WHETHER, WHEN, AND HOW DOES ONLINE REVIEW MATTER TO BUYING DECISIONS?

THREE ESSAYS ON THE EFFECT OF ONLINE REVIEWS ON CONSUMER DECISIONS

By Rae Yule Kim

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ABSTRACT OF THE THESIS

Whether, When, and How Does Online Review Matter to Buying Decisions?
Three Essays on the Effect of Online Reviews on Consumer Decisions

By Rae Yule Kim

Thesis director: Dr. Sengun Yeniyurt

Word of Mouth (WOM) is powerful, and online reviews are the most readily available WOM in electronic commerce. In fact, 82% of American adults see online reviews before making new purchases (Smith and Anderson, 2016). Interestingly, the previous findings of whether or not online review valence influences sales have been inconsistent. In this aspect, the effect of online reviews on sales should be contingent on consumer-level decision making, and thus, the importance of understanding whether and how consumers evaluate online reviews for making purchase decisions cannot be overstated. These three essays investigate how online reviews interact with other promotional signals to predict consumer responses in electronic commerce and add insights into online review literature.

The first study investigates if other product quality signals, such as product attribute cues or brandedness, have substantial influences on whether and how consumers evaluate online review valence for making purchase decisions. Online review valence did not matter to buying decisions when product quality was convincing. The second study extends the finding and investigates whether the effect of online review valence on consumer decisions is influenced by good-enough reference points based on the reference effect theory. The findings suggest the marginal effect of online review valence is negative, and subsequently, the effect of online review valence on sales is not linear and also significantly varies by product quality. The third essay investigates how negative reviews can trigger a backlash effect on sales when price promotions are launched. Negative reviews can have a confirmation effect on consumers' price-quality beliefs. Although managers might be more tempted to offer price discounts for products with negative reviews to compensate for uncompetitiveness in online review sentiments and increase chances of sales, it can provoke the opposite outcome. Price promotions decreased sales likelihood for products with review ratings below three stars (out of five). Especially, launching price promotions for products with extremely negative reviews, such as one to two (out of five) review ratings tended to decrease the chances of sales by 14 to 31%.

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INTRODUCTION

1.1 Online Reviews

Online reviews are the most accessible Word of Mouth (WOM) information in electronic commerce (Edwards, 2006). A recent Pew research shows that 82% of American adults see online reviews before making new purchases (Smith and Anderson, 2016). Word of Mouth information can have a conforming effect on product quality perceptions (Duan et al., 2008; Lee et al., 2008), or help consumers reduce purchase uncertainty (Ho-Dac et al., 2013). In these aspects, managers not only utilize online reviews as credible customer feedback to predict future product success but also increasingly invest in generating positive online reviews by providing financial rewards (Reichheld, 2003; Tuk et al., 2008), where customer reviews are established as a significant marketing communication channel (Chen et al., 2008). In this aspect, IT-based customer solution agencies often adopt online review management as their main service offerings (Womply, 2020). The previous research found that approximately 16% of online reviews on Yelp were generated or influenced by retailers (Lucas and Zervas, 2016). Thus, managers well acknowledge the importance of managing favorable online reputations and often expect that positive online review valence might lead to increases in sales.

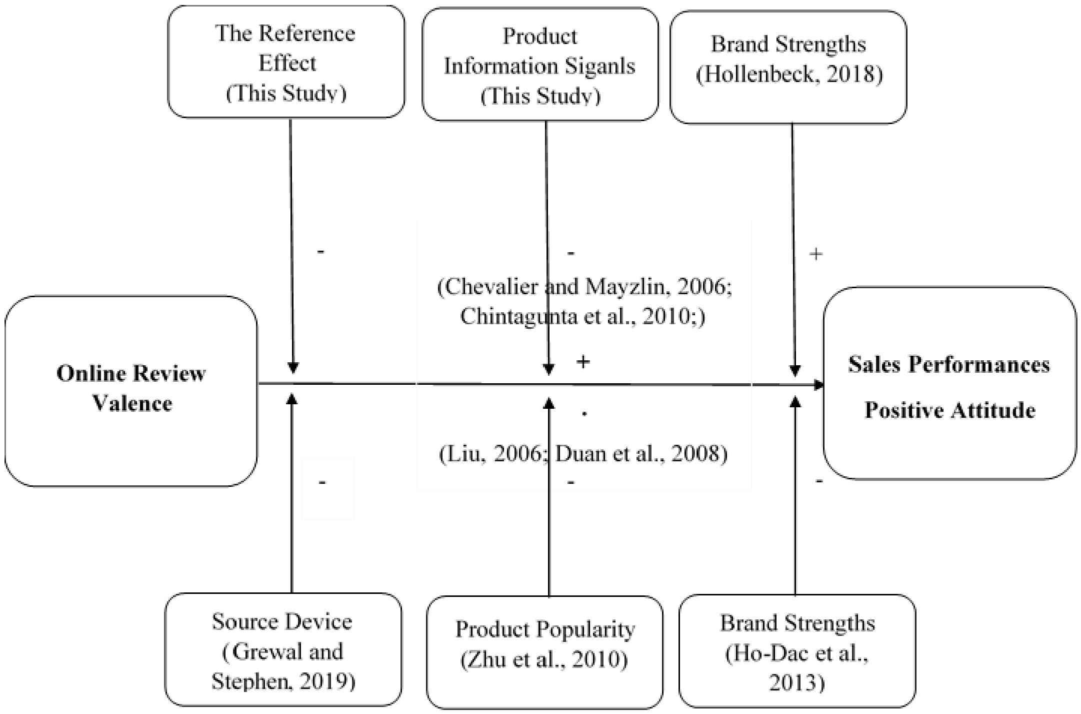
1.2 Do Online Reviews Matter to Sales?

In this aspect, the previous research studied extensively whether online reviews referred to as electronic Word of Mouth (E-WOM), influence sales. Intuitively, products with high review ratings are expected to outperform other products with relatively low review ratings (Edwards, 2006; Duan et al., 2008). However, the previous literature found contradictory results even for the same product category (Liu, 2006; Duan et al., 2008; Chintagunta et al., 2010). Liu (2006) or Duan et al., (2008) found that online review valence was not a significant predictor for box office performances of new release, while Chintagunta found the opposite effect (2010). Thus, although positive online review valence is expected to have positive conforming effects on consumers' attitudes towards product and influence sales positively by reducing purchase uncertainties (Chevalier and Mayzlin, 2006; Liu, 2006; Duan et al., 2008; Lee et al., 2008), the previous findings suggest that it is uncertain whether and how online reviews influence sales performances. The recent literature argues that one should not assume the positive effect of online review valence on sales, since whether and how customer reviews should be contingent on heterogenous consumer factors if they choose to evaluate online reviews for making purchase decisions (Kozinet, 2016). Thus, understanding whether online reviews influence sales performances should focus on when and how consumers tend to rely more on less on electronic Word of Mouth (E-WOM) information to derive purchase decisions (Simonson et al., 2016).

1.3 When Do Online Reviews Matter to Sales?

Only fairly recent literature on online reviews in marketing focuses on consumer-level moderating factors that underlie the evaluation of online reviews for making purchase decision making (Berger 2014; Berger and Schwartz 2011; Lamberton and Stephen 2016; Stephen 2016) (See Fig. 1). Recent literature often assumes that risk avoidance as a psychological trigger for consumers' reliance on online review valence (Zhu et al., 2010; Ho-Dac et al., 2013). Thus, informational cues that help to verify product quality, other than online reviews, is expected to satisfy consumers' needs to reduce purchase uncertainty and subsequently reduce consumers' need to rely on online review valence to obtain product information (Ho-Dac et al., 2013; Stephen, 2016). In this aspect, Zhu et al. found that product popularity moderates the effect of online review valence on sales, where the effect strength of online review ratings was lower for sales of video games that were higher-ranked (2010). Also, Ho-Dac et al. found that the effect strength of positive online review valence in increasing sales was lower for DVD and Blueray players of strong brands (2013). However, Hollenbeck found the opposite effect that the effect strength of online review valence for sales was higher for hotels of strong brands compared to non-branded or hotels of weak brands (2018). Thus, there is limited evidence to determine why the effect of online review valence on sales is low or sometimes even insignificant (Liu, 2006; Duan et al., 2008).

Figure 1.1 Literature Review



Although online reviews are direct feedback about the product experiences and subsequently can reveal product information that is readily observable from sellers' provided information (Chen et al., 2008), it is uncertain whether consumers find online review valence more credible compared to objective product information or brand reputations (Ho-Dac et al., 2013). If consumers utilize online reviews as a product quality signal to reduce purchase uncertainty, not only the brand strengths (Ho-Dac et al., 2013; Hollenbeck, 2018), other product quality cues should interact with online reviews to influence consumer decisions. Furthermore, consumers judgments or preferences are priorly influenced by other product quality cues (Zhu et al., 2010; Ho-Dact et al., 2013), the online reviews might have a minimal impact on consumer decisions when the other product quality signal cues sufficiently address consumers' concerns about purchase uncertainty.

In this aspect, I investigate whether and how online reviews influence consumers' decision making and how online reviews interact with other promotion signals such as product information cues from sellers or price discounts. Promotion signals from sellers should influence consumer judgments and their prior states before evaluating online reviews for decision making, and thus, the effect of promotion cues on consumers' rationales and heuristics might not be random and significantly interfere how online reviews influence consumers' decisions. I utilize choice data about 646,576 consumers' decisions on accommodations with more than ten million ads they compared for new purchases, where consumer preferences for product attributes are relatively homogenous, compared to experience goods, such as movies.

The first essay investigates (1) if consumer decision making is multidimensional and whether product quality signals, other than online reviews, are endogenous for predicting the influence of online review valence on purchase decisions. In this aspect, other product quality signals, such as (2) sellers-provided information cues or (3) product brandedness, should influence whether and how consumers incorporate online review valence into purchase decision making (See Fig. 1.2). The findings indicate that product quality cues, if not incorporated in the model, provoke endogeneity concerns regarding the effect of online review valence on sales likelihood. The results suggest that consumer decision making is multidimensional, and subsequently, the effect of online review valence on consumer decisions should be approached by focusing on how online review valence interacts with other product quality signals to predict purchases. The effect of online review valence on consumer decisions was contingent on product quality, where online review valence *did not matter* to buying decisions when product quality was sufficiently convincing. I also discuss how the effect of product quality cues might help to explain the inconsistent findings of the effect of online review valence on sales in the previous research.

Furthermore, the effect of online reviews on sales should be contingent on the psychological process that underlies consumers' evaluations of online reviews, and linear relationships between online review valence and sales performances are curious (Simonson et al., 2016; Kozinet, 2016). If consumers utilize online reviews to reduce purchase uncertainty (Ho-Dac et al., 2013; Grewal and Stephen, 2019), it is expectable that the marginal merits of online review valence is negative, where an increase in online review ratings among already 'high-enough' ratings might not be an as strong reliever of purchase risk compared to an increase from 'doubtful' to 'satisfactory' ratings. In this aspect, the second study extends the findings from the first essay and investigates *how* the online review influences sales based on the prediction that consumers utilize online review valence to judge or verify product quality. I utilize the reference effect theory from pricing literature and predict that the reference effect can be extended to the context of how consumers evaluate online review valence to make purchase decisions. If consumers utilize online review valence mostly due to risk-aversion and to reduce purchase risks, a certain point of online review valence might sufficiently relieve consumers' doubts – and subsequently, (4) the marginal effect of online review valence is not likely to be consistent. Also, the recent effect is expected to vary by product quality, because consumers perceive higher purchase uncertainty when they buy a product, where its quality is not readily verifiable with objective product information (Roselius, 1971). Reversely, In this aspect, the marginal effect (negative) is expected to be smaller when consumers purchase low-quality products. Reversely, it is predictable that purchase uncertainties can be more effectively addressed with observed product quality information for high-quality products, and subsequently (5) the marginal merit (negative) of online review valence in reducing uncertainties will be bigger. The results suggest that the effect of online review valence on sales is barely linear, and also it is likely to be varied by product quality. Also, I discuss how the inconsistent findings on the effect of online review on sales in the previous research can be explained by the reference effect on how consumers evaluate online review valence to make purchase decisions.

1.4 How Do Online Reviews Matter to Sales?

Extensive research studied whether and when do online reviews influence sales, however, *how* the digital, social media, and mobile (DSMM) marketing interacts with traditional marketing to influence sales performances has been relatively unexplored (Lamberton and Stephen, 2016; Kumar et al., 2017). Kumar et al. found that social media marketing and traditional marketing such as TV advertising and in-store promotions have synergistic effects on sales (2017). Liu et al. found that the recommendation intensity of books positively interacts with online review valence to influence sales (2018). Thus, previous research shows Word of Mouth marketing in DSMM themes tend to have synergistic effects with traditional marketing. In this aspect, I investigate *how* online review valence interacts with price promotions to influence sales, and more specifically, I predict that negative reviews might even shift the positive effect of price promotions on sales, based on price-quality heuristics theory.

The third essay investigates how negative reviews trigger the backlash effect on sales for the products on price promotions. Consumers increasingly doubt the quality of products with discounted prices even subconsciously due to price-quality heuristics (Shiv et al., 2005). Negative reviews can have a confirmation effect and (6) launching price promotions for products with negative reviews might backlash the sales performance. Since I predict that the negative cross-over interaction between negative reviews and price promotions is due to consumer doubts about product quality (price-quality beliefs), (7) other product quality cues, such as brandedness, might help to reduce the impact of negative reviews, and subsequently, (8) moderate the negative cross-over interaction between negative reviews and price promotions (three-way interactions). The findings indicate that launching price promotions decrease sales likelihood for accommodations with review ratings below the market average. Especially, launching price promotions for products with extremely negative reviews, such as one to two (out of five) review ratings tended to decrease the chances of sales by 14 to 31%.

These three essays investigate how online reviews interact with other promotion signals to predict consumers' decision making and make some important contributions to Word of Mouth literature. I investigate empirically how product quality information cues from sellers influence whether and how consumers incorporate online reviews into decision making. Besides, managers might be more tempted to offer price discounts for products with negative review valence to compensate for the relative uncompetitiveness of their products. However, the results of this study suggest such managerial decisions can rather have a backlash effect on the sales potential.

PART II:

WHEN DOES ONLINE REVIEW MATTER TO CONSUMERS? THE EFFECT OF PRODUCT QUALITY INFORMATION CUES

2.1. DOES ONLINE REVIEW MATTER?

Word of Mouth (WOM) is powerful, and online reviews are often the most available source of WOM information in electronic commerce (Edward, 2006). Businesses often utilize online review valence as an indicator of the future success of the product (Reichheld, 2003). One star increase in online review ratings on Yelp might lead to a 9% boost in revenues for the restaurants (Luca and Zervas, 2016). Customers acquired by online reviews tend to have higher long-term equity compared to the ones who are acquired by direct marketing communications (Trusov et al., 2009; Villanueva et al., 2008). In this aspect, the previous literature argues that online reviews emerge as the most impactful element of marketing communications (Chen and Xie, 2008). Customer relations management (CRM) solution agencies commonly adopt online review management as one of the main service offerings, and business investments in generating positive online reviews are increasing (Tuk et al., 2008).

Word of Mouth has been defined through the previous research contexts as consumer interactions regarding their opinions – In this aspect, online reviews are referred to as electronic Word of Mouth (E-WOM) in the previous literature (Duan et al., 2008; Chen et al., 2011; Wang et al., 2019) Online review has been identified as one of the characteristics that distinguish electronic commerce from offline retailing as extensive

Word of Mouth information has been readily available online to consumers (Edwards, 2006; You et al., 2015). In this aspect, extensive research explored the effect of online reviews on sales. The previous findings about the number of online reviews, which is referred to as WOM volume, tended to be consistent since WOM volume was often an effective indicator for product popularity (Duan et al., 2008; You et al., 2015; Liu, 2006). The previous studies in advertising adopted WOM volume as a measure for customer research and advertising effectiveness (Fay et al., 2019). Thus, it is intuitive that more popular and viral products might have higher revenues. Similarly, it is also predictable that products with more positive sentiments of online reviews, which is referred to as WOM valence, have a higher likelihood of sales. However, the previous findings about the effect of WOM valence on sales were inconsistent, even for the same product category (You et al., 2015). The previous research finds that online review valence is not a significant predictor for box office performance of new releases, while another study reports the opposite results (Liu, 2006; Chintagunta et al., 2010). Furthermore, the effect of online reviews tended to not influence downloads of highly ranked e-books, while the results shifted for lowly ranked e-books (Liu et al., 2019). Thus, how online reviews influence sales might be complex than a univariate linear relationship.

The previous research suggests that the effect of online review sentiments on decision making tends to be higher for material purchase compared to experiential purchases, due to consumers' beliefs that opinions about experiences might be subjective and not necessarily applicable to themselves (Simonson, 2016; Dai et al., 2019). The effect of online reviews on sales should be contingent on consumer rationales, whether or how they might incorporate online reviews into making the purchase decisions (Simonson, 2016). In this aspect, this study investigates the mechanisms of whether and how online review valence influence consumers' purchase decisions based on signaling theory and risk aversion (Roselius, 1971; Bae and Lee, 2011). The previous research suggests that online reviews are about the product experiences of early consumers, and buyers are likely to perceive product information from the review sentiment (Duan et al., 2008; Liu, 2006). In this aspect, the effect of online review sentiments on buyer decisions is derived from product quality signaling. Thus, whether and how consumers incorporate online reviews into economic decision making should be influenced by other informational cues that effectively signal product quality. In this aspect, this study utilizes choice data from Expedia.com, where consumers' decision journey and purchase decisions are recorded on an individual level and investigates if other information cues that signal product quality, such as product brandedness or sellers' provided product information effectively moderate consumers' reliance on online review sentiments for decision making and whether other product quality signals can be significant provoking factors for the inconsistent effect of WOM valence on sales. Success in the increasingly competitive market environments is dependent upon understanding in-depth consumer purchase decision rationales and mechanisms (Simonson, 2016). Also, this study aims to provide important insights to e-commerce managers about how to optimize marketing resource allocations between direct-communications and customer review management.

Table 2.1: Literature Review

Study (in chronological order)	Observations	E-WOM Valence (Effect)	Moderating Factor
(1) Chevalier and Mayzlin (2006)	Reviews and books sold on Amazon.com and bn.com in 2003 and 2004	Revenue (+)	Sales platform
(2) Liu (2006)	Reviews of new release movies on Yahoo! Movies from May to September in 2002 and box office performances	Revenue (.)	
(3) Dellarocas, Zhang, and Awad (2007)	Reviews of movies Movie reviews from BoxOfficeMojo.com and Yahoo! Movies, and Hollywood Reporter during 2002 and box office performances	Sales forecasting accuracy (+)	Movie genres
(4) Lee, Park, and Han (2008)	Focus group	Product attitude (+)	Involvement level (+)
(5) Chintagunta, Gopinath, and Venkataraman (2010)	Reviews of new release movies from November 2003 to February 2005 from Yahoo! Movies and box office performances	Revenue (+)	
(6) Duan, Gu, and Whinston (2008)	U.S. box office results in 2003-2004, from Yahoo! Movies, Variety.com, and BoxOfficeMojo.com	Revenue (.)	
(7) Zhu and Zhang (2010)	Video games sales from NPD, October 2000 – October 2005	Revenue (+)	Product popularity
(8) Mudambi and Schuff (2010)	Product reviews on Amazon.com, September 2016	Helpfulness (Inverse U)	
(9) Moe and Schweidel (2011)	Consumers who posted online reviews on BazaarVoice in 2017	Likelihood of posting product ratings (+)	Post-purchase dissatisfaction (+)
(10) Bae and Lee (2011)	Focus group with an equal sex ratio	Purchase intent (+)	Gender
(11) Zhao, Yang, Narayan, and Zhao (2012)	Reviews and book purchases for 30 months period since July 1999	Purchases (+)	Book genres

(12) Chen, Liu, Zhang (2012)	Expert review scores from 14 major media on new releases from 21 major studios	Firm value (+)	
(13) Ho-Dac, Carson, and Moore (2013)	Sales ranks of blue-ray players on Amazon from 2008-2009	Revenue (+)	Brand strengths (-)
(14) Anderson and Magruder (2014)	Restaurant reservation from July to October 2010 with Yelp reviews	Store-traffics (+)	
(15) Hollenbeck (2018)	Customer reviews on hotels in Texas from Tripadvisor.com and Priceline.com from 2000-2015	Revenue (+)	Top hotel brands (+)
(16) Liu, Zhang, and Zao (2019)	E-books downloaded on Yuedu.163.com – A Chinese e-book platform - in 2017	Sales (+)	Product popularity (-), Advertising Intensity (+)
(17) Grewal and Stephen (2019)	Customer reviews and hotel revenues on Tripadvisor.com from 2012-2015	Helpfulness (+)	Review source (Mobile (+), PC (-))
(18) This Study (2020)	Consumer choice on accommodations on Expedia.com in 2017	Consumer Choice (?)	Product quality signal cues (-), Endogeneity from product quality (-)

2.2. CONCEPTUAL BACKGROUND

2.2.1 Online Reviews

The effect of online reviews on sales has been extensively studied well over a decade. However, findings from the previous research provide inconsistent insights about how online reviews might improve sales performance, even for the same product category. The previous research reported contradictory results for the effect of online review valence on box office sales from Yahoo! Movies data, while online review valence was positively associated with ticket sales in one study, and it was not a significant predictor in another study (Liu, 2006; Chintagunta et al., 2010). Online review ratings tended to explain the variations in the book sales on Amazon (Chevalier and Mayzlin, 2006); however, another study found that online review ratings tended to increase downloads for the lowly ranked e-books but not for the highly ranked e-books (Liu et al., 2019). Online review ratings were not a significant influence on sales ranks of blue-ray players on Amazon, regardless of their brand strengths (Ho-Dac et al., 2013). How online reviews might influence sales might be complex as it is uncertain whether and how consumers might incorporate online reviews into decision making (Simonson, 2016). Extensive research conducted empirical investigations of the effect of online reviews on sales, however, the consumer rationales about when and why they see online reviews for making decisions received relatively little attention. For example, some consumers might purchase the movie tickets regardless of the review rating, because they like the movie trailer or the featuring casts. Some consumers might think that they have a unique taste for a movie or a book and tend to disregard the online review ratings for decision making.

Thus, the effect of online reviews on sales might be altered by some consumer factors that influence consumers' reliance on online reviews for making decisions. The previous research finds that product types might influence consumers' reliance on online reviews (Dai et al., 2019). Consumers tend to less value the online review information for experiential products compared to material products because consumers might believe that individual preferences for experiential products, such as events, can be varied (Dai et al., 2019). Besides, consumers' reliance on online reviews for decision making can be significantly varied by cultural orientations, where German and Chinese consumers might rely on online reviews significantly less compared to Australian and Spanish consumers due to low indulgence and uncertainty avoidance (Kim, 2019). Furthermore, the previous study argues that consumers' reliance on online reviews might be varied by gender due to sexual variations in risk-aversiveness or physical disability due to increased risks and needs for information search (Bae and Lee, 2011; Zhang and Yang, 2019). Thus, in the aspect that consumers' reliance on online reviews tends to be varied by purchase risks, consumers might seek less for E-WOM information if other informational cues satisfy their needs to verify the product quality (Roselius, 1971; Woodside and Delozier, 1976). From this perspective, this study explores how product quality information cues provided by the seller might moderate consumers' reliance on online reviews for decision making.

2.2.2 Signaling and Purchase Decisions

Signaling theory in information economics assumes that agents can effectively transfer some information to a receiver via signal cues (Dewatripont and Bolton, 2005). Thus, when consumers make purchase decisions under uncertainty, sellers might induce favorable decisions by signaling positive product quality (Gambetta, 2011). The previous research suggests emphasizing scarcity might effectively signal the high product quality (Stock and Balachander, 2005). From this perspective, the previous literature views online review valence as a signal cue from the experienced consumers, which inform product quality and purchase utility to the potential buyers (Kirmani and Rao, 2000; Yang, 2012). In this aspect, consumers might incorporate online review valence to decision making because they seek to minimize the uncertainty about the product quality and purchase risks (Roselius, 1971; Woodside and Delozier, 1976). Hence, if other informational signals help to verify the product quality sufficiently, consumers might rely less on online reviews for decision making. From this perspective, one reason for the previous research findings of the variations in the effect of online reviews on e-book downloads by the book ranking can be that the ranks might function as a signal for the book quality, and subsequently, consumers might less need to prioritize online review valence for the highly ranked books (Liu et al., 2019). Also, from signaling perspective, one reason for the contradictory results about the effect of online review ratings on movie ticket sales can be that other signals about the movie quality such as advertising intensity, investment amounts, or featuring star actors and actresses might skew the effect of online review valence on box office performances (Liu, 2006; Chintagunta et al., 2010).

Thus, consumers simultaneously consider online review valence and seller's provided information to make product quality judgments (Chen and Xie, 2008), and subsequently, product quality signal cues might effectively reduce consumers' reliance on online reviews for assessing purchase risks. The previous research suggests that sellers can effectively signal high product quality by limiting the product availability (Stock and Balachander, 2005), however, the most commonly used signal cue for the product quality might be 'brands' (Price and Dawar, 2002). Brands function as guarantees of product quality with the established customer-satisfaction reputations associated with the brand name, which tend to build over time (Keller, 1993). In this aspect, the previous literature argues that brand equity, the values ascribed to the brand name, can be an effective signal for product quality when there is insufficient information about the product attributes (Erdem and Swait, 1998). The previous research finds supportive results for brands as a signaling phenomenon, where brandedness, accompanied by product warranties, effectively improved consumer perceptions of product quality (Price and Dawar, 2002). Since we predict that consumers are less likely to rely on online review valence for decision-making when the product quality is easily verifiable with the sellers' provided product quality signals, product brandedness might reduce consumers' needs to verify product quality from online reviews, and subsequently decrease the effect of online review valence on consumer decisions. Thus, we generated three predictions, based on the previous research on signaling. Firstly, consumers make product quality judgments simultaneously from informational signals, including sellers' provided cues or online reviews (Chen and Xie, 2008; Kirmani and Rao, 2000), and thus, the effect of sellers provided signal cues, and online review valence on consumer decisions are endogenous. Secondly, consumers might rely less on online reviews when other informational signals sufficiently verify product quality (Roselius, 1971; Gambetta, 2011). Finally, product brandedness signals positive product quality (Erdem and Swait, 1998; Price and Dawar, 2002), and subsequently, consumers' reliance on online reviews for decision making decreases for branded products.

2.3. METHODOLOGY

2.3.1 Data

This study examines new purchases on Expedia during 2017 to investigate how online reviews, product quality signals, including brandedness, influence consumer decisions. The dataset is recorded on the consumer-level regarding the hotel information pages they viewed or purchased at the time when the consumer viewed the product information page. Thus, choice sets for each consumer are observed with product information, including online review ratings, locations, property class, and price for each purchase option they viewed (see Fig. 1). Thus, most accessible product information provided sellers on the purchase page are location and property class – where these two product characteristics are often considered as critical success factors (CSFs) in the hospitality industry (Fuentas-Medina et al., 2018; Hollenbeck, 2018). The dataset has some important advantages for examining the interaction effect between online review valence and product quality signals on consumer decisions. Firstly, using a consumer-level dataset enables direct investigation of consumer responses. Secondly, since the dataset focuses on accommodation products, product quality signals are relatively homogenous and comparable by the hotel's location or property class. 633,029 consumers are included in the study, and they viewed 21 ads on average for new purchases. Consumers viewed 13,293,602 hotel information pages in total during the observed period. Since we examine the ads which were already viewed by consumers, it is not observed how E-WOM valence influenced the probability of the consumers to view the ad. However, among the ads for which consumers were considering, there was a substantial variance in E-WOM valence (σ=.58, see Table 3). Thus, the dataset enables an investigation of the effect of E-WOM valence on consumer choice among the other competing options that consumers were comparing.

Variable. WV_{ic} indicates online review ratings for the hotel information page *i* that is viewed by consumer *c*. WVI_{ic} is a latent value for WV, which is not correlated to product quality judgments from the seller's provided product information (see Section 3.2). We quantified product quality into OQA_{ic}, which is calculated by the hotel location scores from the hotel's accessibility to the downtown and the property class of the hotel. Hotel's location and property class were displayed to the consumers at the time when they viewed the information page, and thus, they might be considered ‘signals’ about the product quality. P_{ic} indicates the product price of ad *i* viewed by consumer *c*. BDS_{ic} is a binary variable that identifies whether the hotel in the information page *i* viewed by consumer *c* is branded. The variables and their meaning in detail are described in Table 2. The average online review valence (WV_i) tends to be high at approximately 3.87 (see Table 3). The variance of the instrumental variable WVI_i (σ=.56) tended to fit the variance of raw E-WOM valence (WV_i, σ=.58). 66% of the products that were viewed by consumers were branded, which was expectable for the hotel industry.

Figure 2.1: Sample Hotel Information Page

Table 2.2: Variable Setups

Variable	Meaning
CON (Intercept)	Intercept in model estimation
WV_{ic} (E-WOM Valence)	Online review rating of ad *i* at the time when it was viewed by consumer *c*
WVI_{ic} (E-WOM Valence Instrument)	Instrumental variable for WOM valence, where the correlation with the observed product quality in sellers' provided information is controlled. The instrumental variable can be considered as WOM valence which was acquired mainly by unobserved product quality from sellers' provided information.
OQA_{ic} (Observed Product Quality)	Quantified product quality from sellers' provided information for ad *i*. It is calculated by summing hotel stars and location preferability scores.
P_{ic} (Product Price)	Product price of ad *i* at the time when it was viewed by consumer *c*.
BDS_i (Brandedness)	Dummy variable whether the product was branded.
BKG_i (Purchased)	Dummy variable whether the ad was purchased.

Table 2.3: Descriptive Statistics (N=13,293,602)

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Online Review Rating					
WV_i	3.87	4	.58	1	5
WVI_i	.0	.06	.56	-3.53	1.96
Product Information					
OQA_i	3.04	3.02	1.03	1.02	5.99
P_i	146.84	123.99	105.13	36	555
BDS_i	.66	1	.48	0	1
Consumer Choice					
BKG_i	.04	0	.18	0	1

Table 2.4: Pairwise Correlation Matrix

Variable	(1) WV_i	(2) WVI_i	(3) OQA_i	(4) P_i	(5) BDS_i	(6) BKG_i
(1) WV_i	1.000					
(2) WVI_i	.878(.00)	1.000				
(3) OQA_i	.414(.00)	-.071(.00)	1.000			
(4) P_i	.351(.00)	.131(.00)	.467(.00)	1.000		
(5) BDS_i	.102(.00)	.109(.00)	.013(.00)	.019(.00)	1.0000	
(6) BKG_i	.014(.00)	.003(.018)	.024(.00)	-.039(.00)	.007(.00)	1.000

2.3.2 Multicollinearity

Building on the previous findings, online review valence might infer the customer experience quality, and thus, it might correlate to the product quality, since consumers are likely to generate positive reviews for high-quality products (Duan et al., 2008). Furthermore, product quality is also expected to be correlated to the product price, whereby a strong correlation between E-WOM valence and product price is also likely. In these aspects, multicollinearity might be likely, as it is uncertain if the effect is mainly derived from product quality, price, online reviews (Wooldridge, 2005; Duan et al., 2008). To addressing such concerns, the authors utilize online valence from unobserved product quality as an instrumental variable to eliminate the correlation between the observed product quality information and online review ratings. Online review valence and the observed product quality from location and property class had a strong correlation (r=.41, $p<.00$, see Table 4). Product quality was strongly correlated with the product price (r=.467, $p<.00$), and therefore, online review valence was also correlated to the product price (r=.351, p<.00). We utilize the control function approach to address the potential correlation of E-WOM valence with unobserved purchase utility (Louviere et al., 2005; Petrin and Train, 2010, see Appendix 1). The instrumental variable WVI, which indicates online review valence from unobserved product quality, tended to effectively identify the variance of E-WOM valence (r=.878) and control for potential endogeneities from product quality and product price. The correlations of the instrumental E-WOM valence (WVI_i) with observed quality (r=-.071) and price (r=.131) were relatively limited (Kelejian, 1971; Wooldridge, 2013). Thus, this study utilizes the instrumental variable for the online review valence and control for the price effect and the multicollinearity concerns for online reviews and observed product quality.

2.3.3 Model

Multilevel models enable examinations of potential moderator components for binary outcomes when interactions between the variables are not yet divulged (Lancsar and Louviere, 2008; Aguinis et al., 2013). Product quality information cues from sellers and brands should simultaneously affect consumers' purchase decision making with E-WOM valence. Consider that consumer choice likelihood from E-WOM valence is a choice function of θ(WV). θ_0 indicates constant and latent consumers' judgments on choice probability, and θ_1 captures the power of E-WOM valence in increasing choice likelihood. Both latent consumers' judging behaviors and assessments of E-WOM valence are influenced by seller's provided information about the product quality or brandedness. Consumers are likely to have favoritism to branded products with superior quality. E-WOM valence infers product quality from the opinions of the prior consumers. Thus, the observable information cues about product quality (OQA) and product brandedness (BDS) influence consumers' latent judgments (θ0) and consumers' assessment on E-WOM valence (θ1) simultaneously (Leeflang et al., 2009).

$$Pr(BKG_{ic}=1) = 1 / 1+ \exp(-(\theta_0 + \theta_1 WV_{ic}+ \eta_{ic}))$$

$$\theta_0= \upsilon_0 + \upsilon_1 OQA_{ic} + \upsilon_2 BDS_{ic} + \alpha$$

$$\theta_1= \iota_0 + \iota_1 OQA_{ic} + \iota_2 BDS_{ic} + \kappa$$

Where, WV, OQA, and BDS denote online review valence, product quality cues, and brandedness respectively

Model Specification. As a result of incorporating multilevel equations into the E-WOM valence assessment model, the full model is coded as below. ($\iota_{0+}\kappa$) captures the effect of E-WOM valence (WV_{ic}) on purchase likelihood (BKG_{ic}). υ_1 indicates the effect of product quality described in sellers' provided information (OQA_{ic}) on the choice likelihood (BKG_{ic}). υ_2 observes consumers' favoritism towards branded products (BDS_{ic}) when they make purchase decisions. ι_1 captures the interaction effect between E-WOM valence (WV_{ic}) and observed information cues about product quality (OQA_{ic}). ι_2 observes the interaction effect between E-WOM valence (WV_{ic}) and product brandedness (BDS_{ic}) on consumer choice (BKG_{ic}). The interaction effects examine if product quality information cues might reduce the consumers' emphasis on E-WOM valence due to lower purchase risks. ($\eta_{ic} + \alpha_{ic}$) is the combined error term (Wong and Mason, 1984). υ0 is the constant effect.

$$\Pr(BKG_{ic}=1) = 1 / 1+ \exp(-(\upsilon_0 + (\iota_{0+}\kappa)WV_{ic}+ \upsilon_1 OQA_{ic}+ \upsilon_2 BDS_{ic}+\iota_1 WV_{ic}*OQA_{ic} + \iota_2 WV_{ic}*BDS_{ic}+ (\eta_{ic} + \alpha_{ic})))$$

where, WV, OQA, and BDS denote online review valence, product quality cues, and brandedness respectively

2.3.4 Consumer Heterogeneities

Since we are inputting the observed product quality in the second level, how consumers perceive the product quality from the information cues might be heterogeneous and affect the results (Kozinets, 2016). Furthermore, demographic information about the consumers is limited, and direct control for potential gender bias is not an option. In this aspect, we control for the heterogeneity effect by two other random sampling-based estimation methods. Bayesian updates on the estimation model can effectively address potential parametric heterogeneities by effect generalization through addressing the issue by Monte Carlo integration, where the consequential posterior distribution embeds the potential variance in the parameters. Potential random errors are updated to generate a posterior distribution of the estimated effect from the repeated simulations through Markov Chain Monte Carlo (MCMC) sampling algorithms (Imai et al., 2009; Kamakura and Wedel, 2012; Schmid and Mengersen, 2013). GMM has been examined for its consistency in model estimations, where the multiple iterations of Monte Carlo sampling converge the unbiased moments and improve the accuracy of the results even for MLE choice models (Pinkse and Slade, 1998; Giacomo, 2008; Wooldridge, 2013). Some observation points in the dataset might contain significant unobserved heterogeneities, which can skew the estimation results. GMM can be a powerful tool to control for the unobserved influence by selectively estimating the results with the *unaffected* moments drawn from the Monte Carlo sampling algorithm (Wooldridge, 2005; Pinkse et al., 2006). GMM estimation methods have been often adopted in the previous studies to control for unobserved heterogeneities specific to products and firms (Chintagunta et al., 2010; Shaikh et al., 2018).

$$\text{Bayesian Posterior}(\beta) = \Pi\beta(X)^* \ \Pi\ 1/\sqrt{2\pi\sigma}\ \exp\{-1/2((\beta - \mu(\beta))/\sigma)^2\}$$

$$\text{GMM Moments}_i = E[(BKG_i - 1/\ 1 + e^{-(X)i})X_i] = 0$$

2.4. RESULTS

Table 2.5: Estimation Results (N=13,293,602)

Variables	Parameter Estimates			
	MLE	**3SLS**	**Bayesian Posterior (MCSE)**	**GMM**
Intercept CON (υ_0)	-3.97 (.03)***	-3.97 (.03)***	-3.97 (.001)	-3.97 (.03)***
E-WOM Valence WV ($\iota_{0+}\kappa$) (H_B)	.48 (.04)***	.46 (.04)***	.45 (.002)	.46 (.03)***
Product Quality OQA (υ_1)	.15 (.01)***	.15 (.01)***	.15 (.0003)	.14 (.01)***
Brandedness BDS (υ_2)	.10 (.02)***	.10 (.02)***	.10 (.0009)	.10 (.02)***
Interaction Effect				
WV*OQA (ι_1) (H_C)	-.13 (.01)***	-.12 (.01)***	-.12 (.0004)	-.12 (.01)***
WV*BDS (ι_2) (H_D)	-.09 (.03)***	-.09 (.03)**	-.09 (.001)	-.09 (.03) ***

*Significance levels: ***p<.001, **p<.01 * p < .05*

MCSE: Monte Carlo Standard Error (Posterior standard errors)

The numbers in parenthesis are standard errors.

Table 2.6: Endogeneity Check

Variable	**(1)**	**(2)**	**(3)**
E-WOM Valence	✓	✓	✓
Product Quality	✓	✓	
Brandedness	✓	✓	
Interaction Effects	✓		
Endogeneity	.10	.116	.999

Table 2.7: Model Performance Comparison (N=13,293,602)

Variables	Parameter Estimates							
	(1)		(2)		(3)		(4)	
	3SLS	Bayesian Posterior (MCSE)	3SLS	Bayesian Posterior (MSCE)	3SLS	Bayesian Posterior (MSCE)	3SLS	Bayesian Posterior (MSCE)
Intercept CON (υ_0)	-3.97***	-3.97 (.00)	-3.92***	-3.92 (.00)	-4.01***	-4.01 (.00)	-3.38***	-3.38(.00)
E-WOM Valence WV ($\iota_{0+}\kappa$)	.46***	.45 (.00)	.04**	.04 (.00)	.04***	.04 (.00)	.03*	.03 (.00)
Product Quality OQA (υ_1)	.15***	.15 (.00)	.14***	.14 (.00)	.12***	.12 (.00)		
Brandedness BDS (υ_2)	.10***	.10 (.00)	.09***	.09 (.00)	.	.		
Interaction Effect WV*OQA (ι_1)	-.12***	-.12 (.00)	.	.	.	.		
WV*BDS (ι_2)	-.09**	-.09 (.00)	.	.	.	.		
LR Score	479.58 ***	.	359.75 ***	.	330.29 ***	.	4.8 *	
BIC Score	153547.3	.	153640.8	.	153657.1	.	153969.4	
Acceptance Rate	.	.30	.	.28	.	.25		.23

*Significance levels: ***p<.001, **p<.01 * p < .05*

MCSE: Monte Carlo Standard Error (Posterior standard errors)

The numbers in parenthesis are standard errors.

A one-star increase in review ratings was likely to boost sales by 46% ($\iota_{0+}\kappa$=.46, p<.00). In this aspect, improving online review valence might be crucial for increasing sales. However, the interaction effect between product quality from location and property class information cues and online review valence was negative (ι_1=.-12, p<.00), indicating that consumers were likely to rely less on online review valence when other information cues signal positive product quality. Also, consumers were less likely to rely on online reviews for decision making on branded hotels (ι2=-.09, p<.00). Branded hotels were 10% more likely to be booked by consumers compared to non-branded hotels (υ2 =.10, p<.00). Consumers preferred to purchase better quality products (υ_1=.15, p<.00). Consider that consumers are not likely to shift preference towards lower quality, non-branded products for the purchase options with relatively high online review ratings, the results indicate that the effect of online review valence on sales likelihood is likely to diminish as other information signals convince the product quality. We compared the effect of a one-star increase in online review ratings on sales by hotel quality and brandedness in Fig. 2. A one-star increase in online review ratings was likely to increase sales likelihood by 19% for the bottom quartile quality hotels, and approximately 6% for the top quartile hotels. We predicted that consumers might rely less on online reviews for decision making when purchase risks are lower due to other product quality signals (Roselius, 1971; Kirmani and Rao, 2000; Chen et al., 2011; Gambetta, 2011). The effect of online reviews on consumer decisions was lessened when other information cues signaled positive product quality in aspects of location and expert ratings. For the bottom quartile quality hotel, a one-star increase in online review ratings tended to increase sales likelihood by 19% for non-branded hotels and 10% for branded hotels. We predicted that consumers might rely less on online reviews for decision making when other product signal cues such as brands are salient (Woodside and Delozier, 1976; Erdem and Swait, 1998; Price and Dawar, 2002). The effect of online reviews on consumer decisions was lessened when the product was branded. Thus, when the hotel quality seemed more convincing via informational signals, such as its location, property class, or brandedness, online review valence was an increasingly less significant decision factor (see Appendix 2).

Furthermore, we quantified endogeneity of the product quality signals in estimating the effect of online reviews by the standard measure, where correlations of online review valence and residuals are compared between models that do or do not include other product quality information (Wooldridge, 2013). The endogeneity measures indicate that not considering product quality information in estimating the effect of online review ratings result in a strong correlation between the online review valence and the error term ($r=.99$, $p<.00$, see Table 6), suggesting that significantly endogenous variables are not considered and embedded in the residuals. In this aspect, including product information significantly eliminate the endogeneity concern ($r=.11$, $p<.00$). Also, considering the interaction effect between online review valence and other product information cues further decreased the endogeneity measure ($r=.10$, $p<.00$). Thus, consumers are likely to generate product judgments by simultaneously assessing various product quality signals including online review valence (Kirmani and Rao, 2000; Chen and Xie, 2008), and the effect of product quality information cues to influence consumer decisions and it is likely to be endogenous in estimating the effect of online review valence on decision making.

Robustness. The estimation model (Model 1, LR score=479.58, BIC score=153547.3, see Table 7) showed superior performance compared to the other models where the effect of product quality signals other than online review valence or the interaction effects were not considered. Model 4, where online review valence is the only predictor for purchase probability, likelihood ratio score was low at 4.8 (Model 4, LR score=4.8, BIC score=153969.4). Model performance measures including likelihood ratio and Bayesian information criterion noticeably increased for model 3, where product quality information cues regarding the hotel's location and property class were considered together with online review valence for estimating the purchase probability (Model 1→Model 2, LR score=4.8→330.29, BIC score =153969.4→ 153657.1). Adding hotel brandedness as a predictor for purchase likelihood further improved the model performance, where model informativeness and errors tended to be further optimized (Wooldridge, 2013) (Model 2→Model 3, LR score=330.29→359.75, BIC score 153657.1→153640.8). Furthermore, most importantly, including the interaction effects between online review valence and other product quality signals including brandedness not only further improved the model performance (Model 3→ Model 4, LR score=359.75 →479.58, BIC score=153640.8→153547.3), but also caused a notable change in the effect size of online review ratings on consumer decisions (Model 3→Model 4, $\iota_{0+\kappa}$=.03→46). Thus, we observed that the effect size of E-WOM valence was significantly deflated when the interaction effects between E-WOM valence and product quality information cues were not considered in the consumer decision, and hence, the results suggest that not controlling for the effect of other product quality signals might significantly skew the effect of online review valence on sales. Acceptance rates for Bayesian estimations showed a comparable trend. Acceptance rates tended to increase as we considered more the other product quality signals and the interaction effects in the model (Model 1→Model 2→Model 3→Model 4, Acceptance rates=.23→.25→.28→.30). The posterior results were converged over 15,000 trials.

Figure 2.2: The Effect of One Unit Increase in Review Ratings (%) by Product Quality Signals Salience

2.5. DISCUSSION

This study investigated the effect of online reviews on sales on the consumer level, based on a large-scale choice data, which enabled a direct investigation of when consumers rely on online review valence for making purchase decisions. The findings of this study suggest that signals for product quality can significantly moderate the effect of online reviews on consumer decisions. In this aspect, the salience of other information cues that signal product quality can significantly influence whether and how consumers incorporate online review sentiment information into economic decision making. Although the previous research findings have been consistent for the effect of WOM volume on sales (Liu, 2006; Duan et al., 2008; You et al., 2015), and subsequently, WOM volume has been increasingly adopted as marketing outcome variable as a customer reach performance measure (Fay et al., 2019), the previous literature provided contradictory insights about the effect of online review sentiments or WOM valence on sales (Liu, 2006; Duan et al., 2008; You et al., 2015). The findings of this study indicate that convincing signals about the product quality other than online reviews can reduce consumers' reliance on online reviews for decision making to the extent where the effect of online review ratings on purchase likelihood is minimal.

Theoretical Implications. The findings of this study add some important insights into when does online reviews more or less to consumers when they make purchase decisions. Not only gender (Bae and Lee, 2011), category maturity (Ho-Dac et al., 2013), uncertainty avoidance (Kim, 2019), physical disability (Zhang and Yang, 2019), or product types (Dai et al., 2019), product quality signal cues can be an endogenous moderator in estimating the effect of online reviews on sales. The difficulty in analyzing E-WOM effects on sales in aspects of the complexity of eliminating the latent factors regarding the product quality has been acknowledged in the previous research (Liu, 2006). In this aspect, this study focused on accommodation products, where product quality is relatively comparable based on location or property class and controlled for product quality signals other than online reviews. The results suggest that the effect of online reviews on sales might be endogenous to consumer decision making with other signal cues that help to reduce uncertainty about product quality (Liu, 2006; Gametta, 2011). The previous research viewed online review valence as another signal cue for product quality (Kirmani and Rao, 2000), and thus, the authors predicted that consumers would rely less on online reviews if other product quality signals sufficiently relieve the uncertainty about the product quality (Roselius, 1971; Erdem and Swait, 1998). The results of this study suggest that other hotel information cues that signal quality, which include accessibility, or property class, and hotel brandedness, effectively reduce consumers' reliance on online reviews for decision making. Furthermore, the model comparison results indicated that the effect of online review valence on sales likelihood could be deflated if the interaction effects with product quality cues were not considered.

Furthermore, this study observed that product quality signals are endogenous to the effect of online review valence on consumer decisions to a great extent where consumers might not care about online reviews when product quality assessments can be satisfied without evaluating Word of Mouth information. In this aspect, the insignificant effect of online review valence on sales for movies in the previous research might be because the sample might focus on favorable movies (Liu, 2006; Chintagunta et al., 2010) – and the effect might be altered if it was examined on the movies which consumers are not familiar with. Also, the variations in the effect of online review valence on e-book downloads by the book ranks might be because the rank functions as a signal for the book quality, and the high-rank might signal good quality and subsequently reduce consumers' reliance on online reviews for download decisions (Liu et al., 2019). The authors recommend that future research incorporates consumer judgment factors from sellers' provided signals about the product quality when they estimate the effect of online review valence on sales. The results of this study suggest that other product quality signals tend to be endogenous in consumer decision making with online review valence, and not including the moderation effects might deflate the true effect of online reviews on sales. For example, consumer preferences for movie attributes might be highly heterogeneous and challenging to be coded. The authors recommend using a proxy such as sales performance in the preceding period to control for the consumer preference factors when estimating the effect of online review valence on movies.

Managerial Insights. This study provides some important insights for managers. It is an increasingly significant trend that marketing managers are expanding investments in E-WOM valence and user-generated content (Villanueva et al., 2008; Tuk et al., 2008). The previous study found that approximately 16% of restaurant reviews on Yelp.com were likely to be initiated by the businesses (Luca and Zervas, 2016). Business investments in achieving favorable online review sentiments have been increasing, and customer relation management (CRM) agencies have often adopted customer review management as one of the main service disciplines (Womply, 2019). However, the findings of this study suggest that business to consumer (B2C) communications on product quality might be given priority in marketing practices, since consumers make product judgments based on various signals about the product quality, including information cues provided by sellers (Kirmani and Rao, 2000; Chen and Xie, 2008). Reallocating resources to increase the review ratings is not likely to generate significant ROIs for the products of relatively high quality since the E-WOM valence effect on sales tends to be contingent on the product quality described in the sellers' provided information.

2.5.1. Limitations and Future Research

Product Type. The effect of online review valence on sales can be varied by product type and industry (You et al., 2015; Mudambi and Schuff, 2010). Judging the product quality information requires a certain level of background knowledge, consumers who are unfamiliar to the product attributes might find the product quality information incomprehensible and disregard the informational merits of the sellers' provided information about the product quality. This study examined only accommodation products, in which the product quality is easily comparable. We expect that the online review valence effects on purchase likelihoods might be enhanced for search goods in which the product quality is difficult to compare, such as tech products since consumers are likely to find sellers' provided information about the product quality less comprehensive. We recommend future research to explore further on some moderating conditions of the online review valence effects on purchase likelihoods since it is expected that consumers are likely to utilize online review valence at varying extents depending on the helpfulness of the sellers' provided information or product characteristics.

Review Characteristics. Similarly, consumer decisions might be influenced not only by consumer characteristics or product characteristics but also by other online review factors such as review length, readability, or review volume (Duan et al., 2008; Wang et al., 2019; Liu et al., 2019). In this aspect, it is predictable that other online review factors might also influence consumer decisions with product quality signals or online review valence. However, one limitation of this study is that online review characteristics are not observed in the dataset. Online review volume might signal product popularity and subsequently might function as a product quality signal (Duan et al., 2008; Fay et al., 2019). In this aspect, high online review volume might have a positive influence on consumer decisions, and the effect might be moderated by other product quality information cues. To address this concern, this study examined the effect convergence over unobserved heterogeneities based on two different Monte-Carlo estimation methods. Potential errors that can be derived from unobserved factors are reflected in the posterior coefficient distribution through Bayesian updates of the differences between 15,000 simulations on MCMC (Markov-Chain Monte-Carlo) random samples (Chib et al., 2008). The effect tended to converge over numerous simulations, and the posterior results were consistent with the original model. Furthermore, optimal parameters based on the moment condition in GMM estimation tend to converge over multiple MCMC random samples. Also, the GMM estimation results were consistent with the original MLE model estimation results (see Table 5). Thus, the findings indicate that it is not likely that unobserved review characteristics can be provoking factors for substantial errors in the estimation results (Arellano and Bond, 1991; Imai et al., 2009). The authors recommend that future research explore how product quality signals might interact with other online review factors to influence consumers' decision making.

Sentiment Analysis. Also, this study expects to provide important insights into the fast-growing text-mining research on online reviews. The results of this study found that online reviews matter significantly more to consumers who purchased low-quality products due to reasons such as budget limits. Future research can investigate certain sentiments of online review contexts more effectively increase perceived helpfulness, with accounting for when online reviews matter to consumers. Consumers who ended up purchasing low-quality products might seek more information about purchase values and prefer honest opinions. Positive anomaly in E-WOM sentiments might exacerbate perceived helpfulness for relatively low-quality products.

2.6. Concluding Remarks

This paper utilizes signaling theory and investigates how online reviews might interact with other information cues that signal product quality to influence consumer decisions. Consumers are risk-aversive, and one reason why consumers might incorporate online reviews into purchase decisions is that they want to minimize the purchase risks. In this aspect, if the sellers signal positive product quality with verifiable information cues, consumers tend to rely less on online reviews for economic decision making. The findings of this study add insights into moderating factors that influence the effect of online reviews on consumer decisions. Not only the product types or consumer characteristics but product information signaling also might moderate consumers' reliance on online review sentiments for decision making. Investments in customer review management might not always generate significant ROI. Effective business-to-consumer (B2C) communications can effectively reduce consumers' WOM information-seeking behaviors.

PART III:

HOW ONLINE REVIEWS INFLUENCE SALES? INVESTIGATING REFERENT AND RELATIVE EFFECTS OF ONLINE REVIEWS

3.1. HOW DOES ONLINE REVIEW MATTER?

Online reviews have become a critical pillar of marketing. Online reviews are often considered the most significant emerging tenet in the marketing communication mix (Keller, 2007; Chen and Xie, 2008). Managers often utilize online reviews as an indicator of how likely a consumer might recommend the products to others (Godes and Mayzline, 2004). Also, online review sentiments can be an effective predictor for consumers' repurchase intention (Riechheld, 2003; Eisingerish et al., 2013). In these aspects, recent marketing models often adopt the volume of online review generated, and the sentiments in the online reviews as a measure for advertising or marketing spending effectiveness (Kietzmann, Paschen, and Treen, 2018). Marketing campaigns often provide financial rewards for consumers who generate online reviews about their products, and approximately 16% of restaurant reviews were generated by businesses (Tuk et al., 2008; Groeger and Buttle, 2016; Luca and Zervas, 2016). Customer Relationship Management (CRM) agencies have launched customer review management as one of their main service offerings (Womply, 2019).

However, it is still uncertain if incentivizing online review ratings against competitors might be an effective investment strategy. The previous research reported inconsistent results even for the same product category. The previous studies examined the effect of online review ratings on box office performance based on Yahoo! Movies data and reported contradictory results, where online review ratings effectively predicted ticket sales performance (Chintagunta and Venkataraman, 2010) or had an insignificant influence on box office performance (Liu, 2006). Success in the increasingly competitive market environments depends upon understanding in-depth consumer purchase decision mechanisms (Money, Gilly, and Graham, 1998). Online reviews might be one of the main influencers for consumers' purchase decisions, however, limited attention has been given to explore *why* online reviews affect consumer decisions (Edwards, 2006; Chen et al., 2011; Kozinets, 2016).

The previous research assumes that online reviews influence consumer decisions for two reasons in general. One reason why online review affects consumer decisions is because online reviews are the opinions of the experienced consumers and infer reliable information about the product quality (Duan, Gu, and Whinston, 2008; Bruce, Gilly, and Graham, 2012). Thus, online reviews might function as a social influence for new purchases by signaling product quality. Another reason can be that consumers might choose to evaluate online reviews is that they want to reduce purchase risks. The early research on Word of Mouth found that consumers choose to collect others' opinions when decision risks were high (Roselius, 1971; Woodside and Delozier, 1976; Kim, 2020). This rationale is applicable to online reviews. Consumer decisions might be more influenced by online reviews when they need to reduce purchase risks. In this aspect, the effect of online reviews is likely to referent to the good-enough rating, and subsequently, higher ratings above the satisfactory reference point might not affect consumer decisions significantly.

In this study, the authors investigate if the effect of online reviews on purchases is more likely due to social influence or risk-avoidance by examing the relationship between the online review ratings and purchase decision likelihood. We examined 633,029 consumer choices from 13,293,602 hotel purchase pages they viewed on Expedia and found that the relationship between online review ratings and purchase likelihood features an inverse exponential distribution. The results indicate that online review ratings beyond a certain point have a reduced marginal effect on purchase decisions, and consumers are not likely to prefer options with higher review ratings above a certain point. It is predictable that consumers might prefer higher review ratings if online reviews induced significant social influence on consumers' decisions. However, consumers tended to disregard the purchase merits from the online review ratings above a certain point, and it is predictable that consumers utilized a certain point of online review ratings to screen out risky purchase options.

The findings of this study have some important research and managerial implications. This study investigates more dominant logic why online reviews might affect consumer decisions, based on the previous literature. The results suggest that online reviews have a reduced marginal effect on consumer decisions above a certain point, and online reviews might function as a risk-reliever for consumer decisions. The findings provide insights about why the effect of online reviews on sales are inconsistent in the previous literature. The effect of online reviews on sales are not likely to be linear and tend to feature an inverse exponential distribution. For example, consumers are significantly more likely to prefer three-star ratings compared to two stars but not necessarily prefer five-star ratings over four stars. Thus, the variations in the review ratings in the tested sample might skew the effect significance. For example, the previous research might find an insignificant effect of online review ratings on sales if the sample is concentrated on relatively high review ratings, such as three to five stars. Also, the findings provide managerial insights about investment decisions on customer review management. Managers might be able to increase sales significantly by improving online review sentiments if the products have significantly low review ratings compared to the competing products; however, an increase in review ratings that are already relatively high is not likely to increase sales significantly.

3.2. CONCEPTUAL BACKGROUND

3.2.1 Online Review: Social Influence vs. Risk Reliever

The previous research defines Word of Mouth (WOM) as the consumers interacting with other consumers regarding their opinions on the earlier purchases, which influence future purchase decisions (Cheung and Thadani, 2012; Bao and Chang, 2014; Yoon and Choi, 2017). Word of Mouth marketing includes a broad stream of research including consumer interactions on social media, content virality, or online review. Word of Mouth research can be traced back to Roselius (1971) or Woodside and Delozier (1976), which focused on offline communications. The latest research is often categorized into: (1) social media interactions and (2) online reviews. Social media WOM research utilizes field experiments or content mining methods and investigates expressional or contextual triggers for virality (Kozinets, De Valck, Wojnicki, and Wilner, 2010; Berger and Milkman, 2012; Chae, Stephen, Bart, and Yao, 2016). Online reviews – which can be referred to as Electronic WOM - have received extensive attention since the early 2000s. The early research tends to focus on whether online reviews have a substantial influence on sales performance in terms of valence and volume (Liu, 2006; Duan et al., 2008; Chintagunta, Gopinath, and Venkataraman, 2010). The previous research often adopts the term WOM valence (WMV) to denote online review ratings and WOM volume to indicate online review counts (Liu, 2006; Duan et al., 2008). Recent research extends the previous findings by divulging more moderating factors – *when* and *how* online reviews are more or less likely to influence sales (Ho-Dac, Carson, Moore, 2013; Liu, Zhang, and Zao, 2019; Dai and Mogliner, 2019).

Online reviews are the most readily available Word of Mouth from credible sources, which are the consumers who purchased the products (Edwards, 2006; Liu, 2006; You, Vadakkepatt, and Joshi, 2015). Predictably, review ratings infer information about product quality and influence other consumers' purchase decisions. Businesses are increasingly investing in generating favorable reviews, based on the presumption that the positive review rating will attract the consumers (Trusov, Bucklin, and Pauwels, 2009; Luca and Zervas, 2016). Despite the intuition that positive review ratings will increase the sales, the results have been contradictory even for the same product category, such as new release movies (Liu, 2006; Chintagunta et al., 2010).

Online reviews should infer the product quality, and thus, the sentiment in the online reviews might have significant social influence that induces new purchases (Duan, Gu, and Whinston, 2008; Bruce, Gilly, and Graham, 2012). However, from a different perspective, the effect of online reviews on purchase decisions might be heterogeneous for consumers, and it is uncertain if consumers even care about the review ratings (Kozinets, 2016). Another reason why online reviews affect consumer decisions can be because consumers might deliberately choose to evaluate online reviews for certain purposes.

Consumers want to minimize the purchase risk, and Word of Mouth is a significant risk reliever (Roselius, 1971). The early advertising research observed that consumers' seeking behavior for Word of Mouth information is relative to the perceived decision risks (Woodside and Delozier, 1976). If consumers choose to evaluate online review ratings to avoid risks, the effect of user ratings on purchase likelihood will not be necessarily linear. In this perspective, the review rating only has to be satisfactory enough to relieve the purchase risks, and the effects will be stronger when the purchase risks are high.

The effect of online reviews on sales tends to be still uncertain (Kozinets, 2016). This study aims to conduct an empirical investigation on why online reviews might affect sales by examining whether the effect of online review ratings on purchase decisions is more dominantly derived by social influence or risk avoidance. If online review ratings have salient social influence, consumers might prefer the products with a higher review rating. On the contrary, if consumers tend to evaluate review ratings for reducing purchase risks deliberately, it is predictable that the consumers' evaluations of review ratings are referent to a certain rating, which is good enough to relive the risks. If the effect of online reviews on consumer choice is referent to the good-enough point for risk-relieving, consumers might perceive limited merits from the review ratings above the satisfactory reference (Saini et al., 2010; Nicolau, 2012). From these perspectives, the marginal effect of online review ratings is expected to be positive if consumers tend to prefer a higher rating, while the marginal effect is expected to be negative if consumers tend to less care about review ratings as long as the ratings are not too low and signal a risky purchase.

3.2.2 The Reference Effect

The reference effect has been extensively studied in the previous pricing literature – where consumers' price perception or utility judgment can be altered by having the good-enough price points as a reference before making decisions (Biswas et al., 1993). Consumers who had high reference price points are more likely to purchase products when the price decreases (Coulter and Krishnamoorthy, 2013). Reversely, consumers who had low reference price points are more likely to lock-in and less likely to seek price bargains (Saini et al., 2010). The previous research suggests that the reference price point is so prevalent in the mobile service market that it is the key factor for consumers' willingness to subscribe (Blechar et al., 2005). Consumer heuristics about the good-enough reference point can alter how online reviews influence purchase decisions and add an important insight about whether maintaining favorable online reviews against competitors has a substantial effect in increasing sales (You et al., 2015). If the reference effect is salient and consumers tend to evaluate the merits of online reviews compared to the good-enough rating, increases in online review valence below the reference point are likely to have substantial effects on increasing sales. However, increases in online review valence above the reference point might have an insignificant effect. Reversely, if consumers evaluate online review valence relatively to one another, more positive review sentiments might consistently benefit sales.

Relative Effect. If review ratings significantly persuade consumers, it is likely that consumers might choose the most persuasive option, assumed that other influencers for the consumers' decisions such as product prices are controlled (Chevalier and Mayzlin, 2006; Duan et al., 2008). In a case where consumers' purchase decisions are significantly influenced by the opinions of the experienced, consumers might prefer the purchase options with a more positive review rating. Thus the effect of online reviews on purchase probability will be relative to review ratings of the other competing purchase options. In this perspective, the marginal effect of online review ratings might increase for a higher review rating, and the relationship between review ratings and purchase likelihood features an exponential distribution.

Referent Effect. If the persuasive influence of online reviews is limited, the effect of online reviews on consumers' decisions might be contingent on the consumers' deliberation about whether they choose to evaluate the online reviews or not. Consumers tend to utilize WOM information to relieve purchase risks (Roselius, 1971; Woodside and Delozier, 1976). If consumers deliberately evaluate the online review ratings to minimize the purchase risks, the review rating effect on consumers' decisions might be referent to the good-enough point that relieves the risks. For example, if three-stars out of five review ratings are enough to convince the consumers that the products are reliable, the effect of an increase in the review ratings beyond the three stars might not be as dramatic as an increase in the review ratings below three-stars, since online review ratings above the satisfactory reference-point might not necessarily further relieve the purchase risks (Nicolau, 2012). Thus, the review ratings above a good-enough reference-point might have reduced merits in increasing purchase probability, and the marginal effect might decrease for a higher review rating. Hence, the online review rating effects on purchase likelihood feature an inverse exponential distribution.

Risk Avoidance. If consumers mainly assess review ratings to avoid risks, the online reviews might have greater impacts on consumers' decisions when the purchase risks are more pronounced. Sometimes, consumers might choose to purchase low-quality products due to limited budgets or greater values for the price (Hauser and Urban, 1986). In this case, consumers might need to verify the product quality and whether the purchase value is convincing. Thus, consumers might perceive more pronounced purchase risks when they focus on purchase values and seek more WOM information to relieve doubts (Roselius, 1971). In this aspect, the referent effect is expected to vary by product quality, because consumers perceive higher purchase uncertainty when they buy a product, where its quality is not readily verifiable with objective product information (Roselius, 1971). The marginal effect (negative) is expected to be smaller when consumers purchase low-quality products. Reversely, it is predictable that purchase uncertainties can be more effectively addressed with observed product quality information for high-quality products, and subsequently. The marginal merit (negative) of online review valence in reducing uncertainties will be bigger.

3.3. METHOD

3.3.1 Data

In this study, the authors examined 13,293,602 accommodation product information webpages that were considered or considered and purchased by 633,029 consumers on Expedia during 2017. The dataset identifies each hotel product webpage with the consumer who viewed or viewed and purchased the hotel. Consumers included in this study viewed approximately 21 ads for a new purchase on average. The product information webpage displays the hotel's review ratings, hotel quality information regarding property class and location, the price per night, and a button-link for booking (see Table 8). Consumer-level data about the effect of online reviews on sales has great merits as it enables an investigation of the effect of online reviews on a consumer-level and how online review ratings influence decision making compared to the other competing options for the purchase (Liu, 2006; Mudambi and Shuff, 2010). The dataset also recorded product information regarding the hotel's location score and property class or price – and the decision factors other than online review ratings, such as price or product quality, can be controlled for.

Table 3.1: Variable Setups

Variable Type	Variable	Meaning
Predictor	CON	Intercept in model estimation. It can be interpreted as a constant latent effect.
	WV_i	Online review ratings of hotel i
	WVQ_{ni}	Dummy variable for identifying n^{th} quantiles of review rating of hotel i (by half standard deviation)
Control	P_i	Price per night for the hotel i
Identification	C	Consumer identification
Consequence	PD_i	Purchase dummy for hotel i

Variable. WV_i indicates the review rating of the ad i, which ranges from one to five. The choice sets with top and bottom one percentile values were dropped to control for the extreme values. The average rating is relatively high (μ=3.87, see Table 9). *C* indicates consumer identification, where the results are generalized from each consumer's choice. WVQ_n is a dummy variable that indicates n^{th} quantile of online review ratings of ad i, and each quantile ranges in a half standard deviation ($\sigma/2=.29$). If the review ratings significantly persuade the consumers' decisions, the effect is expected to increase per quantiles. Alternatively, if consumers mainly evaluate the review rating to avoid risks, the marginal effect will be reduced near the common reference point, which is used by consumers to relieve risks. Estimating the review rating effect on purchase decisions per the rating quantile allows us to capture the common reference point in which the effect is predicted to stagnate.

Table 3.2: Descriptive Statistics

Variable	Median	Mean	Standard Deviation	Minimum	Maximum
Online Review Valence (WV_i)	4	3.87	.58	1	5
Product Price (P_i)	128.99	146.84	105.13	36	555
Purchase Dummy (PD_i)	0	.04	.18	0	1

3.3.2 Model Specification

Marginal Effect. This study examines the marginal effect of online review ratings on consumer choice by implementing a quadratic function. Quadratic function is an econometric method that is often used to capture decreasing or increasing trends in marginal effects, where the squared variable is added to capture the increasing or decreasing trend in the effect strength of the target variable (Wooldridge, 2013). In this aspect, the marginal effect of online review ratings on purchase likelihood is observed in β_2, where the general effect is observed in β_1. If online review ratings have a significant social influence on consumers' decisions, the marginal effect is likely to be positive, since consumers might always prefer higher review ratings. On the contrary, if online review ratings function as a reliever for perceived purchase risks, the marginal effect is likely to be negative, since higher ratings among relatively high ratings such as five-star ratings over four stars might not have comparable merits as a risk reliever, compared to five-star ratings over two or lower star ratings. Also, we control for the price effect in β_3 so that the general and marginal effects of online reviews on consumer choice are exogenous to the effect of price on consumer choice.

$$\text{Probability}(PD_i=1) = 1 / 1+ \exp(-(\beta_0+\beta_1 WV_{ci}+\beta 2 WV^2_{ci}+\beta_3 P_{ci}+\varepsilon_{ci}))$$

where WV, WV^2 and P donote online review valence, a quadratic function of online review valence, and price respectively

In addition, we estimate the effect of online reviews on purchases by review rating quantiles so that we can observe the non-linear relationship between review ratings and purchase likelihood. We coded each review rating quantiles as a dummy. Each n^{th} quantile of review ratings is identified by the dummy variable $WVQ_{n,}$ which ranges in a half standard deviation. This approach helps to analyze the marginal effect of online review ratings on consumer decisions. The effect per review rating quantiles would feature an exponential distribution if the higher rating tended to be more effective in increasing sales likelihood throughout all rating quantiles. On the contrary, the effect per review rating quantiles will feature an inverse exponential distribution if the higher rating became less effective in increasing sales likelihood for higher rating quantiles. Furthermore, we divided the consumers into two separate groups by product quality of the hotels they viewed and purchased to examine if the effect of online reviews on consumer decisions might be varied by product quality. Product quality is calculated by the hotel's accessibility to the downtown and the hotel's property class. Low and high product quality indicates the bottom and top two standard deviation quantiles, which ranges within the bottom and top 15% product quality scores.

$$\text{Probability}(PD_i=1) = 1 / 1+\exp(-(\lambda_0+\lambda_n WVQ_{ci} +\lambda_{n+1}P_{ci}+\mu_{ci}))$$

where WVQ and P denote dummies for online review valence quantiles and price respectively

GMM Estimation. In addition, we control for other unobserved factors by the Monte-Carlo random sampling-based estimation algorithm - Generalized Method of Moments (GMM). GMM assumes that the model estimation is inevitably vulnerable to the influence which is not observed in the data, and thus the data points where the estimation error was zero were relatively free from the unobserved influence (Wooldridge, 2010). GMM generalizes the unaffected observation points by multiple iterations from random samples and uses them as an instrument to estimate the effect (Arellano and Bond, 1991). Thus, GMM estimation methodologically controls for unobserved heterogeneities that might skew the results (Pinkse and Slade, 1998). The previous research adopted GMM to control for product-specific heterogeneities in estimating the online review rating effect on box office performance, where other movie characteristics such as starring actors might influence the results (Duan et al., 2008; Chintagunta et al., 2010). This study utilizes GMM estimation to control for unobserved consumer heterogeneities such as types of devices to access e-commerce or web environments, which might interfere with decision making.

$$X_i = \beta_0+\beta_1 WV_{ci}+\beta_2 WV_{ci}^2+\beta_3 P_{ci}+\varepsilon_{ci}$$

$$\text{GMM Moments}_i = E[(BKG_i - 1/1+e^{-(X)i})X_i]=0$$

3.4. RESULTS

3.4.1 The Marginal Effect

Table 3.3: Marginal Effect Results (N= 13,293,602)

Predictor	Parameter Estimates			
	Overall (MLE)	**Overall (GMM)**	**Low Quality**	**High Quality**
Intercept (β_0)	-8.02 (.27)***	-8.02 (.29)***	-6.74 (.44)***	-8.61 (1.44)***
Review Rating Effect WV_i (β_1)	2.35 (.14)***	2.35 (.16)***	1.51 (.25)***	3.07 (.69)***
Marginal Effect $WV_i^2(\beta_2)$	-.29 (.02)***	-.29 (.02)***	-.17 (.03)***	-42 (.08)***
LR score (χ^2)	1753.68***	.	124.61***	93.33***

*Significance levels: ***p<.01, **p<.05 * p < .1*

The numbers in parenthesis are standard errors.

The general effect of review rating on consumers' decision is positive and significant (β_1=2.35, p<.01, see Table 10). High review ratings are likely to improve hotel sales effectively. However, the higher rating isn't always the better. The marginal effect is negative (β_2 =-.29, p<.01), which indicates that the increases in the effect size of review rating on purchase decisions are lower for the high ratings. Thus, the relationship between review ratings and purchase likelihood tended to feature an inverse exponential. In this aspect, the effect of online review ratings on sales is likely to be concave. The higher review ratings tended to have reduced merits for upper review rating quantiles. For example, the one-star differences in five stars versus four stars tend to have reduced merits compared to the one-star difference in three stars versus two stars. Furthermore, the marginal effect was noticeably varied, where the marginal merit of an increase in online review valence decreased more sharply for purchasing high-quality products ($\beta_{2,\text{ HIGH-QUAL}}$ =-.42, $p<.01$), where consumers relatively preferred higher ratings consistently for purchasing low-quality products ($\beta_{2,\text{ LOW-QUAL}}$ =-.17, $p<.01$). The results suggest that the effect of online reviews on purchase might be more due to risk-avoidance because the marginal merit of review ratings might not be negative if social influence is salient. If the social influence of online reviews is salient, consumers are likely to prefer the higher rating option, and the marginal effect of review ratings might be positive (Duan et al., 2008; Kim, Yoon, and Choi, 2018).

Table 3.4: Purchase Likelihood by Online Review Rating Quantile

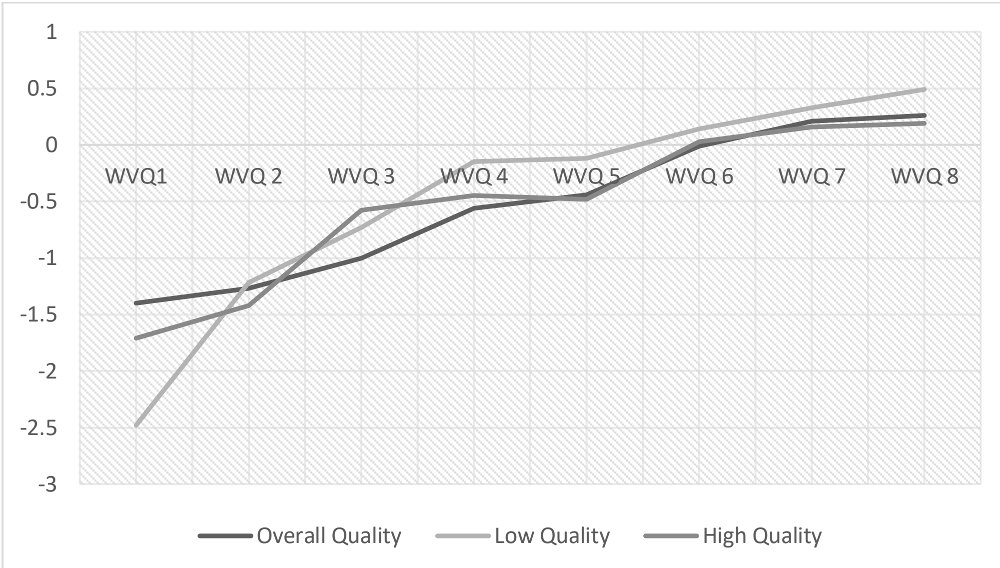
Predictor (WVQ)	Parameter Estimates: Low Observed Quality (N=2,452,364)	Overall Observed Quality (MLE)	Overall Observed Quality (GMM)	High Observed Quality (N=2,433,301)
Intercept	-3.44 (.18)***	-2.99 (.04)***	-2.98 (.04)***	-2.61 (.06)***
8th	.49 (.17)***	.26 (.04)***	.26 (.04)***	.19 (.06)***
7th	.33 (.17)**	.21 (.04)***	.21 (.04)***	.16 (.06)***
6th	.14 (.17)	-.01 (.00)***	-.01 (.00)***	.03 (.06)
5th	-.12 (.18)	-.44 (.05)***	-.44 (.05)***	-.48 (.13)***
4th	-.15 (.18)	-.56 (.07)***	-.56 (.07)***	-.45 (.22)**
3rd	-.73 (.23)***	-1.00 (.12)***	-1.00 (.13)***	-.58 (.32)*
2nd	-1.22 (.44)***	-1.27 (.29)***	-1.27 (.29)***	-.1.42 (1.01)
1st	-2.48 (.01)**	-1.40 (.33)***	-1.40 (.34)***	-1.71 (1.51)
P (Control)	-.004 (.00)***	-.004 (.00)***	-.004 (.00)***	-.004 (.00)***

*Significance levels: ***p<.01, **p<.05 * p < .01*

The numbers in parenthesis are standard errors.

The effect estimation results by online review valence quantiles provide some different aspects of how online review valence influences consumer decisions by product quality (see Table 4 and Fig. 1). Firstly, the effect of online review valence on buying decisions is noticeably varied by product quality. The estimation results suggest that extremely positive reviews ($\lambda_{8,LOW}$=.49(.17)***) and extremely negative reviews ($\lambda_{1,LOW}$=-2.48(.01)***) have significant effects on nudging consumer decisions, while mediocre reviews tend not to have substantial persuasive power. In this aspect, when consumers purchase low-quality products, they are likely to strongly avoid options with extremely negative review valence while they seek options with extremely positive review valence. In the low-quality condition, the marginal effect of online review valence on sales likelihood is consistently substantial. This indicates that the online review valence might have a substantial influence on consumer decisions – and consumers prefer more the higher ratings. When consumers purchase high-quality products, the overall effect of online review valence on buying decisions noticeably deflates, and the effect distribution is close to inverse exponential while the marginal merits of an increase in online review ratings on sales likelihood tended to diminish by 7th quantile ($\lambda_{7,HIGH}$=-.16(.06)***). The finding indicates that the referent or relative effect of online review valence on sales are contingent on the product quality of consumers' consideration sets and subsequently purchase risks. When product quality is sufficiently convincing, consumers might perceive a certain review rating as a good-enough reference point, and review rating above this point might not further increase the purchase likelihood. On the contrary, when product quality is doubtful, consumers might strongly rely on online review information to screen out risky options and prefer options with the best online reputations. The empirical results tend to support that consumers utilize online review valence to avoid purchase risks, however, the online review effect on sales can be still exponential if product quality is doubtful.

Figure 3.1: Purchase Likelihood by Online Review Valence Quantile



3.5. DISCUSSION

The estimation results indicate that achieving a higher review rating compared to the competing option does not always positively influence sales. The effect of online review ratings on consumer choice tended to be referent to a certain point, where the marginal effect of review ratings on purchase likelihood was negative. The finding indicates that a higher review rating among relatively high review ratings is not likely to increase sales likelihood. For example, five-stars review ratings compared to four-stars are not likely to increase purchase likelihood. Thus, the referent effect is salient in how consumers evaluate online reviews for new purchases, and the effect of online reviews on consumer decisions are likely to be inconsistent, depending on the satisfactory reference point. Also, the findings suggest that the effect of online reviews on consumer decisions tends to be varied by easiness to verify product quality, and consumers are more likely to incorporate online reviews into decision making to reduce purchase risks (Woodside and Delozier, 1976).

Thus, review ratings above a certain point had minimal marginal effects on purchase decisions. The results of this study make important contributions to the Word of Mouth (WOM) literature. Due to the referent effect, and subsequently, the negative marginal effect of online reviews on sales likelihood, the variance of review ratings might alter the finding. When online review ratings tend to be generally high for a certain product category, consumers might find online reviews unhelpful and focus on other product information cues to compare the options (Kim, 2020). In this aspect, the effect of online review ratings on sales if it is estimated with linear static analysis, the results might be insignificant if the review ratings in the sample tend to be concentrated in high rating quantiles (You et al., 2015). The difference in the effect of online reviews on purchase likelihood is negligible between the average and the highest ratings. Allocating marketing resources to increase the rating beyond the good-enough reference point is not likely to generate a significant return on investment (ROI).

Limitations and Future Research. The review ratings might not infer the objective information about the products. Word of Mouth sentiments can be varied by e-commerce channels (Fay and Larkin, 2017). Online review valence can be significantly altered by the reviewer's personality or motives for Word of Mouth generations (Wangenheim, 2005; Mathwick and Mosteller, 2016). For the same product, Amazon review ratings do not often correspond to those of Consumer Reports (Langhe, Fernbach, and Lichtenstein, 2015). It is uncertain how consumers perceived the objectivity of the observed review ratings. One explanation is that consumers only utilize the review ratings to avoid risks because consumers might not find the information completely credible or persuasive. Also, consumers made purchases at different time points – and review ratings for a hotel might be varied, depending on the time point when the consumer made a purchase. Yet, we kernelize review ratings by quantiles without accounting for this possibility. Since product identification is not recorded, it is difficult to track the dynamic changes in review ratings for a certain hotel. We rely on Monte-Carlo methods to examine if unobserved factors have substantial effects on the estimation results (Arellano and Bond, 1991). Also, we do not expect that the dynamic change is substantial since online review ratings of hotels tend to be strongly correlated to the hotel's quality regarding the location and property class – and these product factors are static.

Since we estimate the online review rating effect on the product information pages that are already viewed by consumers, it is uncertain how online review ratings influence how likely the consumer might click to view the product information page. This study focuses on how online review ratings might (not) incentivize sales among the 'competing' options. Product information pages which are viewed by the consumer might be within the consumer's consideration set, and thus, focusing on the product information pages which the consumers already helps to examine the competitive effect of online review ratings, whether higher online review ratings have a significant positive effect on purchase likelihood over other options in the consumer's consideration set.

In addition, the Word of Mouth effect should be variant to the strength of expressions and review volume (Vazquez-Casielles et al., 2013; Jaikumar, 2018). Consumers might find the online reviews less credible if the review volume was low or some extreme valence could dominate the perceived review valence. GMM estimations are expected to capture the convergent moments from multiple random samples where unobserved influences were controlled (Wooldridge, 2005). The convergent results suggest that the effects were significant with accounting for the potentially endogenous factors, including review volume and content valence.

One challenge in generalizing the findings in this paper is that the effects were estimated in one industry. The effect of Word of Mouth is expected to be variant by the product category (Allsop et al., 2007; Libai et al., 2010). It is predictable that consumers' familiarities to the products should influence to what extent they will seek for Word of Mouth information. Consumers might primarily rely on others' opinions when they purchase unfamiliar products such as mobile applications or new tech products. Do consumers' perceived familiarity with the products alter the marginal merits of review ratings? We recommend future research to investigate if the product categories will moderate the referent effect of online review ratings on sales.

Managerial Insights. Word of Mouth is powerful. Online reviews significantly increased the accessibility of Word of Mouth information in electronic commerce (Edwards, 2006). Investing in generating customer reviews and managing more positive review ratings compared to the competitors' has become an increasingly common phenomenon (Trusov et al., 2009; Luca and Zervas, 2016). However, the results of this study suggest that high online review ratings might not always increase sales. The marginal merits on sales likelihood were minimal for an increase in the review ratings above the market average, suggesting that consumers might care about the good-enough rating to avoid purchase risks. If the online review rating is already above the market average, increasing the review rating might not significantly improve the sales potential.

3.6. CONCLUDING REMARKS

This paper examined the marginal effect of online review ratings on purchase likelihood and found that the marginal effect is negative. The effect of online review ratings on purchases tended to decrease for a higher review rating. For example, five-star ratings compared to four stars are not likely to attract more purchases. Also, the effect of online reviews on purchases tended to contingent on the product quality, where the effect of online review ratings on purchase likelihood was largely insignificant when consumers purchased products with easily verifiable quality. In this aspect, we predict that consumers might tend to choose to evaluate review ratings to avoid risks. The marginal effect of online review ratings on purchase likelihood was referent to a certain point, where the marginal effects tended to increase below and decrease above the certain rating, which might be a good-enough reference point for relieving purchase risks. Thus, allocating marketing resources to increase review ratings that are above the market average or for a high-quality product is not likely to have a significant effect on sales.

PART IV:

HOW ONLIEN REVIEWS INFLUENCE PRICE PROMOTIONS?

NEGATIVE REVIEWS AND PROMOTION BACKLASH

4.1. PRICE PROMOTION AND SALES

Price discounts are one of the most frequently used marketing promotions that have a significant and immediate impact on sales and profits. Price promotion is often an essential part of a company's marketing policy (Kuntner and Teichert, 2016). Most packaged goods companies allocate two-thirds of their marketing budgets to price promotion (Aliawadi et al., 2009). Nielson's research showed that roughly 20% of retail sales in Western Europe were made on discounted prices (Gedenk, Neslin, and Aliwadi, 2004). The elasticity of price promotion on sales is often higher compared to advertising elasticity (Aliwadi et al., 2009). Brand managers often launch price promotions at the expense of advertising budgets due to the high level of pressure to increase sales (Low and Mohr, 2000). The proportion of price promotion expenses in marketing budgets has been increasing since the Global Financial Crisis (Bogomolova et al., 2015).

Consumers perceive comparable benefits from price discounts to winning bonus packages (Hardesty and Bearden, 2003). In this aspect, brand managers often expect that price promotion triggers purchases that the consumers might not have considered otherwise (Aydinli, Bertini, and Lambrecht, 2014). The effect of price discounts on sales has been extensively investigated in early marketing literature. The previous research tracked coffee-brand sales in multiple stores and found that price elasticity for the promoted price-discounts on market share was significantly higher than price elasticity from the changes in the regular price (Guadagini and Little, 1983). Thus, consumers tend to perceive greater returns per dollar from the promoted price discounts, compared to an unpromoted price change (Blattberg and Neslin, 1989). The previous study predicted that offering temporary price promotion at optimal timing could boost sales by more than 15% (Johnson, Tellis, and Ip, 2013).

Furthermore, the previous research showed that mere discounts in the price of cigarettes had significantly increased smoking rates among adolescents (Redmond, 1999). Price promotions also have several intangible marketing gains. Interestingly, a survey study on Starbucks in Taiwan found that price promotion improved the perceived quality of coffee and increased customers' re-purchase intentions (Huang et al., 2014). The previous research provides evidence that the effect of price promotion is easily applicable to electronic commerce, where price promotion can nudge consumers to perceive reduced needs to process product information and price discounts signal quicker and easier purchases (Zhang et al., 2004; Aydinli et al., 2014). The previous research finds that price discounts on large social commerce websites significantly increase consumers' purchase likelihoods and the average number of quantity of the product purchased (Aydinli et al., 2014). Price promotion on a digital movie had an information spillover effect and increased awareness of the product, resulting in increased sales of the movie even in other competing channels (Gong, Smith, and Telang, 2015). Furthermore, the effect of price promotions is cross-channel, where offline or online price promotions for certain products increase store traffic and digital sales mutually (Gong et al., 2015). Also, the previous research finds that the effect of price promotion is dynamic and cross-category, where consumer expenditure tends to increase even for products that are not on price promotions, the increase in expenditure lasts even after the price promotion ends (Sahni et al., 2017).

Table 4.1: Literature Review

Study (in chronological order)	**Observation**	**Consequence Variable (Effect)**	**Moderating Factor (Effect)**
(1) Guadagnini and Little, 1983	Coffee brand choices of 100 households	Price Elasticity (+)	Price promotion frequency (+)
(2) Blattberg and Neslin, 1989	Literature review on panel data results from 1977 to 1988	Sales (+)	Product type (durable + vs. non-durable -)
(3) Mela et al. , 1997	Store-level panel data from a major consumer packaged good company	Price sensitivity (+)	Consumer loyalty (-)
(4) Jedidi et al., 1999	1,590 households consumption on a certain product category	Purchase quantity (+/-)	Short term (+) Long term (-)
(5) Zhang and Krishnamurthi, 2004	100 households brand choices for butter	Purchase frequency/Purchase quantity (+)	Prior purchase behavior (consumer loyalty +)
(6) Aydinil et al., 2014	42 million consumers choice on Groupon.com	Search intensity (Time, click frequency) (-)	
(7) Gong et al., 2015	Digital movie sales performances	Sales (+) Cross-channel spillover effect (+)	
(8) Sahni et al., 2017	100,000 consumers' expenditure on an online ticket resale platform	Expenditure amount/Cross-category and dynamic spillover effects (+)	
(9) This study, 2020	600,000 consumer choice on 10 million accommodations on a hotel booking website	Sales/Purchase likelihood (+/-)	Negative valence in online reviews (-)

Thus, the previous research studied extensively the benefits of price promotions on sales. However, potential downsides have been given relatively limited attention. This study investigates the moderating effect of negative online review valence on price promotions and when price promotions can have a backlash effect and rather decrease the chances of sales. Price-quality belief theory suggests that consumers' doubts about product quality might increase when the price is discounted (Rao and Monroe, 1988; Shiv, Carmon, and Ariely, 2005). Consumers might seek more Word of Mouth (WOM) information such as online reviews to relieve doubts (Roselius, 1971). Positive reviews are likely to relieve consumers' doubts. Mediocre reviews might not relieve the doubts, but the merits of discounted price might still induce consumers to accept the deal. However, negative reviews might have a confirmation effect on consumers' doubts. If it is the case, products with negative reviews might decrease the chances of sales by launching price promotions, since the discounted price might draw consumers' attention more into the negativity in the review valence. This study investigated when the effect of price promotion on consumer choice, might become reduced or even altered. The authors examined approximately ten million consumer choice on a hotel-booking website and found that online review valence moderate the elasticity of price promotion on purchase likelihood to the extent where the effect becomes negative when online review valence fell under a certain point. Interestingly, the moderation effect size was big enough to turn the price promotion effect into negative when the average online review ratings were below three out of five. The results indicate that price promotion can have immediate negative consequences for sales.

Price promotion is likely to decrease the chances of sales if it is used as a strategy to compensate for relatively low brand performance in customer satisfaction.

4.2. NEGATIVE REVIEWS AND PROMOTION BACKLASH

4.2.1 Word of Mouth Marketing

The previous literature defines Word of Mouth (WOM) as consumer interactions with other consumers where they share their opinions about product experiences, which influence other consumers' purchase decisions (Liu, 2006; Cheung and Thadani, 2012). Word of Mouth marketing includes broad streams of research including User-Generated Content (UGC), online review or Electronic Word of Mouth (E-WOM), and offline communications (Duan et al., 2008; Kozients et al., 2010; Halliday, 2016). The early Word of Mouth research on offline communications can be traced back to Roselius (1971) or Woodside and Delozier (1976), where the authors found that consumers tended to seek more information from peers when they were making riskier purchase decisions. Recent WOM literature can be categorized into two broad streams: social media interactions and online reviews. Social media WOM research utilizes field experiments or content mining and investigates effective narratives for content virality (Kozinets et al., 2010; Berger and Milkman, 2012; Roma and Aloini, 2019; Kaiser et al., 2019). The previous literature on online review – which is often referred to as E-WOM (Electronic Word of Mouth exclusively denotes online reviews) research focused on whether and how online review influence sales (Liu, 2006; Chintagunta et al., 2010; Ho-Dac et al., 2013; Dai and Mogliner, 2019; Kim, 2020). The previous literature often uses the term online review valence or

Word of Mouth (WOM) valence to indicate the general sentiments or the average ratings of customer reviews (Liu, 2006; Duan et al., 2008; You et al., 2015).

A recent Pew Research Center survey found that more than 80% of American adults look at online reviews before making new purchases (Smith and Anderson, 2016). One star increase in customer review ratings on Yelp is likely to increase the restaurant's revenue by 9% and store traffic by 38% ((Anderson and Magruder, 2013; Luca and Zervas, 2016). Customers who are acquired by online reviews have higher growth in long-term equity compared to the others acquired by direct marketing communications (Villanueva et al., 2008). In these aspects, managers often utilize online review sentiments as an effective indicator to predict the future success of products (Reichheld, 2003). Furthermore, customer relations (CR) agencies increasingly adopt customer review management as one fo their main service offerings (Womply, 2020). Online review has been established as one of the most impactful elements of marketing communications (Chen and Xie, 2008). The importance of maintaining favorable online reputations cannot be overstated.

4.2.2 Negative Review and Price Promotion

The previous research provides extensive evidence of the strong correlation between online review valence and sales (Chintagunta et al., 2010; Luca and Zervas, 2016). In this aspect, managers might be particularly more tempted to launch price promotions for the products with more negative online review valence so that they can compensate for the relative incompetence and increase sales (Alvarez et al., 2005). The previous research provides evidence about the positive effect of price promotions, particularly in the short term. Price promotions can signal several hedonic and utilitarian benefits by enabling value expressions, savings, or improved shopping convenience (Inman and McAlister, 1993; Chandon et al., 2000). However, previous research suggests that frequent price promotions can negatively influence the brand's perception (Marshall and Leng, 2002). There is an interesting behavioral finding to explain how price promotions might activate a negative perception of product quality. Rao and Monroe found that people predict product quality from the product's price because we tend to have heuristics about getting what we paid for (Rao and Monroe, 1988). This price-quality belief can be activated and influence our judgments, even unconsciously (Adaval and Monroe, 2002). Shiv et al. found that the price-quality beliefs triggered actual behavior changes (2005). Study participants who drank energy drinks that were offered at a discounted price performed significantly worse compared to the study participants who were given with the regularly priced drinks (Shiv, Carmon, and Ariely, 2005). Thus, price promotions might signal benefits such as savings or convenience (Chandon et al., 2000), it might signal defects in the product. From this perspective, price promotions might activate different reactions from the consumers through the other constructs in the purchase environments, which might redirect the consumers' perceptions of the price discounts.

The findings from the previous studies suggest that people might doubt the product quality if a price discount was offered. Thus, we expect that consumers perceive increased purchase risks for products on price promotions since the discounted price might infer incompetent product quality. When purchase risks increase, consumers tend to seek more WOM information to relieve risks (Roselius, 1971; Woodside and Delozier, 1976). In electronic commerce, the most common WOM source will be online reviews. In fact, 82%

of American adults look at product reviews for new purchases (Smith et al., 2016). In a recent survey, most of the millennials reported that their past purchase decisions were frequently influenced by online reviews (Mangold and Smith, 2012). It is predictable that consumers look at online reviews also for relieving purchase risks. Therefore, online reviews can be a common construct in electronic commerce, which might redirect the consumers' reactions towards the products on price promotions. Positive reviews might relieve consumers' doubts about product quality and enhance the potential benefits of purchasing the product on price promotions, however, negative reviews might have the opposite effect.

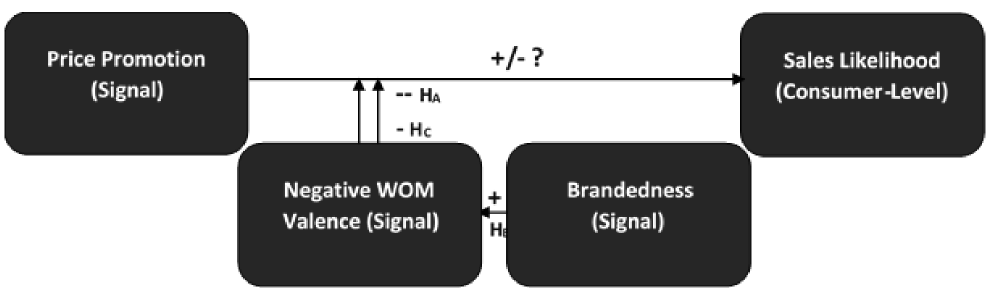
Negative reviews can have a conformity effect and induce consumers to evaluate the product more negatively (Lee, Park, and Han, 2008). Negative emotions in online postings can spread through social networks. The previous research examined 689,003 Facebook postings and found the people write posts in the same emotional state of the postings they saw (Kramer, Guilory, and Hancock, 2014). Similarly, the negativity in online reviews would be contagious to the consumer who saw the review. It is predictable that negative reviews will decrease the chances of sales by inducing consumers to perceive the product quality negatively. Furthermore, if consumers perceive increased purchase risks, negative reviews might have a confirmation effect that the perceived risks are socially justified. From this perspective, if products with negative review valence offer price discounts, the price promotion will have a backlash effect by confirming and enhancing the consumers' doubts about the product quality and decrease sales likelihood (see Fig.1). Therefore, products with negative review sentiments might rather harm their chances of sales by launching price promotions.

4.2.3 Brandedness and Price Promotion

Since we predict that the promotion backlash effect from negative valence in online reviews is due to the price-quality heuristics, product quality cues other than online reviews are likely to interact with consumers' decision making. Brands can be a substantial signal for positive product quality and a significant influence on consumers' purchase decisions (Keller, 1993; Keller and Lehman, 2006). Branded products might have advantages in the competition due to the better brand awareness and reputations which have been built over time. It is predictable that the efficiency of advertising spending might be higher for more dominant firms since prior consumers' bits of knowledge and attitudes might be favorable (Hoeffler and Keller, 2003). Brands often help reduce purchase risks by guaranteeing good product quality, and product quality signals help to reduce consumers' reliance on online reviews for decision making (Mizik, 2014; Kim, 2020). Although the previous research reports significant findings that negative online review valence is expected to decrease sales (Chintagunta et al., 2010; Lucas and Zervas, 2016), the effect is likely to be less profound for branded products.

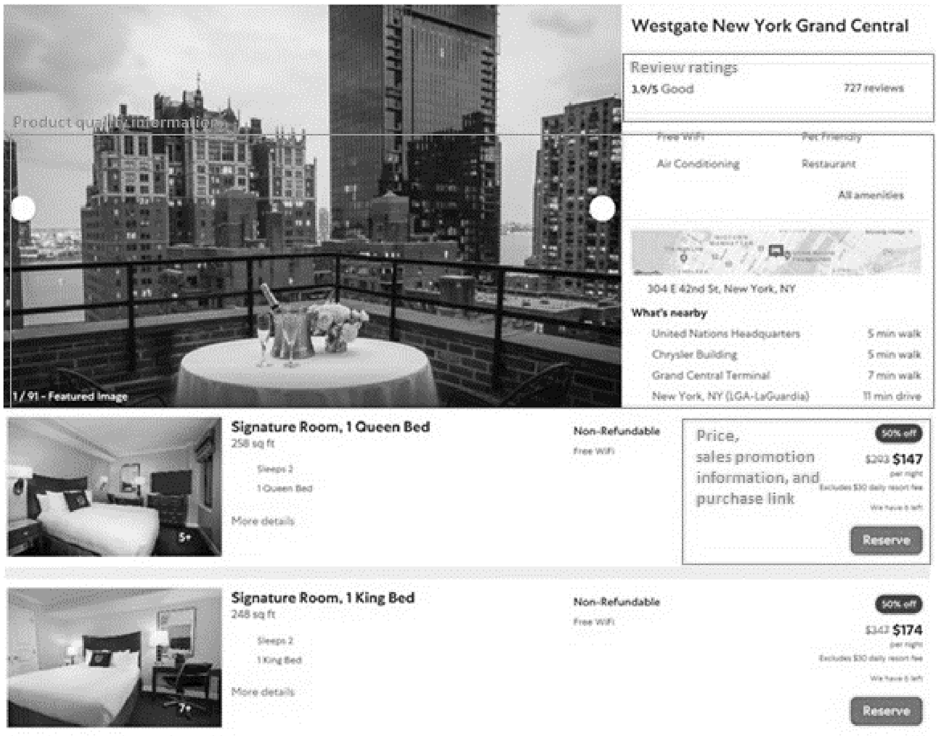
Furthermore, the previous research suggests that price promotions from popular brands such as Starbucks can be perceived as a favor and subsequently improve consumer attitudes towards the brand (Huang et al., 2014). This finding provides an interesting perspective that price promotions can be perceived favorably, and price discounts can impact product quality perceptions. The previous survey study suggests that consumers tend to evaluate price promotion favorably when the price discounts were perceived as customer service rather than sales tactics (Raghubir and Corfman, 1999). Consumers tend to favor price promotions if they are launched by industry or brands which rarely discount prices. In these aspects, price promotions from stronger brands induced consumers to switch from weaker brands (Allender and Richards, 2012). Launching price promotions increased store traffics more effectively when the price was discounted for popular and branded items (Gauri et al., 2017). Thus, it is expectable that brandedness satisfies consumers' doubts about product quality and lessens the effect of price-quality heuristics (Mizik, 2014). Furthermore, the previous research on the negative placebo effect on product quality due to price discounts suggests that the effect can be reduced by some other strong product quality cues such as expert opinions (Shiv et al., 2005). In this aspect, we predict that the promotion backlash effect by negative online review valence can be reduced for branded products.

Figure 4.1: Conceptual Model



4.3. DATA

Figure 4.2: Accommodation Purchase Page Sample



In the dataset, individual-level purchase journeys of consumers who booked accommodations on Expedia.com are recorded for one year in 2017. Accommodation purchase pages are classified by each consumer who viewed or viewed and booked the hotel on the purchase page. A purchase page displays the accommodation's WOM valence (average online review ratings), price promotion flag, location score, and property class are recorded by the hotel information pages (see Table 13 for data structure example). The sample purchase page is described in Fig. 2. The previous research finds that location and the property class tend to be the two determinative characteristics in critical success factors (CSFs) analysis in the hospitality industry (Fuentas-Medina et al., 2018). Although online reviews can be a more reliable signal for product quality since the consumer opinions provide information about unobserved product factors (Chen and Xie, 2008), the previous research suggests that the effect of online reviews on sales can be varied by product characteristics (Mudambi et al., 2010; Ho-Dac, 2013). In this aspect, we utilize these two characteristics to control for the product quality effect, with the price effect, which might interfere in consumers' decision making. We specified how each variable is measured in Table 14. The purchase dummy was recorded by the corresponding hotel – whether the consumer made a purchase on the information page which they viewed. 646,576 consumers made purchases, and they viewed 21 ads on average for new purchases. This study examined 13,293,602 hotel ads in total. Each ad is classified with the consumer who viewed, or viewed and purchased the ad. The hotel information pages on price promotion were flagged with the promoted price, and the price promotions were obvious to the consumers.

Activity Bias. One potential activity bias can be that the hotel ads observed in this dataset are already viewed by consumers, and the effect of online review valence, price promotions, and product quality on how likely the consumers are to view the ad is uncertain (Gordon et al., 2019). However, the variables for the viewed ads tend to be still variant ($\sigma(RV_i)$=.58, $\sigma(BA_i)$=.48, $\sigma(SP_i)$=.43). Therefore, we expect that the dataset still provides substantial insights about how likely online review valence, product quality, and price promotions induce the consumer to purchase the ad among the options for which the consumer consider. Furthermore, generalizing the effect by consumers regarding certain purchase options they viewed allows us to account for the competition factor since the hotel information pages which the consumer viewed for making a purchase are intrinsically in a competition for a consumer choice.

Descriptive statistics for the variables are shown in Table 15. RV_{ic} indicates the average review ratings of a hotel in the purchase page *i*, which was viewed by consumer *c*. BA_{ic} denotes the brandedness of the hotel in the purchase page *i*, viewed by consumer *c*. The quality score is calculated by summing the location score and hotel-stars. SP_{ic} is a price promotion dummy variable for ad *i*, viewed by consumer *c*. The average RV was 3.87. Average online review ratings tend to be consistent with the previous findings of the average review ratings from different channels and product types (Mudambi and Schuff, 2010). 24% of the ads were on price promotions. It is predictable that product quality and online review valence are highly correlated. The correlation coefficient for RV_i and QA_i was relatively high at .41 (see Table 16), which indicates that the collinearity issue is concerning when we estimate the model. We will examine the Variation Inflation Factor (VIF) to determine if the correlations between online review valence product quality provoke substantial concerns for multicollinearity (Liu, 2006; Wooldridge, 2013). We report VIF scores with the model estimation results – the correlations between the variables had limited effects on the results.

Table 4.2: Variable Setups

Variable		Meaning
Identification Variable	**C**	Consumer identification
	I	Hotel purchase page views
Independent Variable	**RV_{ic}** (Online Review Valence)	The average online review rating of the hotel on the purchase page i viewed by consumer c.
	BA_{ic} (Brandedness)	Product quality score of the hotel in the purchase page i, viewed by consumer c. Product quality score is calculated by location preferability and hotel stars.
	SP_{ic} (Price Promotion)	Price promotion dummy of the hotel in the purchase page i, viewed by consumer c.
Control Variable	**PR_{ic}** (Product Price)	Product price of the hotel in the purchase page i, viewed by consumer c. Controls for the price factor, such as lower purchase likelihood due to lower affordability.
	QA_{ic} (Product Quality)	Quantified product quality by the hotel's location and property class
	SE_{ic} (Seasonality)	Identification dummy for summer holidays from July to August. Controls for the holiday effect on purchase likelihood.
	CON_i (Intercept)	Constant latent effect (β_0) in effect estimations.
Dependent Variable	**PA_{ic}** (Consumer Choice)	Purchase choice dummy for the hotel in the purchase page i by consumer c.

Table 4.3: Data Structure (N=13,293,602)

C	I	RV_i	QA_i	SP_i	BA_i	PR_i	SE_i	PA_i
1	1	4.2	3.8	1	1	227	0	0
1	2	3.9	3.2	0	0	221	0	0
1	3	4.5	3.9	0	1	289	0	1
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
2	23	3.2	3.1	1	1	189	0	0
2	24	3.9	3.3	1	0	207	0	1
2	25	4.2	3.7	0	1	233	0	0
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
646,576	13,293,602	3.7	3.3	1	0	193	0	0

Table 4.4: Descriptive Statistics (N=13,293,602)

Variable	Mean	Median	Standard deviation	Minimum	Maximum
RV_i (Review Rating)	3.87	4	.58	1	5
BA_i (Brandedness)	.66	1	.48	0	1
SP_i (Price Promotion)	.24	0	.43	0	1
PR_i (Product Price)	156.85	105.13	89	89	488.18
QA_i (Product Quality)	3.41	3.21	1.04	1.03	5.99
PA_i (Consumer Choice)	.03	0	.18	0	1

Table 4.5: Pairwise Correlation Coefficients

Variable	RV_i	BA_i	SP_i	PR_i	QA_i	PA_i
RV_i	1	.	.	.	.	.
BA_i	.11(.00)	1	.	.	.	.
SP_i	.01 (.00)	-.14 (.00)	1	.	.	.
PR_i	.35 (.00)	.01 (.00)	-.02(.00)	1	.	.
QA_i	.41 (.00)	.01 (.00)	.17 (.00)	.47 (.00)	1	
PA_i	.02 (.00)	.00 (.00)	.03 (.00)	-.04 (.00)	.02 (.00)	1

4.4. METHOD

Three-way Interaction Model. Three-way interaction model can capture an interaction effect between three predictor variables on the consequence variable, in addition to multiple two-way interactions between each variable (Wooldridge, 2010;

Dawson, 2014; see Gul and Chia, 1994; Kotabe et al., 2002; Merlo and Auh, 2009 for applications). In this study, we investigate the promotion backlash effect by negative online review valence, the reduced effect of negative online review valence for branded products, and subsequently the reduced promotion backlash effect by negative online review valence for branded products. The first two effects are examined by two-way interaction coefficients between (1) negative online review valence and price promotions, and (2) negative online review valence and brandedness. The last effect is examined by a three-way interaction coefficient between negative online review valence, price promotion, and brandedness. Thus, we implement a three-way interaction effect model to capture the interaction effect between negative reviews and price promotions, in addition to the three-way interaction between the moderating effect of negative reviews on price promotions and the product quality. Including the three-way interaction term also helps to control for potential biases in estimating the two-way interaction effects where there is a significant three-way interaction effect (Dawson, 2014). The three-way interaction effect is observed in $\beta_{7.}$ The negative online review valence is likely to reduce the effect of price promotions on sales, but less so for branded products, where brand reputation is expected to lessen the effect of price-quality heuristics (Shiv et al., 2005; Mizik, 2014).

Model Specification. We generated the negative online review valence variable RV^{NEG} from online review valence variable RV. We subtracted the online review rating RV_i from the maximum available rating to generate an inverse distribution of RV while maintaining the variance and the scale that was displayed to consumers. We prefer to generate the RV's inverse distribution RV^{NEG} by the substractions from the maximum values, which indicate the distance from the maximum value, to optimize interpretations of the estimation results with other variables that are not rescaled (Wooldridge, 2013). In this aspect, one unit increase in RV^{NEG} indicates one unit further down from the maximum rating. The effect of negative online review valence on purchase likelihood is observed in β_1. The effect of brandedness and price promotion on sales likelihood are captured in β_2 and β_3, respectively. The effect of negative reviews on sales likelihood is likely to lessen if the product provides alternative quality signals such as brandedness (Keller, 2006; Mizik, 2014). β_4 captures the two-way interaction effect between negative reviews and brandedness. Negative reviews are likely to support the negative price-quality beliefs triggered by price promotions (Adaval and Monroe, 2002; Kramer et al., 2014). β_5 captures the two-way interaction effect between negative reviews and price promotion. The enhanced effect of price promotion for branded products is captured in β_6. Finally, the three-way interaction effect between negative online review valence, price promotions, and brandedness, where brandedness lessens the promotion backlash effect by negative online review valence is captured in β_7. We controlled for the price, other product quality cues, and the seasonality effect on sales likelihood in β_8, β_9, and β_{10} respectively.

$$\Pr(PA_{ic}=1) = (1 / 1 + \exp(-(\beta_0 + \beta_1 RV^{NEG}_{ic} + \beta_2 BA_{ic} + \beta_3 SP_{ic} + \beta_4 RV^{NEG} * BA_{ic} + \beta_5 RV^{NEG} * SP_{ic} + \beta_6 BA * SP_{ic} + \beta_7 RV^{NEG} * BA * SP_{ic} + \beta_8 PR_{ic} + \beta_9 QC_{ic} + \beta_{10} SE_{ic} + \varepsilon_{ic}))$$

where RV^{NEG}, BA, SP, PR, QC, SE denote distance from maximum online review valence, brandedness dummy, promotion dummy, price, product quality, and seasonality dummy respectively

Generalized Method of Moments (GMM). GMM assumes that model estimation is not free from the unobserved influence that might skew the results (Wooldridge, 2005). From this perspective, the data points where the estimate errors were zero are relatively unaffected by the unobserved influence (Woodbridge, 2010). GMM treats these relatively unaffected datapoints as instruments for the data when estimating the model. The instrumental data points are estimated based on the results from multiple Monte-Carlo sampling (Arellano and Bond, 1991; Kiler and McMilen, 2012)[3]. Since we adopt a logit model to examine the consumer choice, MLE (Maximum Likelihood Estimation) method already maximizes the fitting data points (Wooldridge, 2013). However, the previous research found that GMM was effective in generating results with consistency even for the logit models if data tend to have prevalent heterogeneities that were unobserved (Pinkse and Slade, 1998; Kiler and McMilen, 2012). Similarly, the previous research recommended estimating structural choice models in GMM since it methodologically limits the effect of unconsidered variables in the model (Imbens, 1992; Giacomo, 2008). The previous research has often adopted GMM to control for unobserved heterogeneities (Shaikh, O'Brien, and Peters, 2018). Chintagunta et al. or Duan et al. used GMM to control for movie-specific heterogeneities in estimating the effect of online review ratings on box office revenues, since consumers could purchase the ticket for the featuring celebrity, regardless of the review ratings (Duan et al., 2008; Chintagunta et al., 2010). It is expected that the GMM results control for the unobserved effects such as enhanced purchase rates for famous hotels despite relatively negative reviews. From this perspective, we will

[3] The estimation results based on GMM converged after 6 iterations. Minimal differences between the original and Monte-Carlo sampling based GMM estimation models should yield convergence in the results despite the unobserved heterogeneities in the sample (Arellano and Bond, 1991).

compare the model estimation results with the parameter estimates by GMM to examine whether the unobserved influence was endogenous as recommended by Arellano and Bond (1991).

$$\text{GMM Moments: } (\text{Purchase}_{ic}) - (1 / 1+ e^{-\beta(X_{ic})})(X_{ic}) = 0$$

4.5. RESULTS

Table 4.6: Estimation Results (N=13,293,602)

Predictor	**Parameter Estimate**			
	(1)	**(2)**	**(3)**	**(4)**
Negative Online Review Valence RV^{NEG} (β_1)	-.27 (.02)***	-.27 (.02)***	-.20 (.01)***	.
Brandedness BA_{ic} (β_2)	.11 (.02)***	.11 (.01)***	.	.
Price Promotion SP_{ic} (β_3)	.37 (.03)***	.39(.02)***	.38 (.02)***	.35 (.02)***
Interaction Effects:				
Negative Online Review Valence and Brandedness $RV^{NEG}*BA_{ic}$ (β_4)	.13 (.03)***	.13 (.03)***	.	.
Negative Reviews and Price Promotion $RV^{NEG}*SP_{ic}$ (β_5)	-.17 (.05)***	-.20 (.05)***	-23 (.05)***	.
Brandedness and Price Promotion $BA*SP_{ic}$ (β_6)	.03 (.00)***	.	.	.
Three-Way Interaction $RV^{NEG}*BA*SP_{ic}$ (β_7)	-.06 (.05)	.	.	.
Control Factors:				
Price PR_{ic} (β_8)	-.005 (.00)***	-.005 (.00)***	-.005 (.00)***	-.005 (.00)***
Product Quality Information QA_{ic} (β_9)	.34 (.01)***	.34 (.01)***	.34 (.01)***	.33 (.01)***

Seasonality (Summer)				
SE_{ic} (β_{10})	.04 (.02)**	.04 (.02)**	.04 (.02)**	.04 (.02)**
Intercept				
CON (β_0)	-3.99 (.03)***	-4.00 (.03)***	-3.92 (.03)***	-3.91 (.03)***
Likelihood Ratio (χ^2)	2896.18***	2894.08***	2825.49***	2625.65***
VIF	1.99	1.7	1.16	1.2

*Significance levels: ***p<.01, **p<.05 * p < .1*

The numbers in parenthesis are standard errors.

Table 4.7: Robustness Check (N=13,293,602)

Predictor	Parameter Estimate	
	MLE	**GMM**
Negative Online Review Valence		
RV^{NEG} (β_1)	-.27 (.02)***	-.27 (.02)***
Brandedness		
BA_{ic} (β_2)	.11 (.02)***	.11 (.02)***
Price Promotion		
SP_{ic} (β_3)	.37 (.03)***	.37(.03)***
Interaction Effects:		
Negative Online Review Valence and Brandedness	.13 (.03)***	.14 (.03)***
$RV^{NEG}*BA_{ic}$ (β_4)		
Negative Reviews and Price Promotion		
$RV^{NEG}*SP_{ic}$ (β_5)	-.17 (.05)***	-.17 (.06)**
Brandedness and Price Promotion		
$BA*SP_{ic}$ (β_6)	.03 (.03)	.03 (.04)
Three-Way Interaction		
$RV^{NEG}*BA*SP_{ic}$ (β_7)	-.06 (.05)	-.06 (.05)
Control Factors:		
Price	-.005 (.00)***	-.005 (.00)***
PR_{ic} (β_8)		
Product Quality Information		
QA_{ic} (β_9)	.34 (.01)***	.34 (.01)***
Seasonality (Summer)		
SE_{ic} (β_{10})	.04 (.02)**	.04 (.02)**
Intercept		
CON (β_0)	-3.99 (.03)***	-3.99 (.03)***

*Significance levels: ***p<.01, **p<.05 * p < .1*

The numbers in parenthesis are standard errors.

The effects of each predictor variable on chances of sales were consistent with the expectations. Negative reviews significantly decreased purchase likelihood (β_1=-.27(.02), see Table 17). Consumers were more likely to purchase a product when it is branded (β_2=.11, p-value=.00). Offering price discounts tended to boost sales likelihood (β_3=.37(.03)). Interestingly, the negative interaction effect between price promotions and negative online review valence was significant (β_5= -.17(.05)). The moderation effect size was large enough to turn the price promotion effect into negative. The product with one-star online review valence could worsen its chances of sales by – 31% when it launched price promotions (see Figure 6). The estimation results indicate that accommodations with lower than three stars review valence have rather higher chances of sales if they do not offer price discounts. Price promotions might induce increased perceptions of purchase risks, and negative reviews might serve as social confirmations of the enhanced doubts (Roselius, 1971; Adaval et al., 2002). In this aspect, the results suggest that online review valence moderate the price promotion effect on sales, and subsequently, price promotion can have a backlash effect on sales, where price discounts are likely to rather decrease sales likelihood by 14-31% for products with negative review valence such as two or one stars.

The interaction effect between negative online review valence and brandedness was significant (β_4=.13, p-value=.00). Although the results indicated that consumers tended to be less sensitive to negative reviews when they made purchase decisions on branded products, the promotion backlash effect by negative online review valence was not reduced for branded products since the three-way interaction effect was not significant (β_7= -.06(.05)). The results suggest that although brands tend to reduce the seriousness of negative review valence, brandedness is not likely to satisfy enhanced doubts due to price promotions (β_6=.03(.03)), and subsequently, brandedness do not influence the price promotion backlash effect by negative online review valence. Thus, launching price promotions might rather backlash sales for products with negative online review valence, regardless of whether the product is branded.

Robustness. The VIF test results indicate that multicollinearity is not likely to be an issue since the correlations between variables have limited influence on model fitting (Wooldridge, 2013). The model comparison results show that negative online review valence is relevant for estimating the price promotion effect ($LR(\chi^2)_{(4)}$= 2625.65 v $LR(\chi^2)_{(3)}$= 2825..49)[4]. The effect of price promotions on sales can be deflated if its interaction effect with negative online review valence is not considered in the estimation ($\beta_{3(3)}$=.38(.02) → $\beta_{3(4)}$=.35) The benchmark model (1), which accounts for the interaction effects of price promotions with negative reviews and brandedness tended to outperform the comparison models ($LR(\chi^2)_{(1)}$= 2896.18 > $LR(\chi^2)_{(3),(4),(5)}$). Estimation accuracy tended to improve as we incorporated negative reviews and product brandedness into the estimation model for the price promotion effect on sales likelihood (($LR(\chi^2)_{(2)}$=2894.08 > $LR(\chi^2)_{(3)}$ =2825.49> $LR(\chi^2)_{(4)}$ =2625.65). The results indicate that consumers tend to consider price promotions, brandedness, and online review valence holistically when they evaluate purchase options and make decisions.

Although findings from real data about consumer responses on electronic commerce can be more directly applicable to managerial practices, investigating real data can be challenging because many factors about consumers' environments, such as

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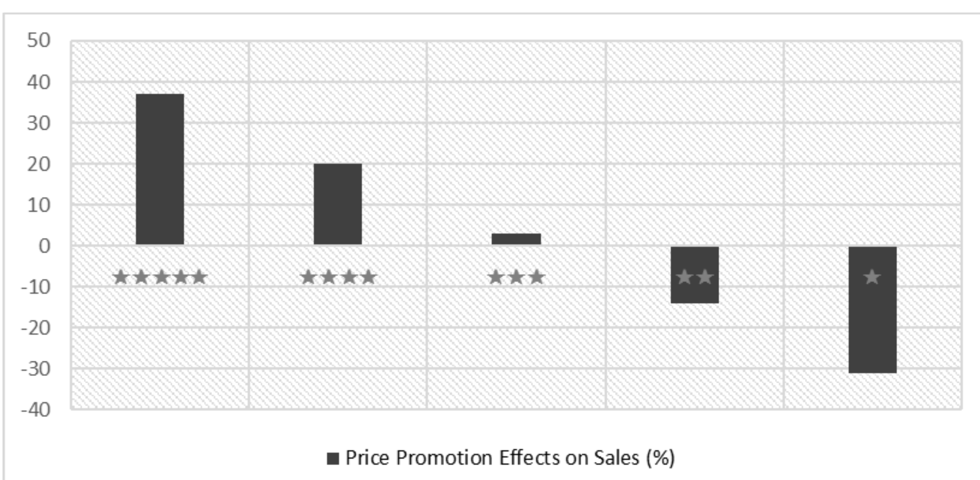
[4] The higher log likelihood ratio χ^2 indicates lower estimation errors.

multitasking or different devices, can be heterogeneous and often unobserved (Voorveld, 2019). In this aspect, the previous research suggests implementing Monte-Carlo estimation methods to examine if unobserved heterogeneities have a substantial influence on model estimations and potentially skew the results significantly (Arellano and Bond, 1991; Duan et al., 2008). The previous studies often adopted the GMM estimation method to control for unobserved heterogeneities regarding consumer demographics or product characteristics (Chintagunta et al., 2010; Shaikh et al., 2018). In this aspect, we re-estimated the benchmark model with the GMM method to examine if the robust moments tend to converge over multiple random samples. The estimation results tended to converge between MLE and GMM estimation models, which indicate that the parameter estimates tended to be consistent through multiple iterations from random samples (See Table 18). Therefore, it is unlikely that the effect was coincidental due to the unobserved heterogeneities such as consumer environments or depth of the price discounts.

Figure 4.3: Price Promotion Effects (β_3) by Online Review Valence



4.6. DISCUSSION

The previous literature argue that the effect of price promotions on sales might have potential downsides in the long-term because intense price promotions can influence consumers' price sensitivity and nudge them to wait for the next price discounts and delay purchases, where price promotions can decrease purchase frequency eventually (Jedidi, Mela, and Gupta, 1999). Also, frequent price discounts lower the consumers' price expectations, and the brand might be put under increasing pressures of lowering overall prices to meet the expectations (Kalwami and Yim, 1992; Mela, Gupta, and Lehmann, 1997). In this aspect, price promotions can lead to decreased profits in the long term or even brand equity (Jedidi et al., 1999; Valette-Florence et al., 2011). However, the powerful short-term uplift effect of price promotions on sales performance has been rarely questioned. The previous research findings on the positive effect of price promotions on sales have been consistent well over a decade.

Extensive research has shown that price promotions have an immediate sales boost effect (Blattberg and Neslin, 1989; Sahni et al., 2017). The previous research finds that price discounts effectively increase purchase frequency, quantity amount or expenditure even more so for loyal consumers (Mela et al., 1997; Zhang and Krishnamurthi, 2004). Also, price promotions tend to nudge consumers to skip the search and make a quick decision and subsequently increase purchase likelihoods (Aydinli et al., 2014). Recent research results show that the positive effect of price discounts on sales has cross-channel and cross-category spillover effects, where price promotions effectively increase web and store traffics and subsequently overall expenditure on other products that are not on price promotions, where the increase in consumptions tend to last even after the price promotion ends (Gong et al., 2015; Gauri et al., 2017; Sahni et al., 2017). Thus, the previous research has reported fairly consistent findings over decades regarding the strong and immediate effect of price promotions on sales. In this aspect, it seems reasonable that sales managers often launch price promotions at the expense of marketing resources that can be allocated to enhance brand equity such as via advertising, because sales managers are often more concerned with fulfilling their short-term revenue goals rather than brand equity in the next decade (Low and Mohr, 2000). However, the finding of this study suggests otherwise. Although managers might expect that price promotions can be a quick solution to boost revenues, even more so for relatively uncompetitive products (Alvarez et al., 2005), launching price promotions for products with negative online review valence can rather make consumers backlash and hurt the chances of sales significantly.

This study found evidence that price promotions can have an immediate negative impact on sales. The results of this study suggest that consumers are likely to perceive increased purchase risks for the products on price promotions and utilize online reviews to relieve the risks. Thus, price promotions can have a backlash effect on the sales potential of the products with negative online review valence. The estimation results show that launching price promotions for accommodations with around one-star online review valence were likely to drop sales likelihoods by more than 30%. In addition to the previous studies that recommend investing in advertising more for the long-term benefits, the findings of this study suggests that it is reasonable to invest more on marketing activities that have slow but long-term gains on brand equity, such as advertising, rather than relying on price promotions to boost sales immediately in short terms. The short-term benefits of price promotions have not been given many suspicions while discounting prices to compensate for negative Word of Mouth (WOM) valence is rather likely to confirm the consumer doubt and decrease sales potential. In this aspect, price promotion cannot be an easy solution to compensate for the product's relative incompetence. It is recommended that brand managers allocate the marketing resources more to advertising from price promotions, for better-off customer satisfaction, brand equity, and future sales growth (Jedidi et al., 1999; Low et al., 2000).

4.6.1 Limitations and Future Research

Promotion Characteristics. The perceived merits of price promotion can be varied by the amount of the price discounted or how the promotion is presented. Price promotions presented in percentage can increase the perceived benefits, especially when the price is discounted by a large portion (Hardesty and Bearden, 2003). The perceived merits of price promotion can be varied by how the promotion is framed. The promotion that emphasizes the frequency of price discounts can infer negative product quality (Darke and Chung, 2005). Also, assortment variety can mitigate the perceived benefits of price promotion (Voss and Seiders, 2003).

The promoted price was flagged and framed in the same format, presented in percentage for the ads observed in the study. The amount of the price discounted was not recorded. However, the unknown depth of promotion is not likely to have skewed the results. We found that price promotion significantly increased the chances of sales. In addition, this study observed some substantial phenomena about the interaction effect between negative reviews and price promotion on sales. It is not likely that products with negative reviews offer significantly shallow price discounts compared to products with positive reviews. Thus, including information about the depth of promotion is not likely to alter the findings.

Product Category. The effect of price promotions on consumer choice might be varied by the product type. Price promotions might be more powerful for the products with high price elasticity. Since we examined one product type, it is uncertain how price elasticity affects the backlash effect. For example, apparel goods that target teenagers might have a higher price elasticity compared to hotels (Pashigian, 1988). Can price promotions still increase sales for teenage apparel even if the products have negative reviews? We recommend that future studies further explore how price elasticity can moderate the interaction effect between negative reviews and price promotion on sales.

4.6.2 Managerial Implications

Brand managers of products with relatively less competent quality or less favorable online reviews might be tempted more to launch price promotions (Alvarez et al., 2005). The managers would expect that offering price discounts would win over purchases from the competing options. However, price promotions can have the opposite effect. The results of this study indicate that price promotion can be an effective strategy if the product is better off in customer satisfaction. The chances of sales for hotels were likely to increase by 37% if they were offered at discounted prices and if the hotels had five-star online review valence. The effect of promotion was likely to reduce by 17% per decrease in the average online review rating. Furthermore, promoting price discounts could decrease the purchase likelihood for hotels with around or lower than three stars online review valence. It is recommended that managers utilize price promotion as a strategy to increase brand share if online reviews have been favorable. However, price promotion can have a backlash effect if it is used to compensate for the relative incompetence of brand performances in customer satisfaction.

4.6.3 Concluding Remarks

Price promotions can increase purchase utility and signal various benefits, such as savings and shopping convenience. Managers often offer price discounts to recompensate for the relatively incompetent products with the expected benefits of price promotions and increase sales. However, this study finds that incompetent products might rather reduce their chances of sales by launching price promotions. Empirical evidence from the hotel industry suggests that price promotions might decrease the sales probability of the products with review ratings merely below the average. Launching price promotions for the products with extremely negative reviews decreased the sales probability by 14-31%.

APPENDIX

Appendix 1. Abstract

Part 2. When Does Online Review Matter to Consumers? The Effect of Product Quality Information Cues

Word of Mouth (WOM) is powerful, and online reviews are often the most accessible WOM information source in electronic commerce. Maintaining favorable online reputation has been the top priority for businesses, and investments in improving online review valence have been increasing. Extensive studies explored how online reviews might influence sales, however, the results have been inconsistent. This study explores whether and how consumers might incorporate online reviews into decision making based on signaling theory and examines when online review valence influences sales and when it might not. In a signaling perspective, online reviews might serve as a product quality signal, and subsequently, consumers might incorporate less the online review information into decision making if other product information cues such as expert ratings or brands help to verify the product quality. The findings from 633,029 consumer decisions on a hotel-booking website indicate that product quality information cues moderate the effect of online reviews on purchase likelihood. Also, product quality information cues were highly endogenous in estimating the effect of online reviews on sales. Online reviews are not likely to be a significant influencer on sales if the seller signal product quality with convincing information cues.

Part 3. How Do Online Reviews Influence Sales? Investigating Referent and Relative Effect of Online Review Ratings on Consumer Choice

A recent survey reports that 82% of American adults look at online reviews before making purchase decisions (Smith and Anderson 2016). Business investments in online review marketing are increasingly significant, and CRM solution agencies commonly adopt customer review management as a main service discipline. Consequently, the previous study found that roughly 16% of reviews on Yelp were initiated by retailers. However, it is still uncertain how online reviews affect consumers' purchase decisions. The previous research has found inconsistent effects of online reviews on improving sales even for the same product category. This study utilizes the reference effect theory and examines if 'good-enough' reference points exist in the relationship between online review valence and sales likelihood. We investigated whether consumers find online review valence more credible compared to objective product information. The results indicate that the marginal effect of online reviews on consumer decisions is negative, and the effect of online reviews on sales is likely to be referent to the good enough rating. In this aspect, consumers are likely to deliberately evaluate the online reviews to avoid risks by comparing the review ratings to the satisfactory reference point.

Part 4. How Online Reviews Influence Price Promotions? Negative Reviews and Promotion Backlash

Can price promotions decrease sales? The previous research predicted otherwise. Price promotions often increase sales in the short term. This study investigates when price promotion can have immediate and negative impacts on sales. The authors utilize price-quality belief theory and predict that purchase risks are increased for products sold at discounted prices. Consumers often utilize Word of Mouth (WOM) information to relieve risks. Negative reviews are likely to have confirmation effects for the consumers' doubts. Thus, price promotion might harm the chances of sales if online reviews are negative. This study examined more than ten million consumer choice on a hotel-booking website and found a significant and negative interaction between price promotion and negative reviews on sales probability. Price promotions had a backlash effect on sales if the average online review ratings were lower than three stars out of five.

Appendix 2. Concluding Remarks

Part 2. When Does Online Review Matter to Consumers? The Effect of Product Quality Information Cues

This paper utilizes signaling theory and investigates how online reviews might interact with other information cues that signal product quality to influence consumer decisions. Consumers are risk-aversive, and one reason why consumers might incorporate online reviews into purchase decisions is that they want to minimize the purchase risks. In this aspect, if the sellers signal positive product quality with verifiable information cues, consumers tend to rely less on online reviews for economic decision making. The findings of this study add insights into moderating factors that influence the effect of online reviews on consumer decisions. Not only the product types or consumer characteristics but product information signaling also might moderate consumers’ reliance on online review sentiments for decision making. Investments in customer review management might not always generate significant ROI. Effective business-to-consumer (B2C) communications can effectively reduce consumers’ WOM information-seeking behaviors.

Part 3. How Do Online Reviews Influence Sales? Investigating Referent and Relative Effect of Online Review Ratings on Consumer Choice

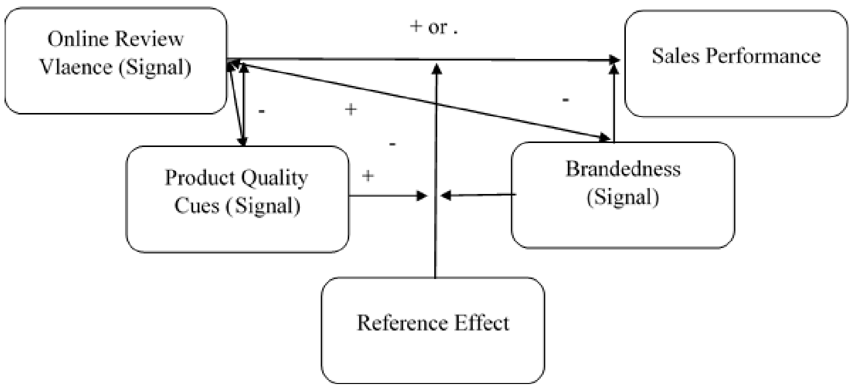
This paper examined the marginal effect of online review ratings on purchase likelihood and found that the marginal effect is negative. The effect of online review ratings on purchases tended to decrease for a higher review rating. For example, five-star ratings compared to four stars are not likely to attract more purchases. Also, the effect of online reviews on purchases tended to contingent on the product quality, where the effect of online review ratings on purchase likelihood was largely insignificant when consumers purchased products with easily verifiable quality. In this aspect, we predict that consumers might tend to choose to evaluate review ratings to avoid risks. The marginal effect of online review ratings on purchase likelihood was referent to a certain point, where the marginal effects tended to increase below and decrease above the certain rating, which might be a good-enough reference point for relieving purchase risks. Thus, allocating marketing resources to increase review ratings that are above the market average or for a high-quality product is not likely to have a significant effect on sales.

Part 4. How Online Reviews Influence Price Promotions? Negative Reviews and Promotion Backlash

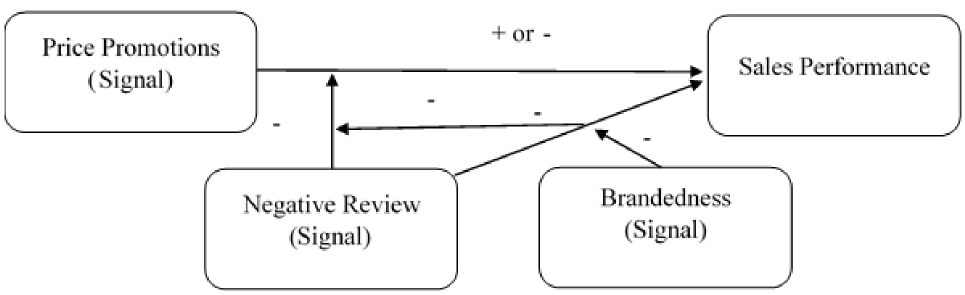
Price promotions can increase purchase utility and signal various benefits, such as savings and shopping convenience. Managers often offer price discounts to recompensate for the relatively incompetent products with the expected benefits of price promotions and increase sales. However, this study finds that incompetent products might rather reduce their chances of sales by launching price promotions. Empirical evidence from the hotel industry suggests that price promotions might decrease the sales probability of the products with review ratings merely below the average. Launching price promotions for the products with extremely negative reviews decreased the sales probability by 14-31%.

Appendix 3. Conceptual Models

Part 2 and Part 3



Part 4



Appendix 4. A Control Function Approach

Assume that consumer choice utility of product i in time point t is $U_{it}= V(Y_{it}, X_{it}, \upsilon_{it}) + \varepsilon^1_{it} + \varepsilon^2_{it}$, and X is a vector of exogenous attributes, and Y is a vector of potentially endogenous attributes, where their correlations with the error term ε are substantial. In this aspect, online review valence (WV), which are customer opinions about the *product experiences* that might not be easily observable from product information provided by sellers, is expected to be correlated with unobserved attributes embedded in the error term ε (Chen and Xie, 2008).

Let ε^1 be utility from unobserved product attributes, and ε^2 be random errors that are exogenous to the study variables. In this aspect, online review valence and ε^1 are expected to have substantial correlations. In this case, the previous research suggests implementing control function, where Y denotes endogenous attributes and Z is an instrument that is supposedly exogenous to the unobserved attributes ε^1. The previous literature utilized lagged price P_{it-1} as relatively more exogenous instrument to unobserved attributes ε^1_{it} compared to price $P_{it,}$ where the exogenous variance of Y is controlled in its covariance to the exogenous instrument Z, and the error term μ_{it} entails the endogenous variance of Y_{it} (Villa-Boss and Winer, 1999; Petrin and Train, 2010). Thus, μ_{it} becomes the new instrument (which is referred to as control function) in the utility function U(X,Y) to control for the endogeneity. We utilized observed product quality as an instrument that is relatively more exogenous to unobserved attributes compared to online review valence. Although the instrument is not completely uncorrelated to the unobserved attributes, if the instrument Z can be considered relatively more exogenous compared to the potentially endogenous variable Y, the previous research recommends to utilize the “imperfect instrumental variables" (IIV), such as lagged price (Villa-Boss and Winer, 1999), lagged review volumes (Hollenback, 2018), since this approach is still expected to have a substantial control effect for endogeneity (Nevo and Rosen, 2012; Conley et al. 2012; Kolesar et al., 2015; Hollenbeck, 2018).

$$Y_{it} = \sigma_0 + \sigma_1 Z_{it} + \mu_{it}$$

We observed that the correlation between the error term ε and online review valence was not substantial and not concerning (<.1, Table 6) (Wooldridge, 2013) - after incorporating observed product quality variables– and thus, the control function might not be necessary to address this issue. However, the control function is still useful to address the collinearity concern between online review valence and product quality. Since the control function entails covariance of online review valence and unobserved product attributes, we utilize the control function as a new instrument for online review valence to address the correlation between online review valence and product quality. The cross-correlations were addressed, and WV variance was effectively identified by utilizing the control function as an instrument (WVI) for online review valence (WV) (Table 4).

Appendix 5. Controlling for the Price Factor

This study relies on Monte-Carlo methods and instrumental variable estimation to address the price factor. Price is not included in the model due to its correlations to the product quality. We added a model that incorporates/control for the price factor – and subsequently, we observed inflations in the effect strengths of online review ratings and product quality on sales likelihood. The results did not alter the findings (Study 1).

Also, we estimated the effect separately on two samples of low and high price options. Low and high prices denote the bottom and top .25 quantiles of price. The effect strength of online review valence on sales likelihood tended to be varied by the price-level, where consumers were more likely to rely on online review valence when their search was oriented towards relatively low-priced products. Interestingly, the interaction effect between online review valence and brandedness became insignificant in low-price condition. One explanation can be that brand names of budget-accommodations, such as *Motel Six*, might not sufficiently satisfy consumers' doubts, and consumers might still rely on online review valence to verify the product quality (Study 2).

Interestingly, in extremely high price condition (top .10 quantile), the effect of online review valence became insignificant. The results correspond to our original findings that consumers might not utilize online review valence as a decision factor when other product quality cues sufficiently satisfy their doubts about product quality. Hotels in the extremely high-price condition had higher review ratings (4.2) than the overall average (3.04), however, the ratings still tended to be substantially varied (S.D. = .44). Product quality scores for hotels in extremely high price condition were noticeably higher (4.17) than the overall average (3.04) (Study 3).

Furthermore, we examined if the effect of online review valence on consumer decisions also tend to be diminished for high-quality products (top .25 quantile hotel quality) since we predict that the insignificant effect of online review valence for the extremely high price condition is due to the product quality effect. The results indicate that the effect of online review, where the price effect is controlled for, becomes insignificant (β=-.04(.05)) for high-quality products while the effect strength (β=-.29(.03)***) noticeably increases for low-quality products (bottom .25 quantile). Hotels in the high-quality condition had higher review ratings (4.3) than the overall average (3.04), however, the ratings still tended to be substantially varied (S.D. = .41) (Study 4)

<Study 1>

Variables	Parameter Estimates			
	(1)	**(2)**	**(3)**	**(4)**
Intercept CON	-3.97 (.03)***	-4.01***	-2.97***	-3.38 (.01)***
E-WOM Valence WV	.46 (.04)***	.72 (.04)***	.09 (.013)***	.03 (.013)**
Product Quality OQA	.15 (.01)***	.37 (.01)***	.	
Brandedness BDS	.10 (.02)***	.10 (.02)***		
Interaction Effect WV*OQA	-.12 (.01)***	-.21 (.01)***		
WV*BDS	-.09 (.03)***	-.16 (.03)***		
Price Factor P		-.005 (.00)***	-.003 (.00)***	
LR Score (χ^2)	479.58***	2822.67***	1027.57***	4.8**
BIC Score	153547.3	151217.4	152959.8	153969.4

*Significance levels: ***p<.01, **p<.05 * p < .1*

<Study 2>

Variables	Parameter Estimates		
	Overall	**High-Price Condition**	**Low-Price Condition**
Intercept			
CON	-3.97 (.03)***	-4.50 (.08)***	-4.64 (.06)***
E-WOM Valence			
WV	.46 (.04)***	.39 (.09)***	.57 (.08)***
Product Quality			
OQA	.15 (.01)***	.25 (.02)***	.43 (.02)***
Brandedness			
BDS	.10 (.02)***	.002 (.02)	.28 (.03)***
Interaction Effect			
WV*OQA	-.12 (.01)***	-.09 (.02)***	-.11 (.02)***
WV*BDS	-.09 (.03)***	-.22 (.06)***	-.01 (.05)
LR Score (χ^2)	479.58***	249.93***	837.70***
BIC Score	153547.3	48177.05	40379.28

*Significance levels: ***p<.01, **p<.05 * p < .1*

<Study 3>

Variables	**Parameter Estimates**		
	Overall	**High-Price Condition**	**Extremely High Price Condition**
Intercept			
CON	-3.97 (.03)***	-4.50 (.08)***	-4.27 (.11)***
E-WOM Valence			
WV	.46 (.04)***	.39 (.09)***	.24 (.15)
Product Quality			
OQA	.15 (.01)***	.25 (.02)***	.09 (.03)***
Brandedness			
BDS	.10 (.02)***	.002 (.02)	.06 (.05)
Interaction Effect			
WV*OQA	-.12 (.01)***	-.09 (.02)***	-.07 (.03)*
WV*BDS	-.09 (.03)***	-.22 (.06)***	-.26 (.11)**
LR Score (χ^2)	479.58***	249.93***	32.74***
BIC Score	153547.3	48177.05	19196.47

*Significance levels: ***p<.01, **p<.05 * p < .1*

<Study 4>

Variables	Parameter Estimates		
	Low-Quality Condition	**Overall**	**High-Quality Condition**
Intercept CON	-3.29 (.05)***	-4.50 (.08)***	-2.27 (.06)***
E-WOM Valence WV	.29 (.03)***	.09 (.01)***	-.04 (.05)
Price P	-.004 (.00)***	-.003 (.00)***	-.004 (.00)***
LR Score (χ^2)	142.08***	1027.57***	537.07***
BIC Score	22807.68	152926.2	19196.47

*Significance levels: ***p<.01, **p<.05 * p < .1*

Appendix 6. Interaction Effects with Product Quality

In this study, we used both expert ratings and accessibility scores to quantify the hotel quality. Due to strong correlation between online review ratings and quantified hotel quality (*r*=.41), instead of incorporating the interaction effect into the model, we estimated the model by product quality quantiles to examine if the effect of online review valence on sales likelihood is varied by product quality (or purchase risk). We used the hotel's location as an alternative indicator for the hotel's quality since its correlation with online review ratings is relatively low below .3 – and estimated the interaction effect between hotel quality and online review valence on consumer choice likelihood. Also, we compared the models based on the likelihood ratio and AIC score to optimize the variable selection. The estimation results are consistent with the findings – (1) the negative marginal effect of online review valence on sales likelihood is significant and informative, and (2) consumers tended to rely less on online reviews when they purchased relatively better quality hotels (β= -1.06(.63)).

Predictor (WVQ)	**Parameter Estimates**			
	(1)	**(2)**	**(3)**	**(4)**
Intercept	-7.76 (.34)***	-7.38 (.00)***	-7.63 (.27)***	-4.2 (.05)***
Review_Ratings	2.09 (.18)***	1.91 (.13)***	2.19 (.14)***	.33 (.01)***
Review_Ratings^2	-.23 (.02)***	-.21 (.02)***	-.25 (.02)***	-
Location_Score	4.29 (1.21)***	2.09 (.03)***	-	-
Review_Ratings* Location_Score	-1.06 (.63)*	-	-	-
Review_Ratings^2* Location Score	.13 (.08)	-	-	-
Price (Control)	-.003 (.00)***	-.003 (.00)***	-.003 (.00)***	.003 (.00)***
LR Score (χ^2)	4305.1***	4300.89***	1753.68***	1547.24***
AIC Score	149656.7	149656.9	152202.1	152406.6

*Significance levels: ***p<.01, **p<.05 * p < .01*

Appendix 7. Control Factors

<Model 1>

Variables	Parameter Estimates (1)	(2)	(3)	(4)
Intercept CON (υ_0)	-3.97 (.03)***	-4.01 (.03)***	-4.13 (.04)***	-4.14 (.04)***
E-WOM Valence WV ($\iota_{0+}\kappa$) (H_B)	.46 (.04)***	.46 (.04)***	.48 (.04)***	.48 (.04)***
Product Quality OQA (υ_1)	.15 (.01)***	.12 (.01)***	.14 (.01)***	.14 (.01)***
Brandedness BDS (υ_2)	.10 (.02)***	.14 (.02)***	.13 (.02)***	.13 (.02)***
Interaction Effect				
WV*OQA (ι_1) (H_C)	-.12 (.01)***	-.12 (0.1)***	-.13 (0.1)***	-.13 (.01)***
WV*BDS (ι_2) (H_D)	-.09 (.03)***	-.08 (.03)***	-.08 (.03)***	-.08 (.03)***
Control Factors				
Price promotion dummy (σ_1)	.	.34 (.02)***	.34 (.02)***	.34 (.02)***
Region dummy 1 (σ_2)	.	.	.13 (.03)***	.13 (.03)***
Region dummy 2(σ_3)	.	.	.05 (.04)	.05 (.04)
Region dummy 3(σ_4)	.	.	.06 (.04)	.06 (.04)
Region dummy 4 (σ_5)	.	.	-.34 (.11)***	-.34 (.11)***
Region dummy 5(σ_6)	.	.	-.09 (.05)*	-.09 (.05)*
Seasonality dummy (σ_7)	.	.	.	.008 (.02)
LR Score (χ^2)	479.58***	852.68***	926.30***	926.47***
AIC Score	153480.2	153109.1	153045.5	153047.3

*Significance levels: ***p<.01, **p<.05 * p < .1*

Variables	Parameter Estimates		
	Low Price	Overall	High Price
Intercept CON (υ_0)	-4.84 (.08)***	-4.13 (.04)***	-4.71 (.09)***
E-WOM Valence WV ($\iota_{0+}\kappa$) (H_B)	.59 (.08)***	.48 (.04)***	.41 (.09)***
Product Quality OQA (υ_1)	.41 (.02)***	.14 (.01)***	.23 (.02)***
Brandedness BDS (υ_2)	.27 (.03)***	.13 (.02)***	.01 (.03)
Interaction Effect			
WV*OQA (ι_1) (H_C)	-.12 (.02)***	-.13 (.01)***	-.09 (.01)***
WV*BDS (ι_2) (H_D)	.02 (.05)	-.08 (.03)***	-.21 (.06)***
Control Factors			
Price promotion dummy (σ_1)	.37 (.03)***	.34 (.02)***	.20 (.03)***
Region dummy 1 (σ_2)	.19 (.05)***	.13 (.03)***	.19 (.05)***
Region dummy 2(σ_3)	.03 (.07)	.05 (.04)	.19 (.06)***
Region dummy 3(σ_4)	.03 (.07)	.06 (.04)	.18 (.07)***
Region dummy 4 (σ_5)	-.48 (.16)***	-.34 (.11)***	-.47 (.25)*
Region dummy 5(σ_6)	.33 (.11)***	-.09 (.05)*	.13 (.07)*
Seasonality dummy (σ_7)	.11 (.04)***	.008 (.02)	.02 (.03)
LR Score (χ^2)	1031.38***	852.68***	315.80***
AIC Score	40140.95	153109.1	48064.36

*Significance levels: ***p<.01, **p<.05 * p < .1*

Variables	Parameter Estimates		
	Overall	**High Price**	**Extremely High Price**
Intercept CON (υ_0)	-4.13 (.04)***	-4.71 (.09)***	-4.61 (.16)***
E-WOM Valence WV ($\iota_{0+}\kappa$) (H_B)	.48 (.04)***	.41 (.09)***	.24 (.15)
Product Quality OQA (υ_1)	.14 (.01)***	.23 (.02)***	.09 (.03)***
Brandedness BDS (υ_2)	.13 (.02)***	.01 (.03)	.05 (.05)
Interaction Effect			
WV*OQA (ι_1) (H_C)	-.13 (.01)***	-.09 (.01)***	-.07 (.03)**
WV*BDS (ι_2) (H_D)	-.08 (.03)***	-.21 (.06)***	-.27 (.11)**
Control Factors			
Price promotion dummy (σ_1)	.34 (.02)***	.20 (.03)***	.12 (.05)**
Region dummy 1 (σ_2)	.13 (.03)***	.19 (.05)***	.30 (.08)***
Region dummy 2(σ_3)	.05 (.04)	.19 (.06)***	.21 (.10)**
Region dummy 3(σ_4)	.06 (.04)	.18 (.07)***	.53 (.11)***
Region dummy 4 (σ_5)	-.34 (.11)***	-.47 (.25)*	-.43 (.42)
Region dummy 5(σ_6)	-.09 (.05)***	.13 (.07)*	.29 (.12)**
Seasonality dummy (σ_7)	.008 (.02)***	.02 (.03)	-.03 (.06)
LR Score (χ^2)	852.68***	315.80***	67.53***
AIC Score	153109.1	48064.36	19175..68

*Significance levels: ***p<.01, **p<.05 * p < .1*

Variables	Parameter Estimates		
	Low-Quality Condition	**Overall**	**High-Quality Condition**
Intercept CON	-3.42 (.09)***	-3.15 (.03)***	-2.58 (.08)***
E-WOM Valence WV	.31 (.03)***	.12 (.01)***	-.06 (.06)
Price P	-.004 (.00)***	-.002 (.00)***	-.004 (.00)***
Control Factors			
Price promotion dummy (σ_1)	.38 (.05)***	.34 (.00)***	.12 (.05)**
Region dummy 1 (σ_2)	.03 (.09)	.08 (.03)***	.26 (.07)***
Region dummy 2(σ_3)	-.01 (.12)	.09 (.03)***	.20 (.08)**
Region dummy 3(σ_4)	.08 (.15)	.11 (.04)***	.27 (.08)***
Region dummy 4 (σ_5)	-.23 (.33)	-.45 (.11)***	-.05 (.31)
Region dummy 5(σ_6)	-.03 (.18)	.05 (.04)	.13 (.09)
Seasonality dummy (σ_7)	.13 (.06)**	.03 (.02)	.01 (.06)
LR Score (χ^2)	195.94***	1522.40***	562.66***
AIC Score	22767.83	152445.4	16537.87

*Significance levels: ***p<.01, **p<.05 * p < .1*

<Model 2>

Predictor	Parameter Estimates			
	(1)	**(2)**	**(3)**	**(4)**
Intercept (β_0)	-8.02 (.27)***	-7.63 (.3)***	-7.40 (.27)***	-7.47 (.27)***
Review Rating Effect WV_i (β_1)	2.35 (.14)***	2.18 (.17)***	2.01 (.14)***	2.00 (.14)***
Marginal Effect WV_i^2(β_2)	-.29 (.02)***	-.24 (.02)***	-.22 (.02)***	-.22 (.02)***
Price (σ_8)	.	-.003 (.00)***	-.004 (.00)***	-.004 (.00)***
Price promotion dummy (σ_1)	.	.	.33 (.02)***	.34 (.02)***
Region dummy 1 (σ_2)	.	.	.	.09 (.03)***
Region dummy 2 (σ_3)	.	.	.	.09 (.04)**
Region dummy 3 (σ_4)	.	.	.	.09 (.04)**
Region dummy 4 (σ_5)	.	.	.	-.45 (.11)***
Region dummy 5 (σ_6)	.	.	.	.05 (.05)
LR score (χ^2)	423.17	1753.68***	2128.7***	2172.67***
AIC score	153530.6	152202.1	151829.1	151795.1

*Significance levels: ***p<.01, **p<.05 * p < .1*

Predictor	Parameter Estimates		
	Overall	Low Quality	High Quality
Intercept (β_0)	-7.46 (.27)***	-6.22 (.44)***	-6.55 (1.37)***
Review Rating Effect WV_i (β_1)	1.97 (.14)***	1.19 (.25)***	2.07 (.66)***
Marginal Effect $WV_i^2(\beta_2)$	-.22 (.02)***	-.11 (.03)***	-.26 (.08)***
Price (σ_8)	-.004 (.00)***	-.003 (.00)***	-.004 (.00)***
Price promotion dummy (σ_1)	.32 (.02)***	.33 (.05)***	.12 (.05)**
Region dummy 1 (σ_2)	.07 (.03)***	.01 (.08)	.26 (.07)***
Region dummy 2 (σ_3)	.09 (.04)***	.02 (.12)	.19 (.08)**
Region dummy 3 (σ_4)	.09 (.04)**	.09 (.15)	.26 (.08)***
Region dummy 4 (σ_5)	-.46 (.11)***	-.23 (.33)	-.05 (.31)
Region dummy 5 (σ_6)	.05 (.05)	-.01 (.18)	.12 (.09)
Branded dummy *(σ_9)*	.08 (.02)***	.09 (.04)*	.02 (.04)
Seasonality dummy *(σ_7)*	.03 (.02)	.13(.05)**	.01 (.06)
LR score (χ^2)	2199.55***	124.61***	93.33***
AIC score	151772.2	22720.58	16526.51

*Significance levels: ***p<.01, **p<.05 * p < .1*

<Model 3>

Predictor	**Parameter Estimate**		
	(1)	**(2)**	**(3)**
Negative Online Review Valence			
RV^{NEG} (β_1)	-.27 (.02)***	-.27 (.02)***	.
Brandedness			
BA_{ic} (β_2)	.11 (.02)***	.08 (.02)***	.
Price Promotion			
SP_{ic} (β_3)	.37 (.03)***	.38(.03)***	.
Interaction Effects:			
Negative Online Review Valence and Brandedness			
RV^{NEG}*BA_{ic} (β_4)	.13 (.03)***	.14 (.03)***	.
Negative Reviews and Price Promotion			
RV^{NEG}*SP_{ic} (β_5)	-.17 (.05)***	-.17 (.06)**	.
Brandedness and Price Promotion			
BA*SP_{ic} (β_6)	.003 (.03)	.04 (.03)	.
Three-Way Interaction RV^{NEG}*BA*SP_{ic} (β_7)	-.06 (.05)	-.05 (.05)	.
Control Factors:			
Price (σ_8)	-.005 (.00)***	-.005 (.00)***	.
Product Quality Information			
QA_{ic} (β_9)	.34 (.01)***	.36 (.01)***	.
Seasonality dummy (σ_7)	.04 (.02)**	.04 (.02)*	.
Intercept			
CON (β_0)	-3.99 (.03)***	-4.17 (.04)***	.
Region dummy 1 (σ_2)	.	.19 (.03)***	.
Region dummy 2 (σ_3)	.	.10 (.03)***	.
Region dummy 3 (σ_4)	.	.06 (.04)	
Region dummy 4 (σ_5)	.	-.42 (.11)***	
Region dummy 5 (σ_6)	.	.002 (.05)	
Likelihood Ratio (χ^2)	2896.18***	3000.72***	.
AIC Score	151073.6	150979.1	153949.8

*Significance levels: ***p<.01, **p<.05 * p < .1*

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