.1.1 Credible Persuasion

Research supports that consumers use product reviews because they provide credible information that can be persuasive to consumers (Riegner, 2007; Vermeulen & Seegers, 2009). Consumer reviews are perceived as unbiased since they are posted by the past consumers, who have experience with the products or service providers. Because online reviews are more user-oriented, consumers often consider them to be more credible and trustworthy than content posted by business providers (Bickart & Schindler, 2001). It is not surprising that online service providers and industry researchers alike have found that consumers trust online reviews more than other firm-controlled marketing communications such as newspapers, TV commercials, or promotional emails (Campanell, 2006). This observation is consistent with Senecal and Nantel's (2004) finding that consumers tend to rely more on non-expert sources because expert reviews may amplify reviewer impact. Dellarocas (2006) also argues that one reason consumer generated reviews may not represent actual product quality is because firms hire professional experts to write consumer reviews that may inflate the product ratings. Chevalier and Mayzlin (2006) find that consumers are more likely to trust brands that offer user ratings and reviews.

To distinguish the truly credible opinions from all kinds of consumer feedback and recommendations on the web, some studies have discussed how consumers choose their information source that helps them find trusted information sources. Forman et al. (2008) examine the role of reviewer identity (e.g., real name and location of the reviewer) in the relationship between Amazon.com book reviews and sales. They find that the prevalence of reviewer disclosure of identity information is associated with increases in helpfulness rating of the review and the subsequent online product purchase. This is because community members assess more positively reviewers who disclose identity-descriptive information, and then use their assessment of reviewers as a heuristic shaping their evaluation of the product reviewed (Zhu & Zhang, 2010).

2.1.2 Social Contagion

Another mechanism of consumer reviews is to create social contagion or peer effect. As consumers post their recommendations and opinions about a product or service in social networking sites, they attempt to persuade their peer consumers to see their point of view and, thus, influence their decision-making (Chu, 2009). Peer consumers are likely to follow the opinions of previous reviewers as a result of pressure to conform to a peer group (Zhang et al. 2009). Thus, consumer reviews can lead consumers to rationalize their purchasing decisions by reinforcing the idea that many other consumers also bought or did not buy the same product or services.

Moe and Trusov (2011) examine how social influences affect the subsequent ratings and sales. They demonstrate that reviewers' rating behavior is significantly affected by previous ratings. In other words, product reviews not only reflect the customers' experience with the product, but they also affect the ratings of later reviews as well. In an experimental setting, Schlosser (2005) finds that consumers who have decided to post their opinions tend to negatively adjust their product evaluations after reading negative reviews. This indicates that consumer posting behavior is affected by social context and the rating of previously posted reviews. She attributes this behavior to the fact that posters strive to differentiate their reviews, and negative reviews are more differentiated since negative evaluators are perceived as more intelligent (Amabile, 1983). Schlosser (2005) also discusses multiple audience effects in the context of online posting behavior. Multiple audience effects occur when individuals facing a heterogeneous audience adjust the message to offer a more balanced opinion (Fleming et al. 1990). This is yet another form of social influence and it suggests that the effects of previously posted ratings on ratings behavior extend beyond the effect of review valence but also includes the effect of variance.

Godes and Mayzlin (2009), however, discount the peer influence of consumer reviews. They examine how a firm should try to create useful WOM, specifically looking into who creates WOM and what kind WOM and matters. They find that that although "opinion leadership" is useful in identifying potentially effective spreaders of WOM among very loyal customers, it is less useful for the sample of less loyal customers.

2.1.3 Uncertainty Mitigation

Consumer reviews tend to help mitigate the uncertainty in product purchase (Senecal & Nantel, 2004; Zhu & Zhang, 2010). Chen and Xie (2008) advocate that, in circumstance of potential uncertainty, online reviews can work as free “sales assistants” to help consumers identify the products that best match their idiosyncratic usage conditions.

Evidence on such mechanism has been provided widely to experience goods (Ghose et al. 2012; Zhu & Zhang, 2010). An experience good is a product or service where product characteristics such as quality are difficult to observe in advance, but these characteristics can be ascertained upon consumption (Nelson, 1970). Experience goods pose difficulties for consumers in accurately making consumption choices. In service areas, research has shown that consumer reviews play a key role in learning experience goods such as hotel rooms, restaurant meals, and travel packages that reward reputation and create inertia (Pine & Gilmore, 1998). For example, Gretzel and Yoo (2008) indicate that online reviews offer quality information to reduce risk in purchasing experience goods. In presence of online reviews, consumers are able to learn the perception of product quality and service satisfaction from previous consumers without experiencing the goods by themselves. Consumer reviews written by precious buyers signal a certain level of evaluation and feedback of experience goods, providing important reference for consumer new buyers to make wise decisions to choose the products that best match their preference.

However, several studies argue that consumer reviews may not reflect true product quality. According to Zhu and Zhang (2010), consumer reviews may merely represent individual consumers' preferences and these reviews have little influence on consumers' decisions. Similarly, Eliashberg and Shugan (1997) argue that consumer reviews serve as predictors rather than influencers of consumers' decision making. Li and Hitt (2008) identify the self-selection bias of online product reviews in early buyers and late buyers that consumer reviews may not accurately communicate a fair evaluation of product quality. Ghose and Ipeirotis (2007) find that reviews are influenced by reviewers' subjectivity and may thus be biased.

2.2 Strategically Important Components of Consumer Reviews

Prior research on consumer reviews has identified three primary review components that are strategically important: valence, variance, and volume. Valence, or the review rating, reflects the level of consumer satisfaction and is the focus of most empirical studies on product reviews (Clemons et al. 2006; Dellarocas et al. 2007). Variation, measured as the standard deviation to the mean rating, captures the degree of disagreement among consumers (Godes & Mayzlin, 2004). Volume, or the number of reviews, as a measure of the volume of discussions, signals brand awareness and popularity of a product on a social media platform (Duan et al. 2008; Zhu & Zhang, 2010).

As a form of online WOM, consumer reviews are able to induce additional sales by making consumers aware of the product brand and persuading them of the product superiority (Clark et al. 2007). Broadly speaking, raising brand awareness and perceived quality map into the awareness components and persuasive components of consumer reviews, respectively. Awareness components (i.e., review volume) convey the existence of the product and thereby put it in the choice set of consumers (Duan et al. 2008), while persuasive components (i.e., review rating and variation) shape consumers' attitudes and evaluation towards the product and ultimately influence their purchase decision (Godes & Mayzlin, 2004). These two types of review components have been studied intensively in prior literature on the effect of consumer reviews but the views are fragmented and mixed. Table 2 presents these studies that focus on consumer review components that influence products sales through persuasion and awareness.

Table 2. Review of Strategically Important Components of Consumer Reviews

Focal Area	Author(s)	Year	Setting	Model and Estimation Method	Performance measure	Finding
Awareness Components						
Review Volume	Chen et al	2004	Retailing	Multiple regression, pooled OLS	Sales	As the number of consumer reviews increases, the overall rating converges to the true quality.
	Godes and Mayzlin	2004	TV shows	Dynamic model, fixed-effects	Rating, post, entropy	The more conversation there is about a product, the more likely someone is to be informed about it, thus leading to greater sales.
	Duan et al.	2008	Movie	Simultaneous equations, 3SLS	Revenue	User ratings do not have any significant effect on their box office sales whereas the number of online postings influences box office sales.
	Liu	2006	Movie	Multiple regression, pooled OLS	Revenue	The explanatory power of review on sales comes from volume of reviews instead of valence of reviews.
	Chintagunta et al.	2010	Movie	Multiple regression, generalized method of moments (GMM)	Sales	Consumers tend to prefer posting reviews for obscure movies but also for hit movies that have already a large number of online reviews.
	Zhang and Dellarocas	2006	Movie	Multiple regression, fixed-effects	Revenue	The significant influence of the valence measure of online reviews, but their volume measure is not significant once quality is controlled.

Table 2. Review of Strategically Important Components of Consumer Reviews, continued

	Dellarocas et al.	2010	Movie	Multiple regression, pooled OLS and random-effects	Revenue	Consumers tend to prefer posting reviews for obscure movies but also for hit movies that have already a large number of online reviews.
	Chevalier and Mayzlin	2006	Book	Multiple regression, pooled OLS	Sales	Volume of reviews is a significant predictor of sales.
	Hong et al.	2012	Restaurant and electronics	Multiple regression, fixed-effects	Standard deviation of the sample size	When number of reviews increases as more consumers rate the product, variance of the mean rating will decrease for a pure search product but the opposite for an experience product.
Persuasive Components						
Review Valence	Dellarocas et al	2007	Movie	Diffusion model, fixed-effects	Sales	A high correlation between online consumer ratings of movies and online user reviews within the first week of a new movie's release can be used to provide good predictions for the movie's total revenues.
	Reinstein and Snyder	2005	Movie	Difference-in-differences, fixed-effects	Revenue	Positive reviews have a particularly large influence on the demand for dramas and narrowly-released movies.
	Chevalier and Mayzlin	2006	Book	Differences-indifferences, POLS	Sales	On average, consumers' ratings can significantly influence book sales.

Table 2. Review of Strategically Important Components of Consumer Reviews, continued

	Duan et al.	2008	Movie	Simultaneous equations, 3SLS	Revenue	Reviews may be influenced by movie sales (endogeneity) and no significant effect of review valence is found on consumer purchase decisions after accounting for endogeneity.
	Chen et al.	2004	Book		Sales	Consumer ratings are not correlated with sales.
	Xie et al.	2011	Hotel	Multiple regression, ANOVA	Booking intention	Awareness is a resulting effect from both positive and negative reviews and even negative reviews might participate in the increase of sales.
	Cui et al.	2010	Electronics	Multiple regression, fixed-effects	Sales	Negative reviews influence sales more than positive ones but also in a positive way.
	Sorensen and Rasmussen	2004	Book	Multiple regression, fixed-effects	Sales	Negative reviews have a positive impact on book sales.
	Chen et al.	2011	Automobile	Multiple regression, negative Binomial	Review volume and rating	Negative WOM is more influential than positive WOM.
	Berger et al.	2010	Book	Multiple regression, fixed-effects	Sales ratio	Negative reviews can boost sales for unknown books, but hurt sales for books with established authors.
Review Variation	Sun	2012	Motion picture and book	Difference-in-differences, two-step feasible weighted least squares	Sales rank	The variance of mean ratings could affect sales.

Ghose et al.	2012	Hotel	Hybrid discrete choice model, GMM	Utility	Less variability in the review ratings could reduce risk and uncertainty perceived by readers and thus results in more sales.
Clemons et al.	2006	Craft beer	Multiple regression, POLS	Sales	The variance in the ratings is highly correlated with the sales growth.
Mudambi and Schuff	2010	Electronics	Tobit regression, maximum likelihood	Helpfulness	Reviews with extreme ratings are less helpful than reviews with moderate ratings for experience products.
Zhu and Zhang	2010	Video games	Difference-in-differences, fixed-effects	Sales	The variation of rating is significant only for less popular and online games.
Li and Hitt	2008	Book	Logistic regressions, maximum likelihood	Sales	Online product reviews have self-selection bias because early buyers and late buyers may have different preferences about a product.
Hu et al.	2006	Book, DVD, and video	Multiple regression, non-parametric DIP test	Sales	Due to the purchasing bias and under-reporting bias, the graphical representation of product reviews has a J-shaped distribution.

2.2.1 Awareness Component: Review Volume

Consumer reviews at the very least conveys the existence of the brand and thereby puts it in the choice set of the consumer (Clark et al. 2007). Prior studies demonstrate the imperative role of social media platforms in the diffusion or distribution of product information among consumers (Dellarocas et al. 2010). As more and more reviews are posted about a specific product, consumers become aware of and initiate interest in this product. The more consumers see the product, the higher chance that they will become aware of it. Therefore, it is very likely that this product will be included in more consumers' choice set.

Review volume mainly has an informative role to enhance consumer awareness (Dellarocas et al. 2010). It induces additional sales by making consumers aware of the product brand and signaling the product popularity (Clark et al. 2007). As Kirby (2000, p. E1) explains, one "may not trust just one non-expert…but if 9 out of 10 non-experts agree, it is probably worth buying." Chen et al. (2004) indicate that, as the number of consumer reviews increases, the overall rating converges to the true quality. Therefore, a large volume of consumer reviews of products could convincingly reflect a high level of product quality and be influential in attracting potential buyers. Godes and Mayzlin (2004) suggest that the more conversation there is about a product, the more likely someone is to be informed about it, thus leading to greater sales. On the basis of a similar rationale, Liu (2006) focuses on the movie industry and finds that the explanatory power of review on sales comes from volume of reviews instead of review valence. Another study focusing on movies reveals similar results that user ratings do not have any significant effect on their box office sales whereas the number of online postings influences box office sales (Duan et al. 2008).

Contradictory empirical results, however, exist in the same industry setting. Chintagunta et al. (2010), in their study which examines the impact of online reviews on the local movie box offices, suggest that it is the valence that seems to matter and not the volume. Similarly, Zhang and Dellarocas (2006) use fixed-effects specifications to control for unobserved movie quality and find that the significant influence of the valence measure of online reviews, but their volume measure is not significant once quality is controlled.

Several studies find that the impact of review volume varies across the product type. For example, Dellarocas et al. (2010) show that consumers tend to prefer posting reviews for obscure movies but also for hit movies that have already a large number of online reviews. The recommendation to owners of review websites is that volume of previously posted reviews should become less prevalent in order to encourage posting of reviews for lesser-known products. In addition, Hong et al. (2012) employ the law of large numbers to demonstrate that when number of reviews increases as more consumers rate the product, variance of the mean rating decreases for a pure search product. However, for a product with more experience attributes, when number of reviews increases, the variance of the mean rating does not decrease but may instead increase depending on how dominant these experience attributes are.

2.2.2 Persuasive Components: Review Valence and Variation

In addition to the awareness effect, Bickart and Schindler (2001), drawing upon intuition from the rich literature on persuasion, hypothesize that Internet forum content may be more persuasive than other traditional sources of information (such as marketer-generated content) since the reported experiences of peer consumers have the ability to generate empathy among readers and may appear more credible, trustworthy, and relevant. Consumer reviews have persuasive effect that shape consumers' attitudes towards new brands and alter their tastes for established brands (Dixit & Norman 1978).

The persuasive effect is most evident in review valence. Positive ratings typically give either a direct or an indirect recommendation for product purchase. Negative ratings may involve product denigration, rumor, and private complaining. The reason review valence matters is relatively straightforward; positive WOM enhances expected quality (and, thus, consumers' attitudes toward a product), whereas negative WOM reduces it. Contextualized in the movie industry, Dellarocas et al.'s (2007) study presents that a high correlation between online and offline consumer reviews of movies and that online review rating within the first week of a new movie's release can be used to provide good predictions for the movie's total revenues. Reinstein and Snyder (2005), also contextualized in the movie industry, find that positive reviews have a particularly large influence on the demand for dramas and narrowly-released movies. Studies in the book industry reveal similar findings. Chevalier and Mayzlin (2006) examine the effect of consumer reviews on book sales at two consumer review sites (i.e., Amazon.com and BarnesNoble.com) and find that, on average, consumers' ratings can significantly influence book sales.

Despite the widely believed the positive impact of reviews on firms' strategies and resulting performances, some research shows different results. There are a number of surprising results indicating that consumer reviews have no sales impact (Duan et al., 2008), or sometimes even a positive sales impact from bad ratings (Cui et al. 2010; Sorensen & Rasmussen, 2004; Xie et al. 2011). Duan et al. (2008) account for the fact that reviews may be influenced by movie sales (endogeneity) and find no significant effect of review valence on consumer purchase decisions. Xie et al (2011) indicate that awareness is a resulting effect from both positive and negative reviews and explain that even negative reviews might participate in the increase of sales. Cui et al. (2010) report an analysis of 332 new products reviewed on Amazon.com, and find that negative reviews influence sales more than positive ones. Sorensen and Rasmussen (2004), in examining consumer reviews on book sales, find that negative reviews have a positive impact on book sales. The authors explain the finding by referring to reviews' "informative" as opposed to "persuasive," component. This component, informing readers of a book's existence and characteristics, might entice readers to purchase a book, even when the persuasive component of the review advises the reader not to do so. Chen et al. (2011) lend support to the importance of negative reviews and find that negative WOM is more influential than positive WOM. In consideration of the interaction effect of review rating and product characteristics (i.e., popularity of books), Berger et al. (2010) give an intuitive explanation of the paradox. They find that negative reviews can boost sales for unknown books, but hurt sales for books with established authors. This happens because negative reviews bring visibility to unknown books. Whereas for authors who are already well known, publicity does not boost the awareness of their books, instead, the valence of the publicity becomes more important.

Another persuasive component is review variation. It is believed by many researchers that a quality product or service would constantly receive positive reviews. Variation of review ratings measures the disagreement of ratings among reviewers and reflects the consistency of opinions about the product quality among reviewers (Duan et al. 2008). For example, Ghose et al. (2012) investigate the impact of consumer reviews on a variety of products and stated that less variability in the review ratings could reduce risk and uncertainty perceived by readers and thus result in more sales. Similarly, Clemons et al. (2006) use online reviews to assess firms’ differentiation strategies in the craft beer industry and find that the variance in the ratings is highly correlated with the sales growth, indicating the existence of hyper-differentiation marketing. Using data from Amazon.com, Mudambi and Schuff (2010) find for experience products, reviews with extreme ratings are less helpful than reviews with moderate ratings. However, instead of assuming variation results in negative sales to all products, Zhu and Zhang (2010) show differential impact of consumer reviews across video games in the same category and suggest the variation of rating are significant only for less popular and online games.

Despite the plausible negative influence of review variation on products, a few studies have found that variation or uneven distribution of consumer rating is essentially a nature of the consumer reviews because reviewers are not a randomly drawn sample of the user population. For example, Li and Hitt (2008) indicate that online product reviews have self-selection bias because early buyers and late buyers may have different preferences about a product. Hu et al. (2006) have shown that, due to the purchasing bias[2]and under-reporting bias[3], the graphical representation of product reviews has a J-shaped distribution: mostly 5-star ratings, some 1-star ratings, and hardly any ratings in between. Anderson (1998) tends to favor variation in the consumer reviews and emphasizes that extremely satisfied and extremely dissatisfied consumers are more likely to initiate online comments and feedbacks.

2.3 Research Challenge: Endogeneity in Consumer Reviews

As shown in Table 2, several recent studies have attempted to identify the relationship between online consumer reviews and product sales and have generated mixed findings. Researchers have not been able to reconcile the stark differences in results and instead have attributed them to methodological shortcomings (Zhu & Zhang, 2010). The confusion mainly comes from the endogeneity issues of consumer reviews (Duan et al. 2008), in particular two aspects – simultaneity and unobservable heterogeneity. These two empirical challenges arise because the regressor is correlated with the error term in the regression, violating the first least squares assumption. Empirical studies based on regression analysis are valid if the estimated regression coefficients are unbiased and consistent, and if their standard errors yield confidence intervals with the desired confidence level (Stock & Watson, 2007). Potential endogeneity implies that regression coefficients are likely to be biased and empirical methods are unlikely to quantify the magnitude of the economic effects of interest. In a

[2] People that buy a product do not constitute a random sample of the population. People buy products that they believe they will enjoy. So, the reviews are written by people that are more likely to like the product. Since only people with higher product valuations purchase a product, those with lower valuations are less likely to purchase the product, and they will not write a (negative) product review. Purchasing bias causes the positive skewness in the distribution of product reviews and inflates the average.
[3]Among people who purchased a product, those with extreme ratings (5-star or 1-star) are more likely to express their views to “brag or moan” than those with moderate views.

review article that provides guidance on addressing endogeneity issues, Roberts and Whited (2013) note that “endogeneity leads to biased and inconsistent parameter estimates that make reliable inference virtually impossible.’’

Thus, attention to the estimation of cause and effect in consume reviews studies is essential to creating knowledge that is robust to alternative scientific explanations and relevant to policy (Sundararajan et al. 2013). Rigorous treatment of identification reduces the risk that we miss confounding factors or mistake spurious correlations for causal relationships that will form the basis of managerial action. Approaches to identification in social media studies are needed to the development of rigorous scientific results that can effectively guide policy.

2.3.1 Simultaneity

Prior studies on consumer reviews have not fully recognized this unique nature of consumer review effect and often treat reviews as exogenous, like traditional marketing effects (Chen et al. 2004; Dellarocas et al. 2007; Forman et al. 2008; Liu 2006). Consumer reviews, however, are not only the driving forces of consumer purchase but also the outcome of product sales (i.e., simultaneity). The causality between sales and consumer reviews works in both directions. Ignoring the dual influencer and indicator roles of consumer reviews is one of the main causes of the confusion (Duan et al. 2008).

Simultaneity may arise in the consumer reviews/performance relation in two forms. The first form is the feedback mechanism between reviewers and firm performance. According to Duan et al. (2008), consume reviews can lead to more product sales, which in turn generate more consumer reviews and then more product sales. In addition, past performance may have a direct influence on the hotel's profit potential, employment turnover, service quality and other performance-based decisions, all of which are factors that may affect the consumer reviews written by past reviewers. Moreover, if consumer reviews is determined by hotel-specific characteristics (e.g., star rating) as suggested by Ye et al. (2010) and these characteristics are related to past performance, then consumer reviews are related to past performance through the effect of performance on hotel characteristics. The feedback mechanism indicates that online reviews are not only a driving force in consumer purchase but also an outcome of product sales (Godes & Mayzlin, 2004; Srinivasan et al. 2002).

The second simultaneity comes from the firm manipulation (Mayzlin et al. 2012). Extant studies show that firms are very likely to strategically manipulate online reviews in an effort to achieve a particular level of performance in a certain period (e.g., holidays). For example, firms regularly post their product information and sponsor promotional chats on social media (Mayzlin, 2006), hire professional experts to write consumer reviews that may inflate the product ratings (Dellarocas, 2006), and proactively induce their consumers to spread the word about their products online (Godes & Mayzlin, 2004). If, as previous studies suggest, hotels manipulate consumer reviews with a view towards achieving an expected level of performance in that period, then while performance may be affected by consumer reviews, the reverse will also be true - consumer reviews will also be affected by performance because the manipulated consumer reviews are in fact performance-driven.

Ignoring online reviews' dual roles of precursor and outcome may misplace causality and lead to erroneous results. This is especially true since the difficulty in identifying natural experiments or exogenous instruments in many settings means that consumer review researchers often rely on POLS or fixed-effects estimates for inference. In this case, consumer reviews and hotel performance are simultaneously determined and both POLS and fixed-effects estimates will be biased (Sethuraman et al. 2011; Stock & Watson, 2007).

A potential solution to the problem of simultaneity is to estimate the effect of consumer reviews on performance using a system of equations (e.g., Duan et al. 2008). In one equation, performance is allowed to depend on consumer reviews and other control variables while in other equations, consumer reviews are allowed to depend on performance and other control variables. However, estimating this system also requires us to identify strictly exogenous instruments - there must be at least one variable in the consumer reviews that is not in the performance equation. In practice, identifying and justifying a strictly exogenous instrument is very difficult. To further complicate matters, the number of such exogenous instruments increases with the number of equations in the system.

2.3.2 Unobservable Heterogeneity

Unobservable heterogeneity is a source of endogeneity if there are factors unobservable to the researcher that affect both performance and the explanatory variables. In this case, statistical inferences may be erroneous because, in addition to the observed variables under study, there exist other relevant variables that are unobserved, but correlated with the observed variables. In the consumer reviews/performance context, it is very likely that this is the case. A positive association between room sales and consumer reviews may be due to some underlying omitted variables. For example, consider the effect of managerial ability of hotels which, while generally unobservable, certainly correlates with consumer reviews and affects performance. Also, a hotel may have higher sales not only because of better ratings received but also because of aggressive deep discounts that appeal to consumers.

Heterogeneity bias can be addressed directly by including the omitted variables in a multiple regression, but this is only feasible if we have data on the omitted variable. If omitted variables could not be directly observed or measurable, a POLS regression of performance on consumer reviews that ignores this unobservable heterogeneity may find biased results. Unfortunately, many researchers conduct their analyses in a cross-sectional POLS context (Chatterjee, 2001; Chen et al. 2004; Chen et al. 2004; Liu, 2006). A cross-sectional POLS setting, however, cannot control for the intrinsic hotel-specific heterogeneity. In particular, it cannot explain whether the difference in room sales is due to the unobserved differences in hotels or the effect of WOM.

A potential solution to the time-invariant or ‘‘fixed’’ part of unobservable heterogeneity, if panel data are available, is a fixed-effects or ‘‘within’’ estimation. Fixed-effects models can ameliorate unobserved heterogeneity concerns as we control for the average differences across hotels and observation periods in any unobservable predictors. The combined entity and time fixed-effects regressions models make it possible to eliminate the effect of omitted variables that differ across entities but are constant over time or that differ across time but are constant over entity. However, it does this at the expense of a strong exogeneity assumption, one that is often not explicitly recognized by researchers. That is, it assumes that current observations of the explanatory variable (e.g., consumer reviews) are completely independent of past values of the dependent variable (typically firm performance), an assumption that we argue is not realistic.

2.4 A Summary

The papers discussed in this chapter are able to represent the extant research status on consumer reviews because they have been widely cited and discussed in all levels of research journals that have published consumer review research. We observe that the literature on consumer reviews has enjoyed rapid growth during the past five years. As consumers rely increasingly on online information to make purchase decisions, it is important for marketers to acquire a deep understanding of the concepts and phenomena connected to online reviews. The literature is still relatively new and more work is needed to guide firm's online review strategies, but enough is known to identify the large streams of investigation and report early results.

Most of these results are inconsistent. It is important to note that these researches are conducted in different empirical setting using different estimation methods. The estimation methods might be the underlying reason for the differences in results (Duan et al. 2008), pointing to the need for replications using advanced methods to explain the inconsistencies. An especially promising development is the application of econometric techniques to gain a rich, attribute-level understanding of consumer behavior or firm strategy. While much work has been done on the topic of online reviews, there are still many question marks and technical challenges to overcome, so we expect this to remain a very fruitful research area for several years to come.

CHAPTER 3

HYPOTHESIS DEVELOPMENT

Our study aims at quantifying the economic value of consumer reviews to businesses. Following previous research on consumer reviews (e.g., Chevalier & Mayzlin 2006; Zhang & Dellarocas, 2006), we conceptualize consumer reviews as a bundle of three distinctive but related components (i.e., valence, variation, and volume) and model room sales as a function of these review components in a dynamic fashion. Specifically, we assess both the persuasion effect and the awareness effect of online user reviews while fully capturing the dual nature of online user reviews. We focus on experience goods (Nelson, 1970) - hotel rooms in our case - whose product characteristics are difficult to observe until consumption. The central proposition is that both persuasion and awareness components in consumer reviews affect hotel room sales in a dynamic mechanism.

3.1 Persuasion and Awareness Effects of Consumer Reviews

As consumers post their recommendations and opinions about a product or service in social media platforms, they attempt to persuade their peer consumers to see their point of view and, thus, influence their decision-making (Chu, 2009). Most review sites allow a user to provide an overall rating to evaluate their experience with a purchase. The rating and its variation could influence other consumers' perception of product quality in a persuasive manner (Liu, 2006). The effect is equivalent to the persuasion effect studied in the advertising literature (Grier & Deshpandé, 2001). According to Jeong and Jeon (2008), ratings for their part can be closely assimilated to an overall service evaluation. In that sense, the customer uses a single scale to express his or her judgment of the experience. Review rating serves as a simplified heuristic to instantly signal a hotel's level of quality as perceived by individual consumers. Hence, rating can be assimilated and used as a proxy of quality as perceived by the past customers (Chen & Xie, 2008; Jiang & Chen, 2007). Consume reviews as reliable WOM enable current consumers browsing the Internet to infer a higher degree of quality when past consumers give the product a high rating.

A rational individual tends to "want good rather than bad" (Becker, 1976).[4] This assumption is widely used in any social and economic behavior modeling. Although it primarily focuses on the quantity dimension, the same rationale can be applied to the quality dimension. That is, consumers, when making their purchase decisions, tend to choose a higher quality product rather than a lower quality one. Intuitively, if we assume consumers are rational and behave in a thoughtful clear-headed manner, it is very likely they would purchase a product with higher ratings than those with lower ratings, other things being equal (Chen et al. 2004). The superior ratings increase the consumers' confidence level of product purchase (Ratnasingham, 1998). As such, there is strong reason to believe that the positive consumer reviews may signal a desirable product quality which entices consumer purchase. We thus hypothesize that high rating communicates to the consumers that the product has high quality, which increases subsequent room sales.

H1: Review valence has a positive effect on room sales.

[4]Also known as choice theory or rational action theory.

Meanwhile, rational consumers are risk-averse (Becker, 1976). When making a purchase, consumers are reluctant to accept a product with uncertain quality rather than another product with more certain (even possibly lower) quality. As a statistical concept, variance is a natural measure to capture the heterogeneity in consumer opinions. This concept of variation is generally associated with uncertainty of product quality (De Maeyer, 2012). Higher rating disperses may indicate previous consumers who write reviews have inconsistent opinions about the product quality. In presence of dispersive review ratings, it is impossible for later consumers to exactly tell the true quality of a product, especially if there is no textual complement to this review rating. Thus, inconsistent opinions should have a negative impact on demand (Sun, 2012). Zhu and Zhang (2010) indicate that high variation carries great risk, while low variation offers a safe bet. Ghose et al. (2012) investigate the impact of consumer reviews on a variety of products and stated that less variability in the review ratings could reduce risk and uncertainty of the hotel quality perceived by readers and thus result in more room sales. Accordingly, we hypothesize,

H2: Review variation has a negative effect on room sales.

Besides influencing a user's perception of product quality, online user reviews at the very least conveys the existence of the brand and thereby increase product awareness among consumers. The volume of reviews is an important awareness component because it is linked to the quantity of information available to the consumer (Chen et al., 2004). As more and more reviews are posted about a specific product, consumers become aware of and initiate interest in this product. The more consumers see the product, the higher chance that they will become aware of it (Dellarocas, 2006). Therefore, it is very likely that this product will be included in more consumers' choice set. Previous theoretical and empirical research provides support for the positive relationship between volume of WOM and product sales (Godes & Mayzlin, 2004; Liu, 2006). The awareness can be an important cue of product popularity, and may even affect reviewer behavior (De Maeyer, 2012). We thus derive the following hypotheses:

H3: Review volume has a positive effect on room sales.

3.2 Dynamic Effect of Consumer Reviews

Consumer reviews, however, is not only the driving forces of consumer purchase but also the outcome of product sales. The causality between product sales and WOM works in both directions. The reverse causality may stem from two sources. First, prior studies have demonstrated that there is a feedback mechanism between consumer reviews and product sales. That is, online reviews play a dual role in the review/sales relationship – it drives product sales but is also influenced by past sales performance (Godes & Mayzlin, 2004; Srinivasan et al. 2002). Second, many researchers observe that firms often strategically use consumer reviews as a marketing channel towards the expected sales in a certain period. For example, in holiday seasons, firms may regularly post their product information and sponsor promotional chats on social media (Mayzlin, 2006), hire professional experts to write consumer reviews that may inflate the product ratings (Dellarocas, 2006), and proactively induce their consumers to spread the word about their products online (Godes & Mayzlin, 2004).

If, as previous studies suggest, then while performance may be affected by consumer reviews, the reverse will also be true - consumer reviews will also be affected by performance because of the feedback mechanism and the firm manipulation. Many studies support this view. For example, Duan et al. (2008) demonstrate the dual effect of consumer reviews that influence the product sales and movie reviews. Duverger (2013) supports that there is a dynamic relationship between hotel market shares and review ratings. In addition, consumers who have patronized a product may use consumer reviews to signal their satisfaction with this product. The constant ratings received from past consumers increase the consumer’s trust level, signal a stable product quality which have been evaluated by past reviewers, and lower the perceived risk (Ratnasingham, 1998), which leads to more purchases of the service (Riegner, 2007) and more constant ratings from the product experience, like what being provided by past reviewers. Similarly, Chen et al. (2004) find that the number of online postings is positively related to past automobile sales controlling for price and quality. Godes and Mayzlin (2004) illustrate that the number of Usenet postings is positively correlated with a TV show’s past performance.

All these studies suggest a demand and supply dynamic path of the distribution of room sales. Consumer reviews, as an expression of satisfaction, not only influences hotel bookings directly but also leads to increased reviews as a form of WOM (Duverger, 2013), which then leads to increased room sales by repeat bookings or switching from the competing hotels’ customers. More sales increase is more likely to experience additional revenue growth because of the positive signal observed from the consumer reviews. Thus, we hypothesize,

H4: Room sales have effect on consumer reviews.

3.3 Lag Effect of Consumer Reviews

According to the Adstock Theory (Broadbent, 1979), any form of advertising has the prolonged or lagged effect on consumer purchase behavior. It is also known as "advertising carry-over." Advertising not only reminds consumers to make immediate brand choice but also teaches consumers to increase brand awareness and salience, which makes it easier for future advertising to influence brand choice.

Consumer reviews, the customer-initiated WOM advertising, follow this lag pattern. Godes and Mayzlin (2004) examine eWOM communication within and across different user networks and find that lagged eWOM is significantly correlated with performance earlier on. Using elasticity as a measure of short-term and long-term WOM effect, Trusov et al (2009) showed that WOM effect, after controlling for endogeneity and autoregressive effects, carry over for several weeks, when traditional marketing activities taper off after a few days. They conclude that researchers should employ models that can also account for the lag effect of WOM marketing. Other studies find that as time goes by the long-term effect of consumer reviews is not strong compared to the short term because of the decay of information over time (Duan et al. 2008). These results would suggest that consumer reviews might have a lag effect on contemporary performance variables such as room sales. Thus, in addition to the preceding hypotheses on the contemporaneous effect of consumer reviews (i.e., H1-H3), we hypothesize that the lag effect of consumer reviews will be correlated with room sales.

H5: The lagged consume reviews have effect on room sales.

3.4 Conceptual Framework

Figure 2 depicts our conceptual framework, which integrates the interrelationship between consumer reviews and room sales into the extant representation of the hotel industry (Duverger, 2013). As shown in Figure 2, past consumer reviews in influence room sales in the same period and future room sales, which in turn affects the generation of contemporaneous and future reviews. Consumer reviews influence room sales in two ways. First, review valence and variation influence consumers' evaluation of hotels and persuade their decision-making. Second, the dissemination of reviews increases consumer awareness of the hotel popularity. A number of other hotel-specific characteristics, such as hotel age, hotel size, and service segmentation, influence consumer reviews and room sales as well. Although not present in the conceptual framework, these hotel-specific characteristics are controlled in the estimation models.

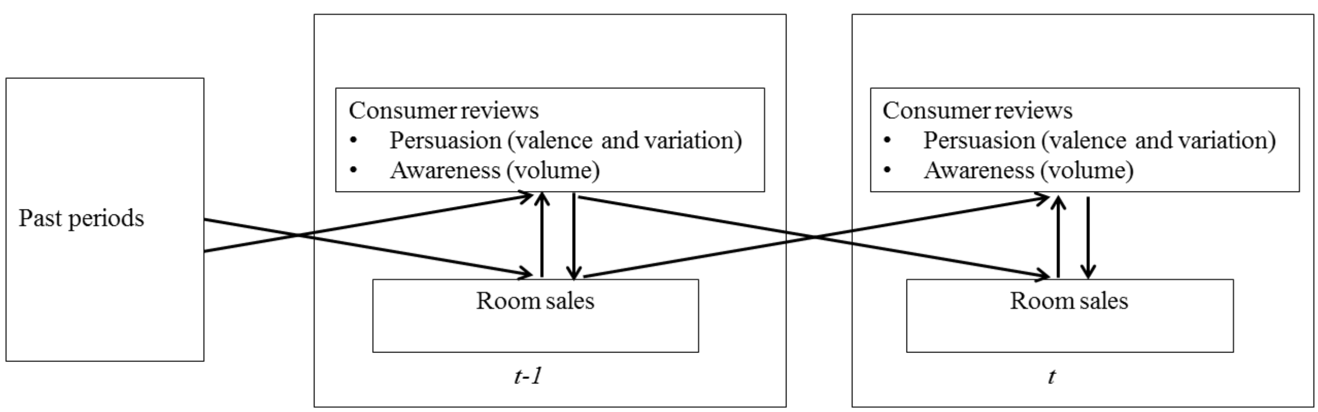

Figure 2. The Conceptual Framework

CHAPTER 4

DATA AND SAMPLE

In this study, we aim to quantify the value of consumer reviews to business. As a context for our inquiry, we choose TripAdvisor.com for hotels, the most prominent consumer review website within the hotel industry where the impact of online dissemination of opinions and reviews is rapid and far-reaching (Litvin et al. 2008). TripAdvisor.com offers over 60 million consumer reviews of over 520,000 hotels on a daily basis (tripadvisor.com, 2012). It acts as a forum for everyday consumer to air their personal opinions regarding service providers' quality whilst also read the recommendations of fellow consumers (Jeacle & Carter, 2011). In the meantime, hotel managers can regularly post their product and service information (Zhang et al., 2009) and also proactively induce their consumers to spread the word about their products online (Godes & Mayzlin, 2009). Therefore, TripAdvisor.com provides a good interactive setting where we can observe consumers' information search behaviors and hotel managers' manipulation and feedback mechanism strategies simultaneously.

4.1 Data Sources

We construct a panel data set including longitudinal and disaggregated hotel-level review and sales data. Specifically, our data include 56,284 hotel reviews on a daily basis, along with 5,711 quarterly sales records of more than 1,000 hotels located in five major hotel markets of Texas (See Figure 3) over ten quarters (2009q1- 2011q2). To our knowledge, this is the largest and most comprehensive panel to date that has been used to study the consumer reviews/hotel performance relationship.

Figure 3. Five Major Hotel Markets in Texas State

Consumer reviews are auto-parsed from TripAdvisor.com using two crawlers that are developed by Ruby.[5] For each hotel, we collect individual reviewers' ratings distributed on a scale of 1 to 5, in which 1 represents "terrible" and 5 represents "excellent". We also collect supplementary information including date and time of review posts, review id, reviewer characteristics, reviewer id, hotel id, city, hotel address, and hotel service segmentation[6].

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[5]Fully automated parsing" refers to the approach used to collect information from a website. Technically, we develop two crawlers using Ruby (1) to download automatically the web pages of hotel reviews and other hotel information from TripAdvisor.com and (2) to remove the HTML formatting from the text and then transformed into an XML file that separated the data into records (the review) and fields (the data in each review) in an automated fashion using a pre-coded computer program on the local machine. We use the crawlers to retrieve all available UGC information for the designated 100 hotels. For each hotel, we obtain all of the posted reviews. Each consumer review is analyzed and selected review features are recorded.
[6]TripAdvisor.com provides service segmentation information about each hotel being reviewed. It uses service segmentation schemes generated by Northstar Travel Media (company website: http://www.northstartravelmedia.com/), a privately owned news media company and the world's largest business-to-business publisher of travel oriented information. Northstar classifies hotels using "Crowns", which are determined on the basis of information from a variety of sources including (a) the hotel's own website, (b) fact based information received directly from hotels using questionnaires for attributes such as amenities, check-in/check-out, etc. (c) guest experiences which mostly from consumer reviews, and (d) reviews by their sister publication, STAR Reviews. About 7,500 properties with Crown ratings also have a STAR review. STAR reviews tend to be for properties with three or more Crowns. Northstar hotel classification

In addition, we obtain multi-quarter, archival data on hotel level sales performance from a research firm that is well known for its hospitality data and research services. Proprietary sales data are used under a nondisclosure agreement that protects the identity of the firm. The dataset consists of room sales information that is matched to the Texas Comptroller's Office database. Our sample consists of hotels exceeding $18,000 in quarterly revenues, which jointly account for some 98% of the lodging revenues in the entire state of Texas. In addition, the room sales dataset provides hotel attributes, including number of guest rooms, hotel age, and hotel chain[7].Our sample includes both independent hotels and chain hotels.

The above different data sources are then merged to create one comprehensive dataset with observations on a quarterly basis. By doing this, we safeguard against common method bias (Podsakoff et al. 2003). We restrict our focus to the hotel subset in which hotel-level reviews and sales data are available during the observation window (2009q1 - 2011q2). That is, any hotel in our sample should have quarterly revenue reported to Texas Comptroller's Office database (Panel 1) and daily consumer reviews posted on TripAdvisor.com (Panel 2) for at least one quarter in the study period. The merged sample is at "hotel × quarter" level, including an unbalanced sample of 4,994 hotel-quarter observations for 843 hotels.

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scheme is most widely used in the hospitality businesses including Sabre, TripAdvisor.com, Expedia.com, and many other OTAs.

[7]"Chains" are defined as one of the "Top 70+" brands, and include but are not confined to the following names: Four Seasons, Gaylord, Westin, W, Hilton, Hyatt, Inter-Continental, Marriott, Omni, Renaissance, Wyndham, Embassy, Homewood, Residence, Staybridge, Clarion, Courtyard, Crowne Plaza, Indigo, Doubletree, Hilton Garden, Holiday Inn, Radisson, Sheraton,AmeriSuites, Bradford, Candlewood, Comfort Suites, Hawthorn, Quality Suites, SpringHill, TownPlace, Amerihost, Baymont, Best Western, Comfort Inn, Country Inn, Drury, Fairfield, Hampton, Holiday Express, La Quinta, Wingate, Budget Suites, Extended Stay, Homestead Village, Intown, Value Place, Studio Plus, Studio 6, Best Value, Days, Econo Lodge, Howard Johnson, Microtel, Motel 6, Quality Inn, Ramada, Red Roof, and Super 8.

4.2 Variable Definitions

Definitions of the variables in this study are provided in Table 3. “revpar” represents room sales. It captures the interaction of average daily room rate (ADR) and hotel occupancy (OCC) at different phases of the lodging cycle. The hospitality industry uses RevPAR as the component of choice to measure fair hotel performance because it simultaneously revealing both the supply-and-demand dynamics of a lodging-market cycle in one index (Ismail et al. 2002; Woods, 1994).

Table 3. Variables Definitions

revpar	The average revenue per available room per hotel in quarter *t.* It is the measure of hotel performance.
valence	The average consumer rating per hotel in quarter *t*, i.e., 1 “terrible”, 2 “poor”, 3”average”, 4 “very good”, and 5 “excellent”.
variation	The standard deviation of the consumer rating per hotel in quarter *t.* It shows the degree of disagreement among consumers for a hotel.
volume	Logarithm of the number of reviews received from reviewers per hotel in quarter *t*
age	Number of years since a hotel first appears in the Texas Comptroller’s Office database to quarter *t*
size	Logarithm of the number of guest rooms per hotel in quarter *t*
segment	An indicator variable that equals 5 for a luxury hotel, 4 for an above average hotel with some outstanding features and a broad range of services, 3 for a full service hotel, 2 for a mid-market economy hotel, and 1 for a budget traveler hotel[8] in quarter *t*

[8]See HospitalityEducatores.com for a more detailed description of what the crown ratings are. (http://www.hospitalityeducators.com/articles/20110215_4#.UcUsPJwyj64)

“Valence" measures the average rating for a hotel (Chen et al. 2004; Chevalier & Mayzlin, 2006; Dellarocas et al. 2007; Duan et al., 2008);“variation” measures the standard deviation of the consumer rating (dispersion from the mean rating) (Clemons et al. 2006; Ghose et al. 2012; Hu et al. 2006; Mudambi & Schuff, 2010; Sun, 2012); and “volume” is the logarithm of number of reviews (Chen et al. 2004; Chintagunta et al. 2010; Dellarocas et al. 2010; Hong et al. 2012).

We consider hotel-specific characteristics that include hotel age measured as the number of years since its establishment (“age”), hotel size measured as the logarithm of the number of guest rooms (“size”), and an indicator variable of the hotel service segmentation (“segment”). Since these variables might also be related to hotel performance, they serve as control variables in our empirical specification of hotel performance as well.

4.3 Summary Statistics

Our observation level is “Hotel × Quarter”. The sample consists of 4,994 year-quarter observations of 843 individual hotels located in five cities over ten quarters. To our knowledge, this is the largest panel to date that has been used to study the consumer reviews/hotel performance relationship. Table 4 provides the sample distribution by city. San Antonio is the largest hotel market, followed by Houston, Austin, Dallas, and Fort Worth.

Table 4. Sample Distribution by City

The table contains the summary statistics of our sample distribution in the hotel markets across five cities in Texas. The results are based on an unbalanced sample of 843 hotels and 4,994 hotel year-quarters from 2009q1 to 2011q2. The consumer review data are auto-parsed from TripAdvisor.com and performance data come from the Texas Comptroller's Office database. RevPAR is the average revenue per available room. Mean values are shown in the table; percentages of the total sample are shown in brackets.

city	observations	hotels
Austin	928 (18.58%)	135 (16.01%)
Dallas	777 (15.56%)	123 (14.59%)
Fort Worth	383 (7.67%)	72 (8.54%)
Houston	1,447 (28.97%)	272 (32.27%)
San Antonio	1,459 (29.22%)	241 (28.59%)
Total	4,994 (100%)	843 (100%)

Table 5 presents the summary statistics of variables. We observe evident seasonality of hotel performance in the Texas hotel market (downward diminishing). Because the sample is unbalanced, the number of hotels differs each quarter –our estimation strategy uses all available observations. The sample includes large and small, dependent and independent hotels, unlike most previous studies that tend to focus on either large or chain hotels. Each quarter, our sample hotels experience some change in the level of consumer review components (min. 0.14% and max. -16.62%). This frequency of change suggests that there is enough time-series variability in our variables. Thus, we can effectively use panel data estimation techniques.

Table 5. Summary Statistics by Year-Quarter

The table contains the descriptive statistics of variables in this study by quarter and the overall summary statics. The results are based on a sample of 843 firms and 4,994 hotel year-quarters from 2009Q1 to 2011Q2. The consumer review data are auto-parsed from TripAdvisor.com and performance data come from the Texas Comptroller's Office database. RevPAR is the average revenue per available room. Valence is the average consumer rating for a hotel. Variation is the standard deviation of the consumer rating of a hotel. Volume is the logarithm of the number of reviews received from reviewers. Age is the number of years since a hotel first appears in the Texas Comptroller's Office database. Size is the logarithm of the number of guest rooms in a hotel. Segment is an indicator variable that equals 5 for a luxury hotel, 4 for an above average hotel with some outstanding features and a broad range of services, 3 for a full service hotel, 2 for a mid-market economy hotel, and 1 for a budget traveler hotel. Median values are shown in parentheses; standard deviations are shown in brackets.

Summary statistics of variables by quarter (N=4,994)										
	2009q1	2009q2	2009q3	2009q4	2010q1	2010q2	2010q3	2010q4	2011q1	2011q2
revpar	66.51	61.75	56.64	53.81	59.44	61.38	55.54	54.66	65.11	65.05
	(63.73)	(57.61)	(52.73)	(48.85)	(54.31)	(58.53)	(50.84)	(49.32)	(61.22)	(61.17)
	[34.95]	[31.62]	[29.47]	[30.88]	[34.01]	[33.14]	[31.01]	[33.36]	[37.10]	[35.02]
Review variables										
valence	3.53	3.70	3.61	3.72	3.58	3.64	3.45	3.64	3.52	3.59
	(4.00)	(4.00)	(3.90)	(4.00)	(3.92)	(4.00)	(3.79)	(4.00)	(3.78)	(4.00)
	[1.21]	[1.14]	[1.15]	[1.21]	[1.14]	[1.05]	[1.16]	[1.05]	[1.13]	[1.12]
variation	0.56	0.56	0.62	0.52	0.59	0.63	0.69	0.68	0.70	0.72
	(0.45)	(0.50)	(0.53)	(0.00)	(0.50)	(0.58)	(0.66)	(0.59)	(0.71)	(0.71)
	[0.65]	[0.64]	[0.70]	[0.63]	[0.67]	[0.65]	[0.66]	[0.68]	[0.66]	[0.64]
volume	0.74	0.83	0.85	0.86	0.89	0.96	1.05	1.04	1.08	1.20
	(0.69)	(0.69)	(0.69)	(0.69)	(0.69)	(0.69)	(1.10)	(1.10)	(1.10)	(1.10)
	[0.76]	[0.83]	[0.86]	[0.90]	[0.89]	[0.91]	[0.94]	[0.93]	[0.93]	[1.02]
Hotel characteristics										
age	19.26	17.66	17.36	17.46	18.42	18.06	18.42	18.13	18.18	18.13
	(14.00)	(13.00)	(13.00)	(13.00)	(14.00)	(14.00)	(14.00)	(14.00)	(14.00)	(14.00)
	[13.05]	[12.75	[12.72]	[13.17]	[13.01]	[12.78]	[13.28]	[13.35]	[12.95]	[13.15]
size	4.94	4.93	4.93	4.96	4.91	4.92	4.90	4.92	4.89	4.88
	(4.87)	(4.87)	(4.87)	(4.89)	(4.86)	(4.87)	(4.82)	(4.86)	(4.83)	(4.83)
	[0.77]	[0.74]	[0.72]	[0.73]	[0.72]	[0.71]	[0.69]	[0.71]	[0.71]	[0.70]
segment	2.72	2.70	2.68	2.74	2.69	2.69	2.61	2.69	2.68	2.69
	(3.00)	(3.00)	(3.00)	(3.00)	(3.00)	(3.00)	(2.50)	(3.00)	(3.00)	(3.00)
	[1.11]	[1.06]	[1.08]	[1.04]	[1.04]	[1.05]	[1.07]	[1.05]	[1.02]	[0.98]
Number of observations	390	434	447	450	503	523	556	533	558	600

Summary statistics of variables					
	Mean	Median	Std. Dev.	Min	Max
revpar	60.00	55.45	33.50	10.40	174.58
valence	3.59	4.00	1.14	1.00	5.00
variation	0.63	0.58	0.66	0.00	2.31
volume	0.97	0.69	0.92	0.00	3.43
size	4.92	4.86	0.72	2.08	7.52
segment	2.50	3.00	1.03	0.00	5.00
age	18.11	14.00	13.03	0.00	63.00

Through the plotting of Figure 4A-4D, we observe that the number of reviews received by hotels keeps growing throughout the study period, indicating that more and more consumers are using the social media platform to publish hotel reviews. Figure 4A and Figure 4B demonstrate the changes of quarterly room sales and review volume. These two plots display similar patterns on a quarter-to-quarter basis. The plots suggest that review volume and hotel room sales might be highly interdependent, which highlights the importance of investigating room sales and review volume simultaneously to uncover the real effect of online WOM. The highly interdependent nature of room sales and review volume also makes the importance of using quarterly data more evident. Figure 4C plots the quarterly average review ratings across all hotels and Figure 4D plots the quarterly variation of review ratings. These two figures show that variations in quarterly consumer ratings persist overtime, suggesting that review valence can change frequently.

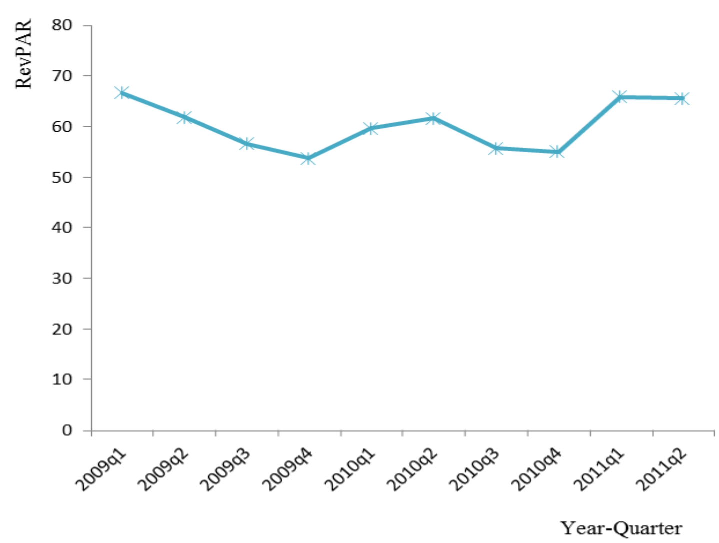

Figure 4A. The Average RevPAR for Hotel Sample

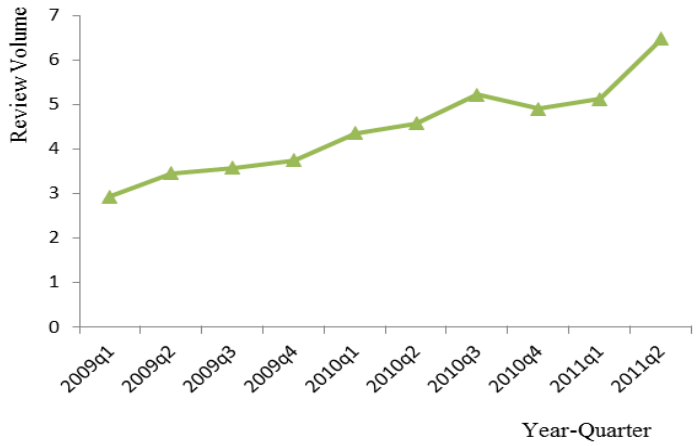

Figure 4B. The Average Review Volume for Hotel Sample

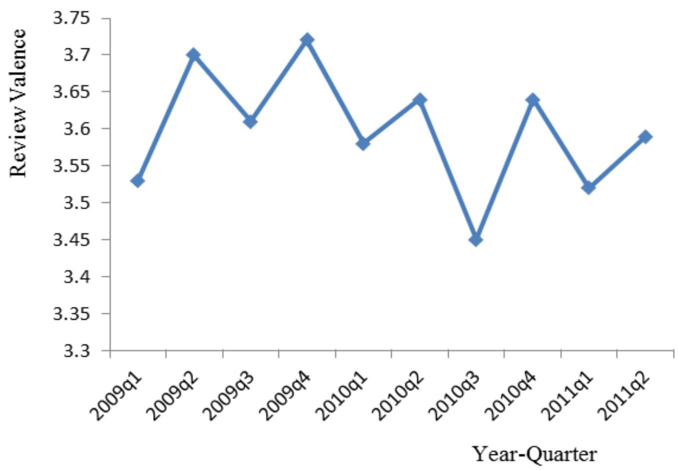

Figure 4C. The Average Review Valence for Hotel Sample

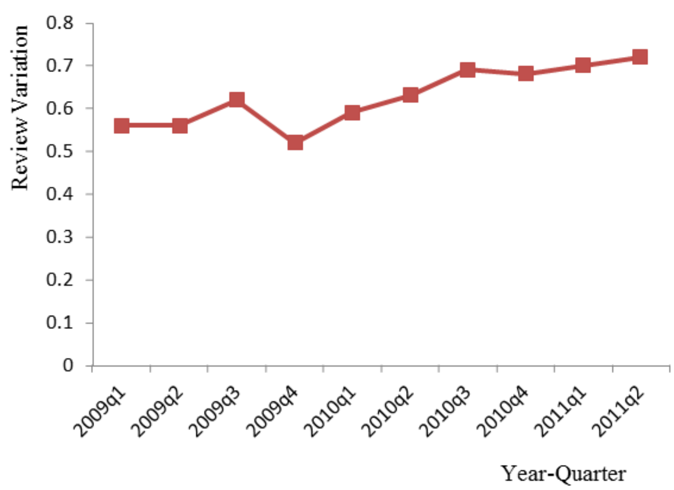

Figure 4D. The Average Review Variation for Hotel Sample

Table 6 organizes the data by service segmentation. We notice that the RevPAR of the higher-tiered hotels is somewhat better than the lower-tiered hotels. Review valence decreases as the service segmentation moves down, indicating that consumer ratings in general are reliable reflection of the hotel service quality (Riegner, 2007). Review ratings are most dispersive for above-average hotels (SD=1.04) but most consistent for mid-market economy hotels (SD=0.46). Higher-tiered hotels seem more popular with a larger volume of consumer reviews. For example, on average 1.72 reviews for luxury hotels, 2.10 for above average hotels, and 1.13 for full service hotels. The age of our hotel sample is above 15 years. Our sample consists of both large- and small-size hotels.

Table 6. Summary Statistics by Service Segmentation

The table contains the summary statistics of our sample distribution by service segmentations. The results are based on a sample of 843 firms and 4,994 hotel year-quarters from 2009Q1 to 2011Q2. Service segmentation is an indicator variable that equals 5 for a luxury hotel, 4 for an above average hotel with some outstanding features and a broad range of services, 3 for a full service hotel, 2 for a mid-market economy hotel, and 1 for a budget traveler hotel. Standard deviations are shown in brackets.

Crown	segment	revpar	valence	variation	volume	age	size
5	Luxury	146.68	4.34	0.80	1.72	18.49	5.34
		(23.00)	(0.58)	(0.57)	(0.62)	(12.28)	(0.41)
4	Above	103.17	3.93	1.04	2.10	23.85	5.79
	average	(31.51)	(0.62)	(0.46)	(0.78)	(14.89)	(0.74)
3	Full service	67.79	3.79	0.73	1.13	18.22	5.15
		(23.15)	(0.92)	(0.63)	(0.85)	(13.16)	(0.56)
2	Mid-market	40.22	3.46	0.46	0.53	15.26	4.49
	economy	(18.69)	(1.27)	(0.67)	(0.65)	(11.23)	(0.46)
1	Budget	23.70	2.14	0.61	0.49	29.82	4.26
	traveler	(12.50)	(1.12)	(0.81)	(0.60)	(9.69)	(0.37)

Finally, we present the correlation matrix (Rodgers & Nicewander, 1988) in Table 7. The correlation coefficients between the independent variables are generally below 0.60 and do not indicate the presence of multicollinearity in our estimation (Kufs, 2011; Wheeler & Tiefelsdorf, 2005).

Table 7. Pearson Correlation Matrix

The table contains the Pearson correlation matrix of explanatory variables used in this. The results are based on a sample of 843 firms and 4,994 hotel year-quarters from 2009Q1 to 2011Q2. Valence is the average consumer rating for a hotel. Variation is the standard deviation of the consumer rating of a hotel. Volume is the logarithm of the number of reviews received from reviewers. Age is the number of years since a hotel first appears in the Texas Comptroller's Office database. Size is the logarithm of the number of guest rooms in a hotel. Segment is an indicator variable that equals 5 for a luxury hotel, 4 for an above average hotel with some outstanding features and a broad range of services, 3 for a full service hotel, 2 for a mid-market economy hotel, and 1 for a budget traveler hotel. Values with *indicate correlations that are significant at $p<0.05$.

	valence	variation	volume	age	size	star
valence	1					
variation	-0.05*	1				
volume	0.21*	0.60*	1			
age	-0.19*	0.13*	0.15*	1		
size	0.05*	0.29*	0.47*	0.33*	1	
segment	0.28*	0.26*	0.47*	0.07*	0.52*	1

4.4 Panel Property

In multi-period panel data, if the population model consists of a time-invariant, unobserved heterogeneity effect (fixed-effects) that is correlated with the explanatory variables, POLS as well as random effect estimators provide regression estimates that are inconsistent. In this case, a fixed-effects model may be warranted. Table 8 shows the result of Hausman test (Prob> chi^2= 0.0000) which rejects the null hypothesis, suggesting that the errors are correlated with the explanatory variables. Therefore, there is no justification for treating the individual effects as uncorrelated with the other regressors and individual within hotel effect is highly related to the review components. In this situation, the random effects treatment may suffer from the inconsistency due to this correlation. We should use fixed-effects model rather than random effect model or POLS.

Table 8. Hausman Test and Tests of Serial Correlation and Heteroskedasty

The table contains the Hausman test for the correlation between explanatory variables and errors, the Breusch-Pagan Test for Heteroskedasticity, and the Wooldridge test for autocorrelation. The results are based on a panel sample of 843 hotels and 4,994 hotel year-quarters from 2009Q1 to 2011Q2. The significance level of tests is at 0.05.

Hausman Test
H_0: difference in coefficients not systematic
$chi^2(5) = 436.17$
$Prob>chi^2 = 0.0000$
Breusch-Pagan Test for Heteroskedasticity
H_0: Constant variance /error variances are all equal
$chi^2(1) = 0.38$
$Prob> chi^2 = 0.5371$
Wooldridge Test for Autocorrelation
H_0: no first-order autocorrelation
$F(1, 534) = 74.602$
$Prob> F = 0.0000$

To test whether a fixed-effects model is warranted, we use a Breusch-Pagan test to check for heteroskedasticity. As shown in Table 8, the result (low chi^2 value 0.38, Prob> chi^2 = 0.5371) does not reject the hypothesis, suggesting heteroskedasticity is not a problem (or is not a multiplicative function of the predicted value). This finding indicates that our use of fixed-effects estimation is warranted.

Having selected the regression estimation to obtain valid statistical inferences, we control for likely serial correlation of errors over time because of repeated measures of the same hotel. Serial correlation causes the standard errors of the estimated regression coefficients to be smaller than they actually are and inflates the estimation R-square (R^2). Although it does appear to arise naturally in time-series data, one would want to look carefully at the data and the model specification before assuming that it is present (Stock & Watson, 2007). We use the Wooldridge (2003) test to check for serial correlation of the errors, with the null hypothesis being that there is no serial correlation. As can be seen in Table 8, the result (Prob>F = 0.0000) indicates significant first-order autocorrelation (*AR(1)*). From a traditional point of view, we need to deploy a fixed-effects estimation model that is able to address the first-order autocorrelation.

Even though fixed-effects estimation may potentially ameliorate the bias arising from unobservable heterogeneity, heteroskedasticity, and auto-correlation, the empirical challenges aforementioned in Chapter 2 remain important problems. First, the fixed-effects estimator requires strong exogeneity assumption - one that is often not explicitly recognized by researchers - and assumes that current observations of the explanatory variable (review components) are completely independent of past values of the dependent variable (hotel performance), an assumption that is not realistic. It is very likely that there is within time period dynamic nature between hotel room sales and review matrices, controlling for other factors such as hotel size, age, and service segmentation, as well as the between time period correlations. We often cannot ascertain if the causation is actually reversed (e.g., performance drives consumer reviews) or if consumer reviews are merely a symptom of an underlying unobservable factor, which also affects performance. As discussed in Chapter 2, two sources of reverse causality have been identified in prior research. First, it is very likely that there is a feedback mechanism between consumer reviews and sales (Duan et al. 2008). There is possibility that current values of consumer review variables are a function of past performance (Wintoki et al. 2012). Second, management’s manipulation on reviews depends on a hotel’s current and future performance expectations that are reflected in hotel sales (Mayzlin et al. 2012; Kornish et al. 2009). As a result, it is possible that our findings may be driven by reverse causality between RevPAR to consumer reviews. Because causality may run in both directions, our test variables (i.e., valence, variation, and volume) are likely to be correlated with the error term. However, including dynamic effect of lagged hotel performance in a fixed-effects model immediately violates estimation because by construction it is correlated with errors in the previous periods.

The usual way of addressing such endogeneity issues is to estimate a two-stage least squares (2SLS) model. However, we face three problems in doing so. First, we do not have good instruments for our test variables other than their lags. With weak instruments, the 2SLS estimators are likely to be biased in the same way as the POLS estimators. Second, our test for serial correlation shows significant serial correlation in errors. This can lead to significantly biased 2SLS estimators. Thus, it is difficult to determine what the parameter estimates actually suggest in traditional fixed-effects models.

CHAPTER 5

MODEL SPECIFICATIONS

Our research interest is to quantify the business value of consumer reviews to hotel performance in a dynamic framework. We apply the dynamic panel GMM estimator to examine the dual role of consumer reviews in predicting room sales and being outcome of room sales. First, we discuss why a dynamic panel model should be used in estimating the dynamic relation between reviews/sales driven by endogeneity. Second, we specify the dynamic panel model with a system GMM estimator in both level and differenced forms. Finally, we explain the diagnostic tests for instrument validity.

5.1 Advantages of System GMM Dynamic Panel Models

Most prior studies of the effect of consumer reviews on performance have estimated ‘‘static’’ models of the form (e.g., Ye et al. 2010): *performance=f(review components, hotel-specific characteristics, fixed-effects),* where review components include valence, variation, and volume. Because of the feedback mechanism and firm manipulation, it is necessary for us to include the past performance as one of the explanatory variables in model estimation. We posit that the appropriate empirical model should be a ‘‘dynamic’’ model of the form: *performance = f(past performance, review components, hotel-specific characteristics, fixed-effects).*

When including the lagged dependent variable, we cause a major change in the interpretation of the equation. Without the lagged dependent variable, the “independent variables” represent the full set of information that produce observed outcome. With the lagged dependent variable, we have in the equation, the entire history of the right hand side variables, so that any measured influence is conditioned on this history; in this case, any impact of independent variables represents the effect of new information (Greene, 2003). Substantial complications arise in estimation of such a model. In both static models, e.g., fixed-effects and random effects models, the difficulty is that the lagged dependent variable is correlated with the disturbance, even if it is assumed that errors are not auto-correlated. Because of these limitations of static panel models, the estimation results may be seriously biased.

A dynamic system GMM panel model which includes the lags of the dependent variable as one of the explanatory variables (Arellano & Bond, 1991) is used to accommodate the dynamic effect. We use the Arellano-Bover/Blundell-Bond system generalized method of moments (GMM) estimator in estimating the dynamic panel model. The system GMM estimator produces coefficient estimates that are consistent and efficient in the presence of endogenous independent variables and fixed-effects. This dynamic panel system GMM estimator is developed in a series of papers by Holtz-Eakinet al. (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). The estimator employs a system of two equations: the original level equation and one transformed by first differencing the variables in the original equation. The first difference transform removes fixed-effects. The system GMM estimator then uses the lagged values of the differences and levels of endogenous variables as instruments to control for endogeneity. Recent studies have used the system GMM model where endogeneity and fixed-effects pose concerns (e.g., Aral et al. 2012). The system GMM estimation procedure controls for endogeneity and eliminates bias because of unobserved heterogeneity (Foster & Szekely, 2008).

Compared with traditional POLS and fixed-effects models, the dynamic panel system GMM estimator improves on them in at least one of three important ways. First, unlike POLS estimation, we can to include firm-fixed-effects to account for (fixed) unobservable heterogeneity. Second, unlike traditional fixed-effects estimates, it allows current consume reviews to be influenced by previous realizations of, or shocks to, past performance. Third, unlike either POLS or traditional fixed-effects estimates, a key insight of the dynamic panel GMM estimator is that if the underlying economic process itself is dynamic – in our case, if current consumer reviews are related to past performance – then it may be possible to use some combination of variables from the hotel's history as valid instruments to account for simultaneity. Thus, an important aspect of the methodology is that it relies on a set of ''internal'' instruments contained within the panel itself: past values of reviews and performance can be used as instruments for current realizations of reviews. This eliminates the need for external instruments.

In summary, by using the system GMM dynamic panel model, we are able to not only incorporate the theoretical important dynamic effect but also mitigate the endogeneity issues that could not be addressed by traditional static models such as POLS and fixed-effects models.

5.2 Model Specifications

To obtain consistent and unbiased estimates (under the assumption that unobserved heterogeneity exists but is fixed or time-invariant), we estimate the relation between consumer reviews and performance using a dynamic GMM panel estimation. The dynamic effect suggests that estimating the effect of consumer reviews on hotel performance, conditional on hotel heterogeneity, requires estimating the following empirical model:

$$y_{it} = \alpha + \sum_s Ksy_{it-s} + \beta X_{it} + \gamma Z_{it} + \mu_{it} + \varepsilon_{it} \qquad s = 1, \ldots, p \qquad (1)$$

where X, Z, and y represent consumer review components, hotel-specific characteristics, and performance, respectively, and μ represents an unobserved fixed effects. ε is a random error term and β is the effect of consumer reviews on performance. In Equation (1), current shocks are independent of historical performance or consume reviews. This is not a strong assumption since it allows current performance to be influenced by past and current consume reviews. The assumption leaves open the possibility that there is feedback mechanism between reviewers and firm performance or that hotels strategically manipulate consumer reviews to affect current or future performance. The basic estimation procedure consists of two essential steps. First, we write the dynamic model of (1) in first- differenced form:

$$\Delta y_{it} = \alpha + K_p \sum_p \Delta y_{it-p} + \beta \Delta X_{it} + \gamma \Delta Z_{it} + \Delta \varepsilon_{it} \qquad p>0 \qquad (2)$$

First-differencing eliminates any potential bias that may arise from time-invariant unobserved heterogeneity. After first-differencing, we estimate (2) via GMM using lagged values of the explanatory variables as instruments for the current explanatory variables. That is, we use historical values of performance, consumer reviews, and other firm- specific variables as instruments for current changes in these variables.

5.3 Diagnostic Tests for Instrument Validity

An important aspect of the dynamic panel estimator is its use of the hotel's history as instruments for our explanatory variables. This means that in estimating Equation (1) or the first-difference transformation in Equation (2), our instruments will be drawn from the set of lagged dependent or explanatory variables, i.e., $y_{t-k.}$ $X_{t-k,}$ $Z_{t-k,}$ where $k > p$. For these instruments to be valid, they must meet two criteria. First, they must provide a source of variation for current consumer reviews. In our discussion of the dynamic effect, consumer reviews are likely choice variables that arise from the feedback mechanism or through hotels' manipulation. Thus, if consumer reviews are dynamic and hotel *i* (given its performance at time *t*-1 or earlier) choose consumer reviews X_{it} to achieve a particular level of expected or anticipated performance at time *t*, then the dynamic model for consumer reviews is $X_{it}= f\,(y_{it-1,} y_{it-2,\ldots.} y_{it-p,}\ Z_{it,}\ \mu_{it}\ )$. In this discussion on the determinants of consumer reviews, we have established a theoretical motivation for this assumption. Later in analysis results, we show that consumer reviews are strongly correlated to historical performance.

Second, the historical or lagged values must provide an exogenous source of variation for current consumer reviews. This means that lagged variables must be uncorrelated with the error in the performance equation in Equation (1). Evidence provides motivation for this. As discussed earlier, the current shocks to performance must have been unanticipated when the hotels monitor the feedback mechanism between reviewers and performance or strategically manipulate reviews. Any information from the hotel's past is impounded into current expected performance within *p* time periods. This means that *p* lags of past performance are sufficient to capture the influence of the hotel's past on the present, i.e., including *p* lags ensures dynamic completeness of Equation (1). Provided we have included *p* lags of performance, any information from the hotel's history that is older than that has no direct effect on current performance and only affects performance through its effect on current consumer reviews and other hotel-specific characteristics. Thus, the hotel's history beyond period *t-p* should be exogenous with respect to any shocks or surprises to performance in the current or future periods. Arellano and Bond (1991) suggest two key tests of this assumption. The first test is a test of second-order serial correlation. The biggest concern is whether or not we have included enough lags to control for the dynamic aspects of our empirical relationship. If we have, then any historical value of hotel performance beyond those lags is a potentially valid instrument since it will be exogenous to current performance shocks. For our GMM estimates, if the assumptions of our specification are valid, by construction the residuals in *AR (1)* should be correlated, but there should be no serial correlation in *AR (2)*. The second test is a Hansen test of over-identification. The dynamic panel GMM estimator uses multiple lags as instruments. This means that our system is over-identified and provides us with an opportunity to carry out the test of over-identification. The Hansen test yields a *J*-statistic which is distributed χ^2 under the null hypothesis of the validity of our instruments.

CHAPTER 6

ESTIMATION AND DISCUSSION

In this chapter, we examine the empirical relation between consumer reviews and hotel performance using the dynamic panel model developed in previous chapter. We first determine how many lags of performance we need to ensure dynamic completeness. Then we present empirical evidence of the strength of dynamic relationship between consumer reviews and the hotel's historical performance and characteristics. Next, we estimate the relation between consume reviews and hotel performance using the dynamic panel GMM estimator and compare the results obtained from static models such as POLS and traditional fixed-effects in order to understand biases that arise from ignoring different aspects of endogeneity. We also conduct diagnostic checks and robustness checks for the model validity and result sensitivity. Finally, we examine the lag effect of consumer reviews on performance and the determinants of reviews in a dynamic framework using additional tests.

6.1 Dynamic Completeness

Empirically, it is important to understand how many lags of performance we need to capture all information from the past. This is important for at least two reasons. First, failure to capture all influences of the past on the present could still mean that Equation (1) is mis-specified (i.e., there might be an omitted variable bias). Second, and perhaps more importantly, we argue that all older lags are exogenous with respect to the residuals of the present; thus, they can be used as instruments. This is important for consistent estimation using the dynamic panel GMM estimator.

Bardhan et al. (2013) and Duverger (2013) uses one lag of firm performance in their dynamic panel model. Glen et al. (2001) and Gschwandtner (2005) suggest that two lags are sufficient to capture the persistence of profitability. Thus, we propose including two lags in our estimates of the consume review/ performance relation (i.e., we set p=2 in Equation (1)). To see if two lags are sufficient to ensure dynamic completeness, we estimate a regression of current performance on two lags of past performance, controlling for other hotel-specific characteristics. Table 9 shows the estimation results. Consistent with Bardhan et al. (2013) and Duverger (2013), our results suggest that including one lag is sufficient to capture the dynamic aspect of the consumer reviews/performance relation. In Column 1, the first lag is statistically significant (0.712, p-value=0.000) while the older lag (i.e., lag 2) are insignificant (0.212, p-value=0.220). In Column 2, we drop the older lag and include only the first lag. The first lag is consistently statistically significant (0.885, p-value=0.000). Thus, while the older lags may include relevant information, that information is subsumed by the more recent lag (i.e., lag 1). The results demonstrate that including one lag is sufficient to capture the dynamic aspect of the review/performance relation.

Table 9. How Many Lags of Hotel Performance are Significant?

In this table, we report results from the estimation of the model:

$$y_{it}=\alpha_1 + \sum_{p=1}^{p=2} Kp y_{it-p} + KZ_{it} + \mu_{it} + \varepsilon_{it} \qquad t\text{=2009q2 – 2011q2}$$

y_{it} is revepar. Z_{it} includes size, segment, and age. The results are based on a sample of 843 hotels and 4,994 hotel year-quarters from 2009q1 to 2011q2. t = 2010q1 - 2011q2. *p*-values are reported in parentheses. ***, **, and * represent significance at the1%, 5% and 10% level, respectively. All estimations are based on robust, hotel-clustered standard errors. Year-quarter dummies (i.yq) are included in all specifications.

	revpar	revpar
revpar (*t*-1)	0.712***	0.885***
	(0.000)	(0.000)
revpar (*t*-2)	0.212	
	(0.220)	
age	-0.065***	-0.089***
	(0.000)	(0.000)
size	-0.459	-0.669*
	(0.138)	(0.062)
segment (2 crown)	-3.661***	-2.922***
	(0.000)	(0.004)
segment (3 crown)	0.112	1.487
	(0.907)	(0.181)
segment (4 crown)	3.734***	6.622***
	(0.003)	(0.000)
segment (5 crown)	10.767***	14.034***
	(0.000)	(0.000)
Constant	2.177	9.208***
	(0.344)	(0.000)
Observations	2,468	3,363
Adjusted R-squared	0.909	0.900

6.2 Strength of Dynamic Relationship

A central argument in our paper is that consumer reviews (i.e., valence, variation, and volume) and other hotel-specific variables are related to past performance. We examine this assertion directly with a test that involves OLS regressions of current levels of consumer reviews and other hotel-specific variables. The results are shown in Table 10.

We present results from OLS regressions of the levels of consumer reviews and other hotel characteristics on performance and characteristics from one quarter before.

Table 10. How Strong is the Present Correlated with the Past?

In this table we report the results of OLS regressions of current reviews (i.e., valence, variation, and volume) and current hotel-specific characteristics (e.g., size and age), on past sales performance and historic values of the hotel-specific variables. Segment as a time-variant variable is not included in the test. Performance is measured by revpar. The firm-specific variables include age, size, and segment. The results are based on a sample of 843 hotels and 4,994 hotel year-quarters from 2009q1 to 2011q2. *t* = 2010q1 - 2011q2. All t-statistics (in parentheses) are based on robust standard errors. ***, **, and * represent significance at the 1%, 5% and 10% level, respectively. Year-quarter dummies (i.yq) are included in all specifications.

	valence	variation	volume
revpar (*t*-1)	0.005***	0.001***	0.005***
	(0.000)	(0.002)	(0.000)
age	-0.011***	0.003***	0.003**
	(0.000)	(0.000)	(0.013)
size	-0.118***	0.122***	0.236***
	(0.000)	(0.000)	(0.000)
segment (2 crown)	0.365***	0.002	0.034
	(0.000)	(0.968)	(0.559)
segment (3 crown)	0.591***	0.134**	0.334***
	(0.000)	(0.015)	(0.000)
segment (4 crown)	0.706***	0.245***	0.959***
	(0.000)	(0.000)	(0.000)
segment (5 crown)	0.727***	0.070	0.520***
	(0.000)	(0.512)	(0.000)
i.yq	yes	yes	yes
Constant	3.610***	-0.207**	-0.878***
	(0.000)	(0.048)	(0.000)
Observations	3,363	3,363	3,363
Adjusted R-squared	0.115	0.099	0.355

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We find that consumer reviews are significantly positively related to past performance (0.005, *p*-value=0.000 for valance; 0.001, *p*-value=0.002 for variation; 0.005, *p*-value=0.000 for volume, respectively). This finding supports our argument that consumer reviews are related to past performance. The results are intuitive in a sense that a hotel that have done well in the past will be rated higher today by consumers, receive more reviews from the past consumers, and consequently have larger variation in reviewers' opinions as the number of reviewers increases.

6.3 The Relationship between Reviews and Performance

We have discussed the estimation difference of fixed-effects models and the system GMM dynamic models in previous sections. In order to compare to past research (e.g., Duverger, 2013; Ye et al. 2010) and highlight the potential problems from ignoring the dynamic relation between current reviews and the hotel's performance history, we evaluate the sensitivity to the estimation methodologies of fixed-effects model and the system GMM dynamic model. We also present the results of other static and dynamic econometric models to ascertain the sensitivity of our estimation results to differences in estimation methodologies and model specifications.

Static models:

1. A POLS model

2. A fixed-effects model

Dynamic models:

3. A dynamic POLS model

4. A dynamic fixed-effects model (system GMM)

6.3.1 Effect Estimation

Table 11 reports the results when we use RevPAR as our performance measure. As we discussed earlier, we include one lag of sales performance in the dynamic model. This makes hotel history lagged one period or more available for use as instruments. We use variables lagged two and three periods (*t*-2 and *t*-3), respectively, as instruments for all the endogenous variables in the GMM estimates.

Table 11. The Effect of Consumer Reviews on Current Hotel Performance

In this table, we report results from the estimation of the model:

$$y_{it}=\alpha_1 + K_1 y_{it-1} + \beta X_{it} + \gamma Z_{it} + \mu_{it} + \varepsilon_{it} \qquad t= \text{2009q1} – \text{2011q2}$$

y_{it} is revpar. X_{it} includes review components (i.e., valence, variation, volume). Z_{it} includes size, age, segment, and year-quarter dummies. The results are based on a sample of 843 hotels and 4,994 hotel year-quarters from 2009q1 to 2011q2. *P*-values are reported in parentheses. ***, **, and * represent significance at the 1%, 5% and 10% level, respectively. For the static models, it is assumed that K_1=0. All estimations are based on robust, hotel-clustered standard errors. We report two-step estimators, which are asymptotically efficient and robust to any panel-specific autocorrelation and heteroscedasticity. *AR(1)* and *AR(2)* are tests for first-order and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of over-identification is under the null that all instruments are valid. The Diff-in-Hansen test of exogeneity is under the null that instruments used for the equations in levels are exogenous. The instruments used in the GMM estimation are: differenced equations: $y_{it-2}, y_{it-3}, X_{it-2}, X_{it-3}, Z_{it-2}, Z_{it-3}$; level equations: Δy_{it-1}, ΔX_{it-1}, ΔZ_{it-1}.

	Static model		Dynamic model	
	POLS	Fixed-Effects	POLS	System GMM
valence	2.959***	-0.026	0.445***	-2.544
	(0.000)	(0.894)	(0.006)	(0.353)
variation	0.876	0.086	0.444	5.236
	(0.362)	(0.818)	(0.184)	(0.342)
volume	4.452***	1.548***	1.073***	10.074***
	(0.000)	(0.002)	(0.003)	(0.002)
age	-0.312***	3.816***	-0.088***	-0.295
	(0.001)	(0.000)	(0.000)	(0.693)
size	-5.568**	-52.428***	-0.924**	48.318
	(0.030)	(0.000)	(0.016)	(0.678)
segment (2 crown)	-17.991**		-3.122***	-34.111
	(0.023)		(0.002)	(0.808)
segment (3 crown)	10.300		0.807	-82.680
	(0.166)		(0.459)	(0.660)
segment (4 crown)	45.161***		5.171***	-44.181
	(0.000)		(0.001)	(0.852)
segment (5 crown)	86.315***		13.121***	49.892
	(0.000)		(0.000)	(0.951)
revpar (*t*-1)			0.878***	0.221**
			(0.000)	(0.017)
i.yq	yes	yes	yes	yes
Constant	78.584***	259.815***	8.636***	-135.602
	(0.000)	(0.000)	(0.001)	(0.786)
Observations	3,363	3,363	3,363	3,363

Table 11. The Effect of Consumer Reviews on Current Hotel Performance, continued

Adjusted R-squared	0.517	0.936	0.901
Diagnostic tests			
AR(1) test (*p*-value)			(0.000)
AR(2) test (*p*-value)			(0.348)
Hansen test of over identification (*p*-value)			(0.410)
Difference-in-Hansen tests of exogeneity (*p*-value)			(0.294)

The system GMM dynamic panel model shows insignificant effect of review valence on hotel performance (-2.544, *p*-vale=0.353). Our findings challenge conventional thinking by showing that review ratings do not affect room sales after controlling for endogeneity, suggesting little persuasion effect for online reviews on consumers' decision making. This result indicates that consumers are fully capable of inferring the true quality of a hotel from online reviews without being influenced by the ratings of the reviews *per se*. This result is consistent with earlier findings with regard to the impact of movie critics by Duan et al. (2008) which shows that ratings may be predictors of performance, but they do not influence performance. Our empirical evidence refutes recent anecdotal observations in the practitioner literature that overestimate or inflate the influence of review ratings (Anderson, 2013).

We observe that review volume has a positive effect on performance with coefficient values of 10.074 (*p*-value =0.002) as reported in the system GMM dynamic model. This finding suggests that a 1% increase in the average quarterly number of reviews received would result in a 0.101 units increase in the average revenue per available room. Similarly, the coefficient on review volume in the fixed-effects model is positive with a value of 1.548 (*p*-value=0.002), indicting 1% increase in the average quarterly number of reviews received would result in a 0.015 units increase in the average revenue per available room. Hence, the estimation results of review volume in both the fixed-effects model and the system GMM dynamic model support a significant increase in hotel performance driven by review volume in a dynamic framework, after controlling for other hotel-specific characteristics such as age, size, and segment. We attribute the awareness effect to consumer reviews as an indicator of the intensity of underlying WOM which plays a dominant role in driving room sales.

This finding indicates that estimation results of review volume are qualitatively similar in a fixed-effects model and a system GMM dynamic model. That is, the estimation of review variables is not sensitive to the use of either fixed-effects model or system GMM dynamic model. However, without strong and valid instruments, potential endogeneity is still a concern in fixed-effects model (Greene, 2003). This may explain inconsistent estimation of some variables. For example, the static fixed-effects model estimate suggests a positive relation between age (3.816, *p*-value =0.000). When we estimate this in a system GMM dynamic model, the significance disappears (-0.295, *p*-value=0.693). Also the static fixed-effects model shows a significantly negative relation between size and hotel performance (-52.428, *p*-value =0.000) which is qualitatively consistent with the results in both static POLS and dynamic POLS models. Once we estimate the same effect in a system GMM dynamic model, the significance disappears (48.318, *p*-value =0.678). The intuition behind these dramatic significance flip with respect to the effect of age and size on performance is an interesting one and illustrates the bias that may arise from ignoring endogeneity and dynamic relationship with past performance.

The static POLS estimate suggests a positive relation between valence and hotel performance (2.959, *p*-value=0.000). This finding is similar to those obtained by a number of prior studies (e.g., Ye et al. 2010). However, once we move to fixed-effects and GMM system dynamic models, these results disappear and the valence is no longer significantly related to firm performance (-0.026, *p*-value=0.894 and -2.544, *p*-value=0.353, respectively). While the fixed-effects model is an improvement over the static POLS models, it is merely an intermediate step. One clear insight that emerges from the fixed-effects model is the importance of within-hotel effect when assessing the effect of consumer reviews on hotel performance in a panel fashion. Note that the R^2 improves from 51.7% in the static POLS model to 93.6% in the fixed-effects model. The unobserved time-invariant within-hotel fixed-effects appear to explain a significant portion of the variation in current performance. This difference is economically significant.

In a dynamic system GMM model which includes fixed-effects, the coefficient on valence is insignificant (-2.544, *p*-vale=0.353). This is in sharp contrast to the results from the simple dynamic POLS model in which the coefficient on valence is significantly positive (0.445, *p*-value =0.006). However, the positive bias in the simple dynamic POLS coefficient estimate is consistent with the bias we expect to have if we ignore within-hotel fixed-effects: if the time-invariant heterogeneity is not controlled, then the simple dynamic model estimates of the relation between valence and hotel performance will be positively biased.

The drop in the magnitude of the estimated coefficients on the consumer review variables when we move from the static POLS model (valence: 2.959, *p*-value=0.000;

variation: 0.876, *p*-value=0.362; volume: 4.452, *p*-value=0.000) to the dynamic POLS model (valence: 0.445, *p*-value=0.006; variation: 0.444, *p*-value=0.184; volume: 1.073, *p*-value=0.003) suggests that current consumer reviews are correlated with past firm performance - another potential indication of the endogeneity that arises from the relation between consumer reviews and hotel performance. Nevertheless, it is possible that there is some unobservable heterogeneity that is not captured by past performance. Therefore, we need a system GMM model that enables us to estimate the review/performance relation while including both past performance and fixed-effects to account for the dynamic aspects of the review/performance relation and time-invariant unobservable heterogeneity, respectively.

Overall, our hypothesis with respect to the positive effect of volume on hotel sales is supported. All model estimations suggest positive relation between volume and hotel performance, similar to that reported in a number of prior studies (e.g., Chen et al. 2004; Duan et al. 2008; Liu, 2006). In particular, both the fixed-effects and system GMM dynamic models reveal qualitatively similar estimation results for the review variables. Our use of system GMM dynamic model shows that the effect of volume on hotel sales is positive, even after accounting for endogeneity and unobserved heterogeneity in the data. This finding indicates the major effect of consumer reviews on top of others is to create popularity (Zhu & Zhang, 2010) or social awareness (Godes & Mayzlin, 2009) through the number of reviews published on a social media platform.

6.3.2 Diagnostic Tests

Table 11 also reports the results of a number of post-estimation tests with respect to the validity of the Arellano-Bover/Blundell-Bond system GMM estimation results, as well as the model instruments. The first is a test of serial correlation in the residuals. The Arellano-Bond test is applied to the residuals in differences. Since the residuals in first differences should be correlated by construction, the test evaluates both first-order and second-order correlation in differences, with the idea being that serial correlation of second order in differences indicates serial correlation of first order in levels. In this case, we will need to use deeper lags as instruments. Table 11 shows the results of *AR(2)* tests of the null hypothesis that indicate that there is no serial correlation in differences of residuals. The *AR(2)* test yields *p*-values of 0.348 for the System GMM dynamic panel model.

Next, we present the results of the Hansen (1982) test of over-identification conducted as part of our system GMM estimation. The system GMM estimator uses multiple lags as instruments. This means that our system is over-identified and provides us with an opportunity to conduct a test of over-identification that tests whether the instruments are exogenous. Table 11 shows the results of the Hansen test of the GMM estimates. The Hansen test yields a J –statistic that has a χ^2 distribution under the null hypothesis that the instruments are orthogonal to the error term. The results reveal *p*-values of 0.410 with *z*-statistics for the system GMM dynamic panel model, which indicates that we cannot reject the null hypothesis that our instruments are valid.

Table 11 also reports the results of a test of exogeneity of a subset of our instruments. The system GMM estimator makes an additional exogeneity assumption that any correlation between the endogenous variables and the unobserved (fixed) effect is constant over time. This assumption allows us to include levels equations in our GMM estimates and use lagged differences as instruments for these levels. Bond et al. (2001)

suggest that this assumption can be tested directly using a difference-in-Hansen test of exogeneity. The null hypothesis suggests that the subset of instruments that we use in the levels equations is exogenous. The *p*-values of 0.294 associated with the Hansen test imply that we cannot reject the null hypothesis that the additional instruments in the system GMM estimation are indeed exogenous.

6.3.3 Robustness Checks

We check the potential sensitivity of estimation results to sample manipulation. We keep a balanced sub-sample of 159 hotels that each have ten-quarter observations by removing those with insufficient data over ten quarters. Then we replicate the dynamic GMM regression on this balanced sample which consists of a full set of ten-quarter observations for each hotel. As shown in Table 12, the results are qualitatively similar to the results in Table 11: we find no relation between hotel performance and different aspects of consumer reviews except for volume. This finding is robust to sample difference.

Table 12. Robustness Check of the Effect of Consumer Reviews on Hotel Performance

In this table, we report results from the estimation of the model:

$$y_{it}=\alpha_1 + K_1 y_{it-1} + \beta X_{it} + \gamma Z_{it} + \mu_{it} + \varepsilon_{it} \qquad t= \text{2009q1 – 2011q2}$$

y_{it} is revpar. X_{it} includes review components (i.e., valence, variation, volume). Z_{it} includes size, age, segment, and year-quarter dummies. The results are based on a balanced sample 159 hotels and 1,590 hotel year-quarters from 2009q1 to 2011q2. *P*-values are reported in parentheses. ***, **, and * represent significance at the 1%, 5% and 10% level, respectively. For the static models, it is assumed that K_1=0. All estimations are based on robust, hotel-clustered standard errors. We report two-step estimators, which are asymptotically efficient and robust to any panel-specific autocorrelation and heteroscedasticity. *AR(1)* and *AR(2)* are tests for first-order and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of over-identification is under the null that all instruments are valid. The Diff-in-Hansen test of exogeneity is under the null that instruments used for the equations in levels are exogenous. The instruments used in the GMM estimation are: differenced equations: $y_{it-2}, y_{it-3}, X_{it-2}, X_{it-3}, Z_{it-2}, Z_{it-3}$; level equations: $\Delta y_{it-1}, \Delta X_{it-1}, \Delta Z_{it-1}$.

	revpar
valence	4.849
	(0.360)
variation	3.903
	(0.579)
volume	5.190***
	(0.002)
age	-3.591
	(0.589)
size	-63.274
	(0.649)
segment (2 crown)	
segment (3 crown)	434.435
	(0.351)
segment (4 crown)	543.794
	(0.515)
segment (5 crown)	-193.966
	(0.954)
revpar (*t*-1)	0.233**
	(0.011)
i.yq	yes
Constant	-105.828
	(0.923)
Observations	1,431

Table 12. Robustness Check of the Effect of Consumer Reviews on Hotel Performance, continued

Diagnostic tests	
AR(1) test (*p*-value)	(0.000)
AR(2) test (*p*-value)	(0.540)
Hansen test of over identification (*p*-value)	(0.352)
Difference-in-Hansen tests of exogeneity (*p*-value)	(0.379)

6.4 Do Reviews Affect Performance with a Lag?

Our analysis thus far has focused on assessing the effect of current consumer reviews on current hotel performance. However, it is possible that consume reviews in this period affects hotel performance in the next period, i.e., consumer reviews affect hotel performance with a lag.

Using lagged review variables in the regression does not eliminate either unobservable heterogeneity (since X_{it-2} is possibly still correlated with μ_{it},), or the dynamic aspects of the consumer review/performance relation, since values of consumer reviews at time *t*-2 could have been determined by performance at periods before *t*-2. However, using lagged reviews as opposed to current reviews reduces the impact of simultaneity since past reviews and current performance are not determined in the same period. Thus, estimating the effect of lagged reviews on current performance enables us to do two things. First, it enables us to assess the effect of consumer reviews on hotel performance using a different set of assumptions from those in Table 11. Second, it allows us to apply an alternative dynamic panel estimator that does not rely on the instrument set that we use in the dynamic GMM.

Table 13 shows the estimation results of the effect of current performance on lagged consumer reviews using the dynamic GMM panel estimator. The results show that there is no relation between lagged consumer reviews and hotel performance, indicating that consumers make purchase based on most recent reviewers (less than one quarter or 13 weeks) instead of old reviews. Intuitively, this finding suggests that, given the frequency of reviews published by consumers for a single hotel on a daily basis, most of the consumers may only browse and remember the most recent reviews when searching hotel information. Theoretically, this finding is an exceptional case of the advertising Ad Stock theory that describes the prolonged or lagged effect of advertising on consumer purchase behavior (Broadbent, 1979). According to the Ad Stock Theory, every ad copy is assumed to have a unique half-life. For a TV ad, it takes about two weeks for the awareness of a copy to decay to half its present level (Broadbent, 1979). Some academic studies find half-lives of approximately four weeks (Newstead et al. 2009) and industry practitioners typically report half-lives between 2–5 weeks (Joseph, 2006). As a form of WOM advertising, consumer reviews serve as a free advertisement to build brand awareness and online community yet offer a low-cost way to crank up hotel marketing programs (Dellarocas, 2006; Zelasko, 2010). Our finding suggests that the decaying half-life of consumer reviews is likely to be less than 6.5 weeks (i.e. one quarter or 13 weeks). To our best knowledge, our study is the first to provide empirical evidence of the consumer reviews' decaying half-life. However, due to the quarterly data limitation we could not specify in how many weeks/days the effect of a consumer review disappears. This will be an interesting direction to explore using more micro-level data.

Table 13. The Effect of Lagged Consumer Reviews on Current Hotel Performance

We estimate an empirical model of the form:

$$y_{it}=\alpha_1+ K_1 y_{it-1}+ \beta X_{it-1} + \gamma Z_{it-1} + \mu_{it} + \varepsilon_{it} \qquad t= \text{2009q1 – 2011q2}$$

y_{it} is revepar. X_{it} includes review components (i.e., valence, variation, volume). Z_{it} includes size, age, segment, and year-quarter dummies. The results are based on a sample of 843 hotels and 4,994 hotel year-quarters from 2009q1 to 2011q2. The contemporaneous review variables (not shown) are included in the model specification. *p*-values are reported in parentheses. ***, **, and * represent significance at the 1%, 5% and 10% level, respectively. One lag of performance (i.e., revpar (*t*-1)) is included in all specifications. All estimations are based on robust, hotel-clustered standard errors. We report two-step estimators, which are asymptotically efficient and robust to any panel-specific autocorrelation and heteroscedasticity. *AR(1)* and *AR(2)* are tests for first-order and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of over-identification is under the null that all instruments are valid. The Diff-in-Hansen test of exogeneity is under the null that instruments used for the equations in levels are exogenous. The instruments used in the GMM estimation are: differenced equations: $y_{it-2}, y_{it-3}, X_{it-2}, X_{it-3}, Z_{it-2}, Z_{it-3}$; level equations: $\Delta y_{it-1}, \Delta X_{it-1}, \Delta Z_{it-1}$

	revpar
valence (*t*-1)	1.971
	(0.676)
variation (*t*-1)	2.690
	(0.705)
volume (*t*-1)	3.191
	(0.408)
age	0.064
	(0.939)
size	1.189
	(0.989)
2.hotelclass	69.916
	(0.789)
3.hotelclass	55.407
	(0.823)
4.hotelclass	110.364
	(0.746)
5.hotelclass	-1,226.116
	(0.473)
revpar (*t*-1)	0.785***
	(0.000)
i.yq	yes

Table 13. The Effect of Lagged Consumer Reviews on Current Hotel Performance, continued

Constant	-62.841
	(0.837)
Observations	3,363
Diagnostic tests	
AR(1) test (*p*-value)	0.803
AR(2) test (*p*-value)	0.564
Hansen test of over identification (*p*-value)	0.498
Difference-in-Hansen tests of exogeneity (*p*-value)	0.529

CHAPTER 7

CONCLUSIONS AND IMPLICATIONS

The social media frenzy has taken the world by storm in the last few years, and the trends will shape the hotel industry in the future (Deloitte Hospitality, 2010). The business case for investing in social media has received increasing scrutiny in recent years. Websites such as TripAdvisor.com are often the hotel managers' first point of call. Understanding whether and how online reviews affect hotel performance is vitally important for hotels that rely on online WOM to disseminate information about their experienced products and service. This study drills down deeper into the hospitality analytics data to quantify the value of consumer reviews on hotel performance. A longitudinal panel-data sample of 56,284 hotel reviews on a daily basis, along with 5,711 quarterly hotel performance records within a 10-quarter observation window is used in a dynamic panel system GMM model.

7.1 Summary of Results

Evidenced by our data analysis, the results exhibit a dynamic relationship with endogeneity in the consumer review components, as well as several control variables, supporting H4 (Room sales have effect on consumer reviews.) In addition, we find that a 1% increase in the average quarterly number of reviews received would result in a 0.101 units increase in the average revenue per available room. The analysis reveals that review volume has a positive impact on hotel performance after controlling for other hotel-specific characteristics, showing support to H3 (Review volume has a positive effect on room sales). This result is robust and qualitatively consistent with those obtained from fixed-effects estimations. However, other review components (i.e,, valence and variation) are not significantly associated with room sales in a dynamic framework, rejecting H1 (Review valence has a positive effect on room sales.) and H2 (Review variation has a negative effect on room sales.)

In estimating the effect of consumer reviews on performance, we discuss in details the appropriateness of a dynamic panel system GMM model in estimating the effect of reviews on performance and explain its advantages compared to other static models such as POLS and fixed-effects models in addressing endogeneity (i.e., simultaneity and unobserved heterogeneity), a typical concern in using panel data.

First, when we apply POLS and fixed-effects to the static model as previous studies have done, we find, as these precious studies have, statically significant relations between certain review components (i.e., valence, volume) and hotel performance: there is a positive relation between review volume and hotel performance, and the relation between review valence and hotel performance varies from significantly positive to non-significant as we move from POLS to traditional fixed-effects estimations.

Second, when we apply simple POLS to the ‘‘dynamic’’ model including past performance but temporarily ignoring unobservable heterogeneity, we get the first clear indication of the importance of dynamics in the reviews/performance relation. First, the R^2 rises from 51.7% in the ‘‘static’’ POLS model to 90.1% in the ‘‘dynamic’’ model, while the magnitude of the estimated coefficients on both review valence and review volume fall dramatically. Second, the effect of age and size on hotel performance (3.816, *p*-value =0.000 and -52.428, *p*-value =0.000, respectively) in the static fixed-effects model become insignificant (-0.295, *p*-value = 0.693 and 48.318, *p*-value =0.678, respectively) once we add the dynamic effect. The intuition behind this dramatic significance flip with respect to the effect of age and size on performance is an interesting one and illustrates the bias that may arise from ignoring endogeneity and dynamic relationship with past performance.

Third, when we apply the dynamic GMM panel estimator to the ‘‘dynamic’’ model - when we fully account for unobservable heterogeneity, simultaneity, and the relation between current consumer review components and past hotel performance – we find no statistically significant relation between firm performance and review valence and review variation. This is one of the key results of our paper and is in contrast with results from prior studies (where some find a positive and some find a negative relationship). In contrast, review volume remains significantly positive as a robust indicator of hotel performance in the dynamic GMM panel model and across previous estimation, suggesting that what in fact matters to hotels in managing social media marketing is the review volume.

To test the lag effect of consumer reviews, we add multiple lags of consumer reviews into the dynamic panel model. We find that, at a quarterly observation level, the lagged consumer reviews are not significantly associated with room sales, rejecting H5 (The lagged consume reviews have effect on room sales). Our finding suggests that the decaying half-life of consumer reviews is likely to be less than 6.5 weeks (i.e. one quarter or 13 weeks). This finding provides an empirical support to the review reading behavior of consumer that consumers may only browse and remember the most recent reviews when searching hotel information.

7.2 Discussion and Implications

This study comes right in time to interpret the landscape of consumer reviews and social media marketing to the hospitality industry. Developing hypotheses based on applicable literature, this study searches for empirical evidences in the circumstance when consumer review analytics emerge as the driving force of online business excellence. Driven by a variety of well-established evidence of the dynamic mechanism between consumer reviews and hotel performance, this work provides solid grounds for its empirical evidences, yet justifying, testifying, and even modifying the propositions in previous literature; supported by convincing filed data, this work is one of the first in hospitality literature to utilize social media analytics in hospitality industry; utilizing advanced methodologies and approaches, this work brings into the hospitality community scientific thinking and makes possible the fair dialogues between hospitality and business research. The findings provide implications for researchers and the industry in light of the increased interest in social media marketing.

7.2.1 Theoretical Implications

From a theoretical dimension, our theoretical explanations and findings expand the current literature in the effects of consumer reviews on hotel performance. Recently hospitality researchers have argued that consumer reviews indeed contribute to room sales (e.g., Duverger, 2013; Ye et al. 2010; Zhang et al. 2009), however these studies have come short of integrating the different aspects of review components and there is a dearth of systematic empirical evidence on how different review components affect hotel performance. It is important to understand the specific role of consumer reviews in improving the hotel performance. Our study provides a fresh perspective into whether and how social media drive hotel room sales performance. It represents one of the first attempts at identifying both the persuasion and awareness effect of online consumer reviews. We examine the impact of review valence, variation, and volume on hotel room sales using recently available data that captures the impact of UGC and eWOM on room sales. Our results are more comprehensive than those in previous studies because most of these studies only consider one or two aspects of online reviews. For example, Ye et al. (2010) consider the average rating and the number of reviews only, Zhang et al. (2009) use the average rating only, and Duverger (2013) focuses on the valence (and its quadratic form) of hotel reviews only.

Prior studies have examined the effect of consumer reviews on product or firm performance and the results are mixed because of either short-life product setting or biased estimation methods without addressing endogeneity. For example, Chevalier and Mayzlin (2006) examine book sales at Amazon.com and find that online reviews influence book sales, but, using a similar data set from Amazon.com, Chen et al. (2004) find the opposite. Similarly, in the movie context, Zhang and Dellarocas (2006) find that online reviews influence box office sales, but Duan et al. (2008) find the opposite. Researchers have not been able to reconcile the stark differences in results and instead have attributed them to methodological shortcomings. For example, Duan et al. (2008) point out that the mixed findings could be the result of researchers conducting their analyses in a cross-sectional context and not controlling for unobserved differences in product quality.

Our study demonstrates that the review volume is significantly positively associated with room sales, and this result is robust in both static and dynamic frameworks that account for endogeneity issues, whereas other review components (i.e., valence and variation) do not affect hotel performance. We thus attribute the awareness effect of online reviews as a primary effect in the dynamic mechanism between reviews and room sales. This finding is consistent with Duan et al. (2008), one of the few studies that address the endogeneity issue in estimating the review effect, which finds that the volume of online reviews matters but the average rating does not. Our finding also echoes prior marketing research that suggest that awareness effect of consumer reviews takes the central stage in the feedback mechanism (Bettman, 1979; Lilien et al. 1992). It is through WOM dissemination that a popular hotel generates buzz, which in turn leads to even higher room sales.

In addition, our finding challenges conventional thinking by showing that ratings and their variation do not affect room sales after controlling for endogeneity of user reviews and product heterogeneity, suggesting little persuasion effect for online user reviews. Review valence may reflect hotel quality, but they do not influence sales. This result indicates that consumers are fully capable of inferring the true quality of a hotel from online reviews without being influenced by the ratings of the reviews *per se*. Our finding refutes recent anecdotal observations in the practitioner literature which over-estimate or inflate the effect of review ratings to hotels (e.g., Anderson, 2013).

Our research has established a relationship between online WOM information and offline hotel room sales. However, we did not directly observe how WOM information would affect consumers' choices and purchasing decisions. One important and interesting extension of our research will be to investigate the consumer's decision under the influence of word-of- mouth information, especially in the digital environment. In addition, not all WOM is equal. Consumers need to distinguish the “true” and “honest” opinions from all kinds of feedback and recommendations on the web. Under such circumstances, how consumers choose their information source and the mechanisms that help consumers to find trusted information sources will be of particular interest for future research. Moreover, further study to characterize and identify the impact of the online WOM information from different resources and formats would also be beneficial to our understanding and design of online feedback and information systems.

7.2.2 Managerial Implications

From a managerial perspective, this study quantifies the economic impact and business value of consumer reviews to the hotel business. The business case for investing in social media marketing has received increasing scrutiny in recent years (Williams et al. 2010; Ye et al. 2010). It is interesting to note that hotel brands such as Marriott or Hilton that volunteer consumers’ reviews and ratings directly on their website (De Lollis, 2012). Alternatively, some hotels still utilize the external review platforms such as TripAdvisor.com but have been shown to strategically manipulate online reviews via this intermediary in an effort to influence consumers’ purchase decisions (Dellarocas, 2006). At the time many hotels jump on the bandwagon of social media marketing, this study provide an important practical reference of managerial decision making on whether or not to incorporate consumer reviews as the marketing mix and to what extent should the business be prepared to invest financial resources to stimulate additional WOM. The monetary value of a WOM referral from consumer reviews can be calculated; this yields an important estimate for the financial incentives the hotel businesses might offer to stimulate word-of-mouth.

According to the findings, a 1% increase in the average quarterly number of reviews received would result in a 0.101 units increase in the average revenue per available room. These figures imply that each 1% increase in consumer review is worth about $0.1 dollars per quarter. By posting 100 consumer reviews, each social media user could bring in about 10 dollars to the hotel. Compared to the traditional owned media (e.g., company website) and paid media (e.g., print, TV, online banner, and email), the economic effect of social earned media, after adjusting for event frequency, is significantly greater than traditional owned and paid media because of the greater frequency of the social earned media activity (Stephen & Galak, 2012).

The full impact of consumer reviews, however, is likely to be under-represented because our data may miss some benefits from increasing WOM activity. First, in this study we have not considered the cross-effects of social media to other traditional media. According to Stephen and Galak (2012), social earned media appears to play an important role in driving traditional earned media activity. This positive externality from consumer reviews or WOM referrals is important to leverage the effectiveness of the full adverting agenda. Second, Metcalfe's law (e.g., Reed 1999) states that the value of a network is proportional to the square of the number of users of the system. Our approach does not consider the important aspects of social contagion that one user may have on retention and site usage by other existing network members. Thus, one logical next step would be to develop an individual level model which allows for user-specific contributions to the network and examine how many additional room sales have been gained from the social contagion and network effect.

Given the important economic impact of consumer reviews, we are aware that the costs for social media services have to be weighed against these benefits. According to Hennig-Thurau et al. (2010), the digital character of social media implies that there are virtually no marginal costs for producing extra copies of digital products and that individuals can easily distribute their consumer reviews to a global audience without having to pass through traditional ‘‘gate keepers’’ such as publishers. Consumers with an internet connection can write consumer reviews about a specific hotel or restaurant. Firms are also able to communicate with consumers by writing managerial responses using a free business account that is provided in many social media platforms. For example, TripAdvisor allows hotel managers to sign up a free business account to respond to guest reviews (tripadvisor.com, 2013).[9] Some of these managerial responses even help consumers solve product-related problems, which reduces service costs and increases quality (Mathwick et al. 2008). In consideration of the economic benefits and marginal costs, it is believed that the return of investment (ROI) of social media tops other traditional paid or owned media (e.g., TV, print, and firm website) at a significant scale (Stephen & Galak, 2012).

In addition, this study offers managers a tool to improve the metrics they use for assessing the effectiveness of social media marketing. Our approach reveals strategically important review components that can determine the social media success of hotel business. We find that room sales are significantly influenced by the volume of online reviews, suggesting the importance of awareness effect (Duan et al. 2008). This finding

[9] Hotel managers can also use this free account to update business details, showcase their hotels with professional photos, receive e-mail notification of new reviews, promote business with free widgets and badges, and compare business with competitors by tracking hotel performance (tripadvisor.com, 2013).

indicates the major effect of consumer reviews, on top of others, is to create popularity (Zhu & Zhang, 2010) or social awareness (Godes & Mayzlin, 2009) through the number of reviews published on a social media platform. In contrast, we find that the rating of online reviews has no significant impact on hotel performance after accounting for the endogeneity, indicating that online user reviews have little persuasion effect on consumer purchase decisions. Therefore, we attribute the effect to online user reviews as an indicator of the intensity of underlying WOM that plays a dominant role in driving hotel performance.

The result suggests that consumers are not influenced by the persuasion effect of online WOM, although they are affected by awareness effect generated by the underlying process of WOM. We show that consumers are rational in inferring hotel quality from online user reviews without being unduly influenced by the rating, thus presenting a challenge to businesses that try to influence sales through "planting" positive product reviews. Our findings of awareness effect, however, suggest that the underlying WOM process could have a significant impact on sales, suggesting that businesses should embrace and facilitate WOM activities. Hotel businesses shall therefore focus more on the mechanisms that facilitate dispersion of underlying word-of- mouth exchange rather than try to influence online ratings. Hotels' online marketing strategies need to adjust accordingly in order to monitor and to integrate social media as part of an overall customer relationship management initiative (Duverger, 2013).

How to make consumer reviews a viable marketing channel remains a challenge. We argue that hotel managers need to establish a positive feedback mechanism between consumer reviews and room sales by monitoring online critiques to improve performance and “listen-in” on the online conversation in an attempt to preserve their market share (Yu, 2010). Meanwhile, managers should understand the important review component that should be strategically manipulated. Opportunities to strategically use managerial efforts to lead the consumer awareness should be explored. Coordinated investments in social media can provide firms with greater capacity to generate growth options that help to realize room sales.

At the same time, we suggest that the insights offered by the case of TripAdvisor.com have important broader implications, potentially providing an understanding of consumer review platforms in the proliferation of review mechanisms that increasingly appear to pervade the contemporary hospitality industry. Our results highlight potential inefficiencies in current consumer review platforms and social media. For example, our finding suggests that the decaying half-life of consumer reviews is likely to be less than 6.5 weeks (i.e. one quarter or 13 weeks). It is thus necessary for social media platforms to recognize the recency effect of consumer reviews in their webpage layout, for example, positioning the most recent reviews in the upper level of a review page. In addition, a weighting algorithm should be adopted in social media platforms, for example, the most recent reviews and ratings received from consumers should become the major criteria of hotel evaluation. Facing the recent anecdotal confusion about the fairness of hotel evaluation (e.g., hotel ranking)[10], managers and shareholders in the intensely competitive hospitality industry are increasingly asking for the accountability of consumer reviews in communicating the hotel value to consumers (Mayzlin et al. 2012). We thus encourage the owned brand.com or the third party social

[10]The Digital Marketing Inner Circle, “How Can We Improve Our Hotel Ranking in Hotel List Search?” (http://www.sinotechblog.com.cn/index.php/component/content/article/48-direct-marketing/659-how-to-promote-your-hotel-in-tripadvisor-and-ctrip).

media platforms that publish consumer reviews to not only adopt the weighting scheme based on the review recency but also standardize and publicize this algorithm.

7.2.3 Methodological Implications

In much of the extant empirical consumer review research, researchers attempt to either explain the causes or examine the effects of social media marketing decisions related to one or more of these endogeniety issues. Empirical research often involves determining the causal effect, if any, of a hotel characteristic (X) on some measure of hotel performance (Y). This is usually done using the inference from a regression of Y on X along with several control variables (Z). The question is often framed as: holding Z constant, does X have an economically and statistically significant causal effect on Y?

This question of endogeneity has complicated empirical research in consumer reviews. For example, in presence of a feedback mechanism between reviewers and firm performance, consume reviews lead to more product sales, which in turn generate more consumer reviews and then more product sales (Duan et al. 2008; Godes & Mayzlin, 2004; Srinivasan et al. 2002). In addition, firms regularly post their product information and sponsor promotional chats on social media (Mayzlin, 2006), hire professional experts to write consumer reviews that may inflate the product ratings (Dellarocas, 2006), and proactively induce their consumers to spread the word about their products online (Godes & Mayzlin, 2004).

This study addresses this question that is not fully answered in the literature that has heretofore ignored the possibility of dynamic relation between consumer reviews and hotel performance. We argue that the cross-sectional variation in observed consumer reviews is driven by both unobservable heterogeneity and the hotel's history. As such, any attempt to explain the effect of consumer reviews on performance that does not recognize these sources of endogeneity may be biased. In this study, we first discuss the theoretical explanations behind the GMM estimator and explain why it is appropriate for estimating the reviews/performance relation in a dynamic framework. We then show the advantage over POLS and fixed-effects estimators which are biased when the dynamic relation between the variable of interest and the explanatory variables is important. We specifically use a well-developed dynamic panel generalized method of moments (GMM) estimator to alleviate endogeneity concerns. The estimator incorporates the dynamic nature of internal review choices to provide valid and powerful instruments that address unobserved heterogeneity and simultaneity. We find no causal relation between review valence and variation and current hotel performance. The result is inconsistent with some earlier work and policy recommendations of many commentators. To strength our empirical argument, we illustrate that some commonly used estimators (i.e., valence and variation) that find a relation may be biased because the ignored dynamic relationship between current performance and past performance. We discuss why it may be appropriate to consider the dynamic panel GMM estimator in consumer review research.

Our model fully specifies the dual causal relationship and reveals the true effect of online WOM on hotel room sales. Our results help reconcile some of the conflicting results in the prior literature, and explain how some reported correlations could arise from ignoring one or more aspects of the endogeneity inherent in the consumer reviews-performance relation. One of the key points we raise in the paper, building on work by Wooldridge (2002) and Roodman (2008), is that if there is a dynamic relation between current values of an explanatory variable and past realizations of the dependent variable, a static model such as POLS may be biased in certain aspects that are different from that of the dynamic relation. As we noted earlier, in our empirical analysis we find, similar to Duan et al. (2008), a non-significant relation between current review valence and hotel performance. Under these conditions, a POLS regression of review valence on performance may be positively biased. We also find that some hotel-specific characteristics such as hotel size is not significantly associated with room sales performance in a dynamic framework, while a traditional fixed-effects regression that ignores the dynamic relationship may be negatively biased. We suggest that this may explain, at least in part, the mixed results from previous studies on the effect of consumer reviews and other hotel-specific characteristics on hotel performance.

In our experience, a caveat note hospitality researchers should be mindful is that the dynamic panel estimation methodology has its limitations. It relies on using the hotel's history (lags of dependent and independent variables) for identification. Thus, there is a potential problem with weak instruments, which becomes greater as the number of lags of the instrumental variables increases. This represents an empirical trade-off. Increasing the instruments' lag length makes them more exogenous, but may also make them weaker. While weak instruments do not appear to drive the specific results in our paper, this may be an important issue in other settings. In addition, we are quick to note that the dynamic panel GMM estimator does not solve all endogeneity problems. When available, natural experiments or carefully chosen strictly exogenous instruments remain the ''gold standard'' for consistently identifying the effect of an explanatory variable on a dependent variable. However, given the infrequent occurrence of natural experiments, such as unexpected regulatory changes, and the relative paucity of exogenous instruments, inference in consumer review research is likely to continue to rely on cross-sectional regressions using panel data.

Overall, our paper contributes to the literature by providing economic justification for the use of dynamic panel data estimation in consumer review research, discussing the conditions under which it improves inference beyond POLS and traditional fixed- effects estimates, while highlighting its limitations. On a broader note, through this study we demonstrate that dynamic effect is likely to be particularly important in hospitality research since much of our research seeks to determine the effect of different stimulating variables (e.g., consumer reviews, pricing strategy, customer relationship management, etc.) on hotel performance, an aspect of research that is particularly susceptible to biases that may arise by ignoring the effect of historical performance on current stimulating variables. Our empirical attempt of addressing dynamic mechanism in this study welcomes replications in future research.

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Appendix A. Sample Preparation

To estimate parameters at the same observation level, we aggregate daily consumer review data to a quarterly level so as to match the observation level of the revenue data. By doing this, we are able to capture the variability in variables because of the substantial observations on a quarterly basis. Then we use one-on-one merging techniques such as fuzzy merging and exact merging of STATA 12.0 to connect the sales data to the review data for all hotels. If some hotels have less than ten-quarter sales or review data - for example there are some new hotels established after 2009q1 - we still keep them for sample completion purpose. Using this unbalanced sample, we minimize the sample selection bias and ensure that the hotel sample represents the actual hotel market in the five Texas markets. Finally, we use the Winsor module in STATA 12.0 to winsorize variables by limiting extreme values in the data and to reduce the effect of possibly spurious outliers in the data (Wilcox, 2001). The detailed sample preparation procedures are as below:

	Sample	Hotel-quarter observations	Hotels
Removing data not in our study period from 2009q1 to 2011q2			
Aggregating the daily-based 56,284 hotel reviews to quarterly level			
Initial samples covering period from 2009q1 to 2011q2			
initial sales sample with IDa[11]	Sample A	11,960	1,290
initial review sample with IDb[12]	Sample B	5,711	1,067
Reducing initial samples to uniquely identified hotel samples			
reduced sales sample with IDa	Sample a	1,290	1,290
reduced review sample with IDb	Sample b	1,067	1,067
1:1 fuzzy merging by city, zip code, hotel name, and address between a (master) and b (using)			
merged reduced one sample with IDa and IDb[13]	Sample C	997	997
Exact matching by first 5 substring by address	Sample C-1	915	915
Exact matching by first 5 substring by hotel name	Sample C-2	842	842
Correcting mismatched hotel by manual check	Sample C-3	940	940
Removing hotels with duplicated review pages or sales records	Sample C-4	929	929
1:m merging by IDa between C-4 (master) and A(using)			
initial sales sample with IDa and IDb	Sample A1	8,861	929
1:m merging by IDb between C-4 (master) and B(using)			
initial review sample with IDa and IDb	Sample B1	5,244	929
1:1 merging by IDa, IDb, year, quarter, zipcode, hotel name, address, and city between Sample A1 and Sample B1			
final sample	Final Sample	4,994	843
Winsorizing variables to correct spurious outliers			

[11]For each hotel in the sales dataset, there is a unique id (IDa) for each hotel.
[12]For each hotel in the review dataset, there is a unique id (IDb) for each hotel.
[13]IDa and IDb co-exist in the merged dataset. Together they are bridging variables, along with year, quarter, zipcode, hotel name, address, and city, to connect review dataset and sales dataset.

Appendix B. Implementing Dynamic GMM Estimation in Stata

Dynamic GMM estimation can be implemented in Stata (Version 12) using the xtabond2 command. As is the case with other panel data estimators in Stata, xtabond2 requires us to specify that our data are a panel by using the xtset command. Comprehensive details of using xtabond2, the full range of options available, and specifications test can be found in Roodman (2009).

Assume the dataset consists of a dependent variable, y, and two explanatory variables, x1 and x2. One can obtain a "system" GMM estimate of the effects of x1 and x2 on y as follows:

```
xtabond2 y l.y x1 x2, gmm(y x1 x2, lag (a b)) <(options)>
```

The lagged dependent variable (l.y) is included as an explanatory variable. The gmm command invokes our lagged instrument set. lag (a b) indicates what lags we wish to include as instruments; a indicates the most recent lag we should use while b represents the most distant lag. If we think x1 and x2 are merely predetermined, then we can set a as 1. However, if we assume that x1 and x2 are endogenous, then we can set a as 2 or greater. If we wish to use all the lags greater than a, then we can write our xtabond2 command as:

```
xtabond2 y l.y x1 x2, gmm(y x1 x2, lag (a . )) <(options)>
```

If we are willing to assume that we have a strictly exogenous variable (for example, z), xtabond2 allows us to partition our dependent variables (Hausman & Taylor,1981) into endogenous and exogenous variables, using 'gmmstyle' and 'ivstyle' commands:

```
xtabond2 y l.y x1 x2, gmm(y x1 x2, lag (a .)) iv(z) <(options)>
```

Based on the preceding discussion, we obtain the GMM results presented in Table 11, using the following code in Stata (Version 12):

```
xtabond2revparl.revpar valence variation volume age size segment i.yq,
gmm(revpar valence variation volume, lag(2 3) collapse) iv(i.yq size age segment)
twostep robust small
```

where we include year-quarter indicators (i.e., i.yq) on the right-hand side of our dynamic panel model to remove time-related shocks form the errors. All review components are considered endogenous and are instrumented with lagged values of the variables in both levels and their own first differences. We estimate the two-step system GMM estimator that is robust to patterns of heteroscedasticity and autocorrelation. In the two-step GMM option, we specify a lag (2 3) option that instructs STATA to use the second lag and the third lag of the endogenous variables as instruments in the transformed equation, and the first lag for the levels equation, which represents the standard treatment for endogenous variables (Roodman, 2009). Our results remain qualitatively similar as we continue to add the number of instruments used by specifying more lags to be used as instruments.

Since we use lagged values of the differences and levels of endogenous variables as instruments for identification, the validity of the models depends on the assumption that these instruments are not correlated with the error term. This requires that the error terms (after purging fixed-effects) are not serially correlated. In our case, if valence is endogenous (i.e., valence is correlated with error term (*t*)), then our choice of $\Delta\text{valence}_{t-1}$ as an instrument (where $\Delta\text{valence}_{t-1} = \text{valence}_{t-1}, \text{valence}_{t-2}$) should not be correlated with error term (*t*). However, if the error term is auto-correlated (i.e., the error term (*t*) is correlated with error term (*t*-1)), then our choice of $\Delta\text{valence}_{t-1}$ as an instrument will produce biased estimates. In such a situation, we will need to use a deeper lag. Stated differently, the precondition for the second lag to be used as an instrument requires that the error term (in levels) not be serially correlated of order one. We perform the Arellano-Bond test (1991) for autocorrelation, which has a null hypothesis of no serial correlation and is applied to *AR(2)* in differences to test for *AR(1)* in levels. In addition, we perform the Hansen test indicates whether the instruments or a subset of instruments used in the Arellano-Bover/Blundell-Bond estimation are exogenous as a group (null hypothesis).