MARKETING SCIENCE
Vol. 00, No. 0, April 2018, pp. 000–000
ISSN 0732-2399 | EISSN 1526-548X | 00 | 0000 | 0001

INFORMS
DOI 10.1287/xxxx.0000.0000

Creation and Consumption of Mobile Word-of-Mouth: How are Mobile Reviews Different?

Sam Ransbotham
Boston College, sam.ransbotham@bc.edu

Nicholas H. Lurie
University of Connecticut, lurie@uconn.edu

Hongju Liu
University of Connecticut, hongju.liu@business.uconn.edu

Mobile users can create word-of-mouth (WOM) wherever they are and whenever they want. This real-time creation process may be associated with differences in the content and consumption value of mobile versus non-mobile word-of-mouth. We analyze 275,362 reviews from 117,827 reviewers describing their experiences at 134,976 restaurants as well as a dual platform subsample of 21,026 reviews written by 673 reviewers who wrote at least four mobile and four non-mobile reviews. We also examine how the introduction of the mobile platform affected WOM consumption. We find that WOM content is more affective, more concrete, and less extreme when created on mobile devices. These differences in content (more affective, more concrete, and less extreme) vary in their relationships with the perceived consumption value of mobile content. Beyond the indirect relationship between platform and consumption value through content, reviews created on mobile devices are associated with lower consumption value. This direct relationship grows stronger over time. Although consumers initially value real-time mobile content similarly to non-mobile content, even after controlling for a large set of content and contextual variables, over time consumers value mobile reviews less than non-mobile reviews.

Key words: mobile; reviews; word-of-mouth; econometrics

1. Introduction

The exploding growth of online word-of-mouth (WOM) is enhanced by the increased ability of consumers to create and access this content wherever they are and whenever they want. A proliferation of applications based on mobile devices provide consumers with location-dependent information to comment on experiences at all times and everywhere. Unlike with traditional word-of-mouth, consumers can create mobile WOM during as well as before and after purchase. Examples include the ability to write reviews of restaurants in mobile versions of TripAdvisor, Yelp, and Google and to send real-time thoughts in Twitter while watching a movie. These differences in the creation process may affect the content and consumption of mobile versus non-mobile word-of-mouth.

Growing evidence indicates that consumers are increasingly likely to rely on information from other consumers (Ransbotham and Kane 2011, Weiss et al. 2008). Empirical research shows that the valence, dispersion, and volume of consumer reviews predict sales in traditional (i.e., desktop) online environments (Chevalier and Mayzlin 2006, Duan et al. 2008). Other research shows that online ratings tend to become more negative over time since consumers with higher evaluations tend to be the first to purchase and review products (Li and Hitt 2008). Still other research suggests that the perceived value of consumer-created content depends on characteristics such as contribution length, review valence, as well as the perceived similarity of the creators and readers of consumer-created content (Chen and Lurie 2013, Forman et al. 2008, Godes and Mayzlin 2004, Weiss et al. 2008). However, little is known about how platform source affects the consumption value of word-of-mouth and how it may change over time.

From a managerial standpoint, encouraging consumers to create mobile WOM has both pros and cons. For example, mobile reviews may not benefit from reflection and consumers may affectively respond to their current experiences (Miller 2009, März et al. 2017). Additionally, the mobile platform may encourage feedback from less engaged customers (Kriss 2013). However, it is unclear whether concerns about differences in mobile content are justified and whether there are differences in the content and value of mobile versus non-mobile online WOM.

We examine these issues by proposing that the real-time creation process of mobile word-of-mouth should be associated with differences in the *content* of word-of-mouth created on mobile versus non-mobile devices. Namely, it should be more affective, more concrete, and less extremely positive or negative. These differences in content should be related to its *consumption value* (i.e., the perceived value of reading a particular review) for consumers. In addition to an indirect relationship between platform and consumption value through content, there should be a direct relationship between creation platform and consumption value. In particular information indicating that a review was written on a mobile platform should be associated with different consumption value. Furthermore, the association between creation platform and consumption value should grow stronger over time as consumers gain experience with the mobile platform.

We explore these ideas using 275,362 reviews from 117,827 reviewers describing their experiences at 134,976 restaurants on the review website Urbanspoon. Of these, 119,880 reviews (44%) were written on mobile devices, while 155,482 (56%) were written on non-mobile (i.e., desktop or laptop) devices. To help address potential self-selection issues and differences among mobile and non-mobile reviewers, we examine the entire sample and a dual platform sample of 21,026 reviews written by 673 reviewers who wrote at least four mobile and four non-mobile reviews. To examine the direct effect of the mobile platform on consumption value, and how it changes over time, we compare WOM value before and after the introduction of an application that allowed consumers to write reviews on mobile devices. We analyze review content to evaluate differences in language use for mobile versus traditional WOM using the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker et al. 2015) and a dataset of word concreteness (Brysbaert et al. 2014). We compare differences in rating extremity for reviews written on mobile and non-mobile platforms. We assess the consumption value of WOM by measuring the number of “likes” each review receives over time.

Our descriptive analysis finds that mobile content is more affective, more concrete, and less extreme in its valence than non-mobile content. We also find that WOM that is more affective, more concrete, and less extreme has lower consumption value. Furthermore, even after controlling for a large set of content and contextual variables, the mobile platform is directly associated with lower consumption value. In addition, the negative relation between platform and consumption value grows stronger over time. Although consumers initially value real-time mobile content similarly to non-mobile content, over time they begin to perceive differences in platform-specific content and value mobile reviews less as they gain experience with the mobile platform.

Our conceptual development and results examine how differences in the way in which users create mobile content is related to WOM characteristics and consumption value and how consumer evaluations of mobile content change over time. As such, we add to prior research on mobile consumer behavior (Andrews et al. 2015, Ghose et al. 2012, März et al. 2017) and research on factors that affect the content and impact of online WOM (Chae et al. 2017, Berger et al. 2010, Godes and Mayzlin 2004, Li and Hitt 2008, Moe and Schweidel 2012, Toubia and Stephen 2013). In this way, our research identifies a number of potential aspects that warrant further study and provides a framework for future research on mobile word of mouth.

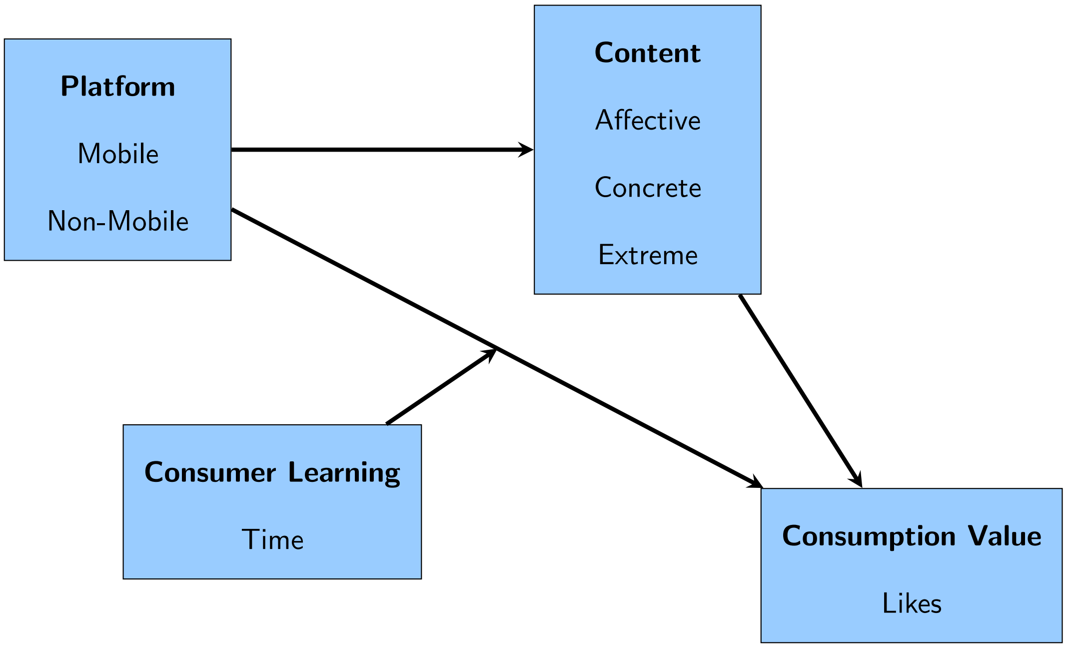
2. Theoretical Background

We theorize that the creation of WOM on mobile platforms has both indirect and direct relationships with WOM consumption value. Indirectly, the real-time creation process associated with the mobile platform affects the content (expression and rating extremity) of reviews which, in turn, affects the consumption value of the content to consumers. Directly, the mobile platform is associated with lower consumption value. We propose that this negative relationship between platform and value strengthens over time as consumers learn about the relative quality of content created on mobile versus non-mobile platforms. Figure 1 shows our conceptual model and related measures.

2.1. Real-time creation process

A distinguishing characteristic of mobile technology is greater portability and accessibility across a variety of consumer activities and contexts (Hoffman and Novak 2012, Shankar and Balasubramanian 2009). Mobile devices allow consumers to overcome the physical and social challenges of using computers in places without desks or wireless access, or where pulling out a large computer might be socially awkward. Mobile devices are rarely far from their owners; 72% of US adults are within five feet of their smartphone the majority of time (Jumio 2013). Greater accessibility means that consumer activities, including word-of-mouth, occur in places and at times they never occurred before. Constant accessibility allows consumers to use mobile devices to spontaneously act on thoughts, desires, and curiosity by seeking information and connecting with distant others with minimal forethought (Andrews et al. 2015).

Figure 1 **Platform Differences in WOM Creation and Consumption**



Greater portability and accessibility means that consumers can create mobile WOM during or immediately following consumption (Miller 2009). Consumers increasingly tweet real-time evaluations of movies and TV shows and evaluate food as they eat it (Miller 2009). They share product or service information (i.e., a restaurant review) with other consumers at the moment the product or service is consumed or available.

The real-time creation process associated with mobile WOM should make it less reflective relative to non-mobile WOM. That is, while non-mobile users generally create WOM after consumption, through retrospection and memory about the experience, mobile consumers spend less time thinking about and processing their experiences before engaging in WOM. Greater spontaneity, and less reflection, should increase the use of emotional response in evaluating alternatives. In other words, evaluation of experiences should involve more hot (versus cold) reasoning (Ariely and Loewenstein 2006, Loewenstein 2000) and therefore be more affective. In other words, mobile WOM should reflect more visceral responses than non-mobile word-of-mouth.

Creating WOM during or shortly after consumer experiences should also reduce the psychological distance between these experiences and related WOM. Evaluating temporally near and far events affects concerns for desirability (i.e., what) versus feasibility (i.e., how; Trope and Liberman 2003, 2010) and the relative importance of central versus peripheral product features (Trope et al. 2007). More generally, a focus on the present leads to a more concrete mindset whereas a focus on the future leads to a more abstract mindset (Trope and Liberman 2003, 2010). Although work on temporal construal traditionally examines the mental representation of future events (Trope and Liberman 2003), psychological distance applies in similar ways to retrospective evaluations (Trope and Liberman 2010). Therefore, language used in mobile WOM should reflect a more concrete (versus abstract) mindset than non-mobile WOM.

Finally, greater accessibility should increase the use of mobile devices in low-motivation contexts. That is, although consumers will engage in WOM on both mobile and non-mobile platforms for experiences that are strongly positive or negative, they should be less likely to use non-mobile platforms for WOM about neutral — and less memorable — experiences for which the motivation to engage is WOM is lower (Anderson 1998, Godes and Mayzlin 2004). In contrast, because mobile devices are always available, they are likely to be used to generate word-of-mouth about less memorable experiences. This greater likelihood of providing neutral WOM suggests that mobile WOM will be less extreme, on average, than non-mobile WOM.

2.2. Consumption Value

We propose that the mobile platform will have indirect as well as direct relationships with consumption value. The indirect relationship will be through changes in WOM content. The direct relationship will occur through associations between the labeling of content as “mobile” and its perceived quality. This relationship should become stronger over time as consumers learn about the mobile platform.

2.2.1. Indirect effect of platform through mobile content. Differences in the content of mobile WOM should be related to its consumption value to consumers (e.g., März et al. 2017). Some of the relationships between content and value are challenging to predict. For example, given that emotional content increases psychological arousal, and is more likely to be shared with others

(Berger and Milkman 2012), one might predict that WOM that is more affective should have higher perceived value. In other words, mobile WOM should convey greater emotional excitement; this should be associated with greater consumption value. In contrast, one might argue that less affective content, that suggests greater thinking and reasoning by WOM creators, will be associated with higher consumption value.

Whether concrete WOM is more or less valued should depend on its match with the social distance between the creators and receivers of content as well as its match with the temporality of consumer decisions (Kim et al. 2008, Zhao and Xie 2011). For example, given that consumers do not typically know the authors of online reviews personally, and greater social distance leads to more abstract construal (Trope et al. 2007), this should enhance the weight given to abstract relative to concrete content (Kim et al. 2008). This implies that, to the extent that the real time creation process associated with mobile platforms leads to more concrete word of mouth, it should be less valued. However, one might argue that, if consumers read online reviews to help them make near-term decisions, they should more highly value lower construal level content. Such an argument would imply that concrete content should be associated with greater consumption value.

Although associations between WOM content and consumption value are subject to debate, the relationship between rating extremity and consumption value is more straightforward. In particular, if the real-time creation process associated with mobile reviews leads to more neutral and less extreme reviews, this should reduce the value of mobile reviews. To the extent that more extreme reviews provide a stronger case for choosing or not choosing a particular product and provide more diagnostic information (Forman et al. 2008, Mudambi and Schuff 2010), less extreme (i.e., neutral) mobile WOM should be less valued.

2.2.2. Direct effect of creation platform. Consumers have a number of motivations for using online reviews as an information source including risk reduction, reducing search time, advice seeking, and learning about other consumers' behavior (Berger 2014, Hennig-Thurau and Walsh 2003). The selection and evaluation of particular information sources should depend on the perceived value of these information sources in addressing receiver needs (Weiss et al. 2008).

As consumers develop associations between different platforms and the relative quality of information provided by these platforms, they should shift their information consumption behavior to platforms perceived as providing more valuable information. In making quality assessments, consumers should consider central aspects—such as argument quality—as well as peripheral cues—such as the extent to which reviewers use two-sided arguments (Cheung et al. 2012, Petty et al. 1983). The association between a peripheral cue and evaluations may be incidental (akin to classical conditioning; Rucker and Petty 2006) or be driven by thoughts provoked by the cue.

While the content of word of mouth should serve as a central cue to quality, and therefore consumption value, one peripheral cue that consumers may use to assess quality is the labeling of a review as "mobile." To the extent that the mobile platform is perceived as a lower quality information source, there should be a direct and negative association with consumption value.

2.2.3. Moderating role of platform learning. When a new platform is introduced, consumers are likely uncertain about how that platform affects information value (e.g. new operating systems, Karahanna et al. 1999). With time, consumers should learn about the relative value of the mobile platform (Hsieh et al. 2011) as an information source (Ratchford et al. 2001). That is, initially, consumers may see mobile reviews as novel and potentially valued information sources since they may be seen as more contemporaneous with the reviewer's experience (Chen and Lurie 2013). However, as they gain additional experience reading and evaluating review quality; for example, assessing the extent to which their own experiences match those of the reviewer, they should develop quality associations for WOM identified as "mobile." If consumers increasingly associate mobile reviews as being of lower quality than non-mobile reviews, they should reduce their consumption of mobile reviews; more so as the mobile—quality association clarifies over time.

In summary, we predict that 1) there will be an indirect effect of platform on consumption value through content, 2) there will be a direct effect of platform on consumption value, and 3) the direct effect of platform on consumption value will grow stronger over time.

3. Method

3.1. Data

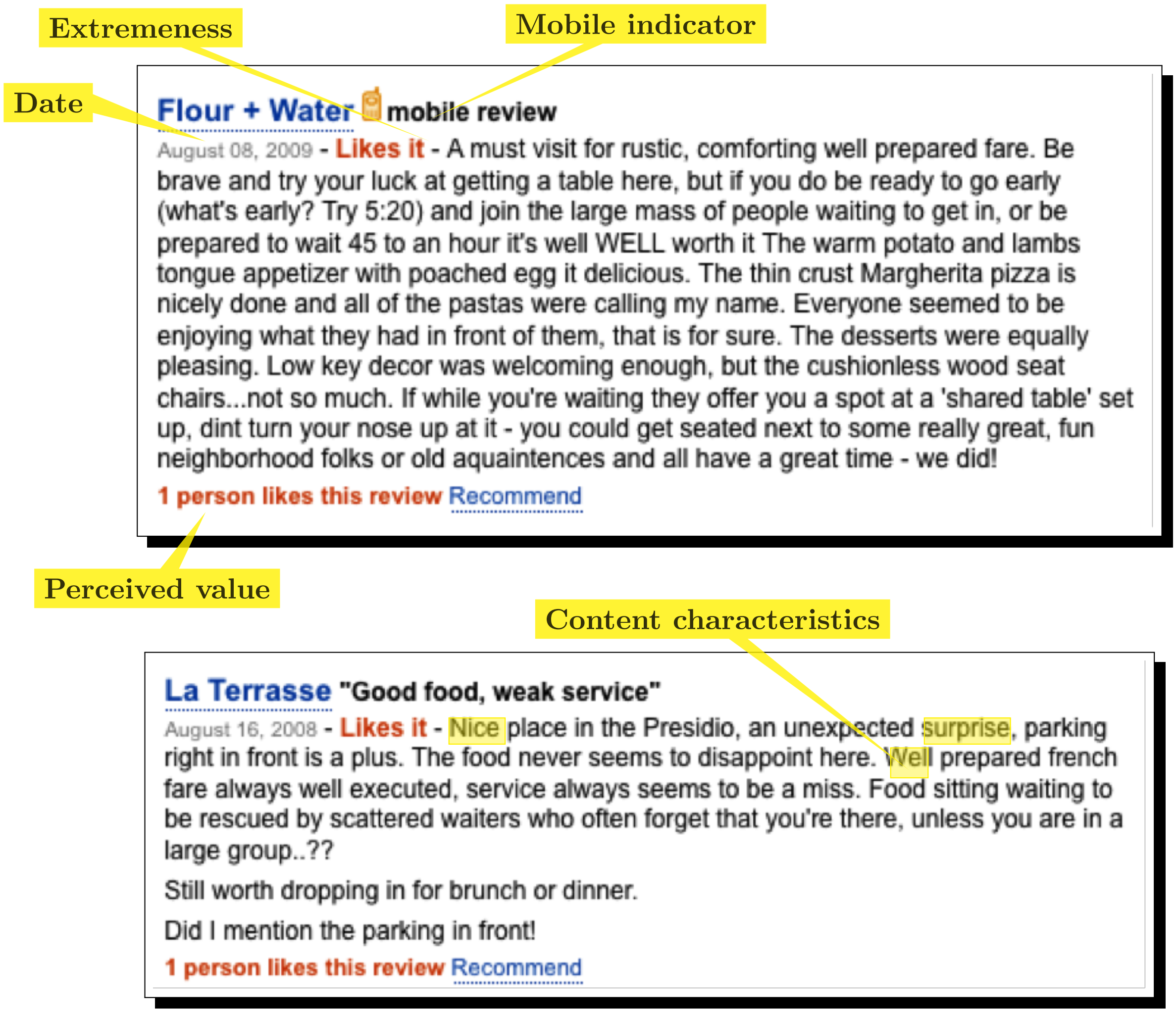
To explore these ideas, we use reviews from Urbanspoon (`http://Urbanspoon.com`), an Internet-based user generated content company that began in 2006. Urbanspoon provided restaurant information and allowed users to review their dining experiences. Our study period of October 2006 to November 2009 focuses on a time when the company recognized the growing importance of mobile devices. Initially, the company offered only the traditional (desktop oriented) web interface for creating reviews. In the middle of our study period (July 2008), the company begin to allow users to create reviews using a mobile application. We focus on the period from October 2006 to November 2009 for two reasons. First, during this period, presentation of reviews from non-mobile and mobile (Figure 2) were uniform, differing only by the indicator of the source of the review. Second, we are able to observe how content consumption changes with the introduction of the mobile platform and how it evolves over time as consumers learn about the new platform. We use the variable, *Mobile*, coded as 1 to indicate the review came from a mobile device or 0 otherwise.

Table 1 provides descriptive statistics for the focal variables; Table 2 shows the correlations. Our full review dataset contains a total of 275,362 reviews from 117,827 reviewers describing their experiences at 134,976 restaurants. Reviewers wrote 119,880 reviews (44%) on mobile devices and 155,482 (56%) using non-mobile devices. We explore the entire sample and a dual platform subsample of 21,026 reviews. The dual platform subsample contains only reviews from the 673 reviewers who wrote at least four mobile and four non-mobile reviews. The dual platform subsample helps control for reviewer-specific effects that might explain differences in mobile and non-mobile reviews. For example, it might be that mobile reviewers differ from non-mobile reviewers and this, rather than differences in the creation platform, explains differences in WOM content creation and consumption. (Later models consider this potential endogeneity specifically.)

3.2. Content Variables

In addition to meta-attributes directly available from the Urbanspoon data, we are interested in examining differences in WOM content. Following prior research (e.g., Berger and Milkman 2012,

Figure 2 **Sample Mobile and Non-Mobile Reviews**



Ludwig et al. 2013, März et al. 2017), to evaluate differences in language use for mobile versus traditional WOM, we process the full text of reviews using the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker et al. 2015). LIWC measures the number of words in a given text that reflect particular linguistic or psychological processes and spoken categories of language. This number of words is then scaled to a percentage based on the overall number of words in the text. LIWC is based on writing and spoken utterances from blogs, expressive writing, novels, natural speech, the New York Times newspaper, and Twitter (Pennebaker et al. 2015); numerous studies (see Tausczik and Pennebaker 2010) support the validity of LIWC scales to measure psychological constructs. We focus on the following attributes in our analysis because theory suggests that the real-time nature of the mobile platform will lead to differences in these measures; we use other

Table 1 Descriptive Statistics

Variable	Non-Mobile Reviews Mean	Max	Median	Std. Dev.	Mobile Reviews Mean	Max	Median	Std. Dev.
Likes	0.94	60.00	0.00	2.35	0.30	54.00	0.00	1.05
Age (days)	241.52	1123.00	206.00	171.79	155.71	477.00	144.00	73.78
Sequence	3.23	103.00	2.00	4.62	2.45	70.00	2.00	2.85
Length (/100)	0.81	17.57	0.57	0.84	0.32	8.65	0.25	0.27
Complexity (ARI)	8.75	30.00	8.25	4.39	5.92	29.88	5.73	3.22
Reviewer Reviews	26.86	489.00	5.00	61.91	9.68	489.00	3.00	19.28
Reviewer Popularity	0.53	59.00	0.14	1.17	0.21	42.00	0.00	0.60
Restaurant Reviews	5.47	103.00	3.00	7.48	3.87	103.00	2.00	4.65
Restaurant Popularity	0.70	53.00	0.00	1.64	0.35	43.00	0.00	1.05
Site Engagement	0.75	2.86	0.65	0.50	0.50	1.68	0.55	0.16
Past	3.90	33.33	2.88	3.99	3.15	37.50	0.00	4.42
Perceptive	2.35	60.00	1.92	2.54	2.25	50.00	0.00	3.41
Personal	2.55	37.50	2.21	2.12	3.10	40.00	2.56	3.06
Informal	0.75	60.00	0.00	1.58	1.08	60.00	0.00	2.62
Cognitive	8.88	60.00	8.70	4.93	7.85	50.00	7.50	6.17
One-Sided	0.76	1.00	1.00	0.34	0.81	1.00	1.00	0.35
Social	6.46	46.15	6.00	4.57	5.25	58.33	4.55	5.25
Affective	7.54	81.82	6.67	4.71	10.75	71.43	9.52	7.05
Concrete	0.59	12.50	0.42	0.59	1.15	12.50	0.89	0.92
Extreme	0.28	1.00	0.00	0.45	0.23	1.00	0.00	0.42

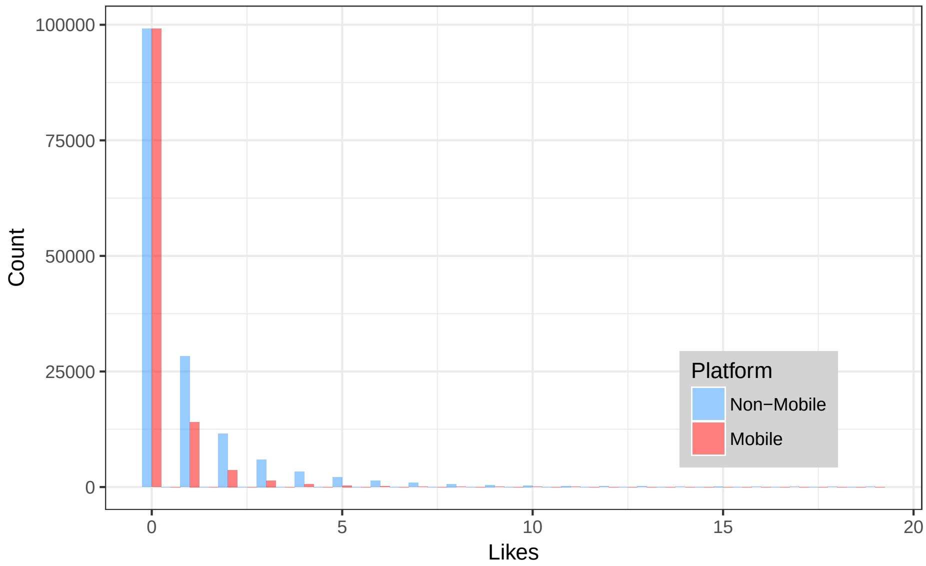
275,362 reviews; 155,482 from non-mobile devices and 119,880 from mobile devices. Minimum is 0 for all variables. Differences in mean (t-test) and median (Wilcoxon sign rank) by platform are all statistically significant ($p < 0.001$).

content and context variables later (Section 3.3.2) to control for alternative explanations for the value of the review.

- **Affective** We measure *Affective* content as the percentage (of the total) of words reflecting positive and negative emotion (LIWC; Pennebaker et al. 2015). Examples of affective words are “anxious,” “awful,” and “sad.”

- **Concreteness** We augment LIWC measures by measuring *Concreteness* (Brysbaert et al. 2014), which rates the concreteness of 39,955 words and expressions from 1 to 5 using Internet-based crowdsourcing. For example, within the context of restaurant reviews, “ambiance” has a concreteness rating of 2.31 while “chicken leg” has a concreteness rating of 4.82 (Brysbaert et al. 2014). We created a custom dictionary for LIWC in which words were counted in the category *concrete* if they had a concreteness rating of three or greater. (Our results are qualitatively robust to using a threshold concreteness rating of four as well.)

Figure 3 **Distribution of Likes Per Review by Platform**



Note. The count of the number of likes for reviews in each platform restricted to reviews with fewer than 20 likes

- **Rating Extremity** Reviewers rate restaurants on an ordinal scale (doesn't like, neutral, like, and really like). Consistent with prior research Mudambi and Schuff (2010), we characterize *Extreme* ratings as those for which the rating is either "doesn't like" or "really like."

3.3. Value and Control Variables

3.3.1. Perceived Value of the Review In Urbanspoon, users can indicate whether the review was valuable to them by clicking on a "Like" button. We measure the perceived value of a review, *Likes*, through the total number of likes that a review received. This count measure has been used in other research on WOM as a measure of review usefulness (for a review, see Purnawirawan et al. 2015). Figure 3 shows the distribution of likes per review by platform; we restrict the figure to reviews with fewer than 20 likes because there are few reviews with more than 20 likes and little difference between platforms for these reviews.

3.3.2. Text Characteristics Using LIWC (Pennebaker et al. 2015), we control for additional content variables that may affect review value. For variables that are log transformed, we add 1 to avoid taking the natural log of zero.

- **Past** Because language tense may affect inferences about when the review was written, we measure *Past Tense* wording. Examples of past tense words are "already," "previously," and "prior."

Table 2 Correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Likes	1																			
2	Age	.185	1																		
3	Sequence	.144	−.001	1																	
4	Length	.129	.077	.058	1																
5	Complexity	.121	.222	.054	.460	1															
6	Rev. Reviews	.015	.005	−.038	.085	.054	1														
7	Rev. Popularity	.209	.120	.028	.066	.073	.130	1													
8	Rest. Reviews	.195	.059	.815	.072	.070	−.037	.046	1												
9	Rest. Popularity	.482	.052	.258	.094	.083	−.038	.110	.309	1											
10	Site Engagement	.209	.876	.001	.091	.230	.017	.126	.054	.067	1										
11	Past	.041	−.026	.054	.208	.102	−.011	−.002	.060	.067	−.012	1									
12	Perceptive	.004	−.011	.007	.047	.046	.014	.005	.009	.008	−.012	.037	1								
13	Personal	−.013	−.030	−.027	−.100	−.016	−.051	−.026	−.036	−.013	−.031	−.130	−.089	1							
14	Informal	−.019	−.032	.002	−.066	−.089	−.004	−.016	0	−.011	−.032	−.039	.006	−.015	1						
15	Cognitive	.009	−.003	.019	.120	.118	.056	.031	.022	.016	−.002	.067	−.036	−.146	−.033	1					
16	One-Sided	−.028	−.020	.002	−.161	−.082	−.036	−.027	.003	−.012	−.019	−.122	.003	.063	.025	−.114	1				
17	Social	.048	.030	.036	.160	.125	−.043	−.008	.042	.049	.036	.072	−.023	−.025	−.043	.054	−.026	1			
18	Affective	−.061	−.088	−.019	−.292	−.249	−.075	−.060	−.025	−.036	−.091	−.198	.009	.238	.174	−.192	.246	−.071	1		
19	Concreteness	−.098	−.094	−.071	−.442	−.461	−.066	−.061	−.087	−.086	−.103	−.233	.034	.165	.081	−.281	.078	−.148	.336	1	
20	Extremeness	.053	.033	.006	.114	.072	.027	.048	.008	.022	.034	.164	.013	−.032	−.013	.103	−.227	.007	−.160	−.094	1
21	Mobile	−.164	−.295	−.097	−.346	−.337	−.174	−.157	−.123	−.122	−.299	−.088	−.017	.104	.078	−.092	.071	−.122	.262	.344	−.062

275,362 reviews

- **Perceptive** Because perceptual words, such as "see," "hear," and "feel," may affect the degree to which a review conveys the writer's experience, we control for *Perceptual Processes.*
- **Personal** Because words on topics such as work, home, and religion may affect the degree to which a review resonates with the reader, we control for the category *Personal Concerns.*
- **Informal** Because swear words, online abbreviations such as "lol," and filler words may affect review fluency and impact, we control for *Informal* language.
- **Cognitive** We measure *Cognitive* content through words reflecting insight, causation, and discrepancy. Examples of cognitive words are "specifically," "complete," "consequentially."
- **One-Sided** To assess the use of one-sided arguments, we create a variable *One-Sided* and code it as the absolute value of the difference in positive emotion words and negative emotion words, divided by the total of the number of emotion words; $onesided = \frac{|positive-negative|}{(positive+negative+\epsilon)}$. A value of 1 indicates the review contains either only positive or only negative words; a value of 0 is equally balanced between the two. We include an arbitrarily small value, ϵ, in the denominator so that reviews with neither positive nor negative words have a value of 0 for this measure.
- **Social** We measure *Social* concerns through the use of words related to family and friends that reflect concern about others (versus the self).

3.3.3. Review Meta Data Additional attributes of the review (beyond LIWC related measures) may affect review value.

- **Age** Reviews that have been available to users longer will have more time to accumulate likes.
- **Sequence** Beyond age, review creation order may influence value in that later reviews may provide marginally less value than early reviews (Li and Hitt 2008).
- **Length** Reviews vary in length. We count the number of words in the review to measure the quantity of content. For presentation, we scale *Length* by dividing the number of words by 100.
- **Complexity** We measure the reading *Complexity* of each review using the automated readability index (Smith and Senter 1967). The automated readability index is $ARI = \left(\frac{4.71 \times letters}{words}\right) + \left(\frac{0.5 \times words}{sentences}\right) - 21.43$, and estimates the U.S. school grade required to understand the review.

3.3.4. Reviewer Characteristics Some reviewers may be more influential that other reviewers, independent of the content of any particular review. In some models, we include reviewer fixed effects but this cuts the sample size considerably. Therefore, we alternatively include *Reviewer Reviews*, which is the number of reviews the reviewer had written prior to and including the focal review; we use the natural log of reviews (adding 1 to avoid taking the natural log of zero) to control for positive skew in this count variable. We also include the average likes received for other reviews by the same reviewer, *Reviewer Popularity*; again using the natural log of this value.

3.3.5. Restaurant Characteristics Some restaurants are inherently popular, increasing the number of readers but, at the same time, increasing the number of reviews competing for user attention. In some models, we include restaurant fixed effects but this cuts the sample size considerably. Therefore, we include the natural log of the number of prior reviews for the restaurant, *Restaurant Reviews.* We also include the natural log of average likes received by other reviews for the same restaurant, *Restaurant Popularity.*

3.3.6. Site Characteristics Interest in restaurant reviews in general, and our focal platform in particular, may have changed during the study period. Therefore, we measure *Site Engagement* as the total number of likes for all reviews on the platform in the month preceding the review. For robustness, we considered three alternative measures. First, using Google Trends, we built a measure of interest in restaurant reviewing by gathering the relative weekly search volume of the term "Yelp," another well-known restaurant review platform. Second, using Google Trends, we built a similar measure of interest in Urbanspoon itself by gathering the relative weekly search volume of the term "Urbanspoon." Finally, we considered a measure of the share of interest in Urbanspoon versus Yelp by dividing the Urbanspoon weekly search trend by the Yelp trend. This might be informative if either site had a substantial change in their share of reviewing activity during our study period. All three measures are highly correlated with *Site Engagement*; results are similar using either of the four measures of restaurant reviewing interest.

4. Results

We begin with comparisons of mean and median differences in content attributes, then use independent linear models on the full sample and dual platform subsample, with and without reviewer fixed effects. Poisson regression models describe the relationship between content characteristics and perceived value; additional Poisson and linear mixed models investigate the robustness of these focal results using alternative specifications and sampling frames. We follow these with matching models and sensitivity analysis of potential bias from lack of random assignment to platform. Additionally, we investigate the possibility of differences in presentation order by platform. Finally, we consider how consumer perception changes after the introduction of the mobile platform.

4.1. Mobile WOM Content

Table 3 compares the mean and median values of focal attributes for reviews created on mobile versus non-mobile platforms. Comparisons use either t-tests (for differences in means) or continuity-corrected Wilcoxon rank sum tests (for differences in medians). We find that mobile content is more affective ($t = 135.76$, $p < 0.001$), more concrete ($t = 210.07$, $p < 0.001$), and less extreme ($t = -32.72$, $p < 0.001$). Results are qualitatively similar in the dual platform subsample as well, indicating that platform differences are not likely driven by differences in reviewer characteristics. While these basic comparisons do not control for variables other than the focal attribute, they illustrate that observed differences are a) not artifacts of the more complex models that follow and b) prevalent in both the complete sample and dual platform subsample.

Each cell of Table 4 indicates coefficient (β) estimates for the mobile indicator variable from a series of regressions using the content measures as dependent variables; intercepts are included in each model but for presentation are not shown in the table. Column C1 shows the results of independent linear regressions using the natural log of each content measure as the dependent variable in the full sample (adding 1 to avoid taking the natural log of zero), Column C2 includes reviewer fixed effects, Column C3 focuses on the dual platform subsample only, and Column C4 the dual platform subsample with fixed effects to control for reviewer characteristics.

Table 3 Mobile versus Non-Mobile – Comparison of Means and Medians

	Full Sample				Dual Platform Subsample			
	Means		Medians		Means		Medians	
Variable	Δ	t	Δ	$W \times 10^{10}$	Δ	t	Δ	$W \times 10^{7}$
Length	−48.64	−215.11***	−32.00	1.45***	−29.21	−42.05***	−20.00	7.14***
Complexity	−2.83	−195.27***	−2.51	1.32***	−1.68	−35.19***	−1.58	6.69***
Past	−0.75	−45.98***	−2.88	1.09***	−0.06	−1.07	−0.84	5.54***
Perceptive	0.10	−8.56***	−1.92	1.06***	0.04	0.96	−0.54	5.51***
Personal	0.54	52.32***	0.36	0.88***	0.40	11.16***	0.27	4.93***
Informal	0.33	38.62***	0.00	0.99***	0.15	5.17***	0.00	5.53***
Cognitive	−1.02	−46.98***	−1.20	1.05***	−1.00	−12.16***	−0.98	5.83***
One-Sided	0.05	37.03***	0.00	0.69***	0.02	4.19***	0.00	0.45***
Social	−1.21	−63.22***	−1.45	1.10***	−0.67	−10.54***	−0.91	5.83***
Affective	3.21	135.76***	2.85	0.66***	1.97	24.11***	1.75	4.20***
Concrete	0.99	210.07***	0.91	0.42***	0.60	35.20***	0.54	3.39***
Extreme	−0.05	−32.72***	0.00	0.98***	−0.02	−3.18***	0.00	0.53**

Comparison of review attributes by platform. Positive numbers indicate that that the mean (median) is greater for the mobile platform while negative numbers indicate that the mean (median) is greater for the non-mobile platform. Mean comparisons are based on t-tests; median comparisons use continuity-corrected Wilcoxon rank sum tests. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 275,362 reviews in the complete sample and 21,026 reviews in the dual platform subsample from reviewers who have created 4 or more reviews on both platforms.

Across these different models and samples, results are similar and consistent with the results in Table 3. Mobile content is more affective ($\beta = \{0.256, 0.173, 0.163, 0.170\}$, $p < 0.001$) and more concrete ($\beta = \{0.381, 0.256, 0.233, 0.224\}$, $p < 0.001$). For extremeness, the results are mixed; models without reviewer fixed effects find that mobile content is less extreme ($\beta = \{-0.038, -0.014\}$, $p < \{0.001, 0.01\}$) but models that include reviewer fixed effects do not find a statistically significant relationship. Results are similar using binary logit models for rating extremity.

Table 4 Differences in Mobile Review Content

Dependent Variable	Column C1	Column C2	Column C3	Column C4
Affective	0.256***	0.173***	0.163***	0.170***
	(0.003)	(0.008)	(0.010)	(0.011)
Concrete	0.381***	0.256***	0.233***	0.224***
	(0.001)	(0.004)	(0.005)	(0.005)
Extreme	−0.038***	−0.007	−0.014**	−0.001
	(0.001)	(0.003)	(0.004)	(0.005)
Sample	Full	Full	Dual Platform	Dual Platform
Reviewer fixed effects		Included		Included
Observations	275,362	275,362	21,026	21,026

Regressions use independent ordinary least squares (C1, C3) or fixed effect panel regressions (C2, C4) using the natural log of the attributes as dependent variables (adding 1 to avoid taking the natural log of 0). Heteroscedasticity-consistent (HC3) standard errors (C1, C3) or clustered standard errors (C2, C4) in parentheses. The dual platform subsample only includes reviews from reviewers who have contributed at least 4 mobile and 4 non-mobile reviews. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

4.2. Consumption Value

4.2.1. Mobile Content We propose that characteristics associated with the review platform affect how users write reviews; these differences in content should be associated with the perceived value of these reviews. Some content differences may be associated with an increase while others may be related to decreased WOM value. Our focal measure of perceived value is a count of the number of users who indicate they like the review. We use Poisson regressions that examine how content attributes affect perceived value. (Results are similar using negative binomial models.)

Table 5 summarizes the results of the analysis of WOM value. To control for alternative explanations, all models include all content variables (i.e., Past, Perception, Personal, Informal, Cognitive, One-sided, and Social) beyond our three focal content variables (i.e., Affective, Concrete, and Extreme) and base estimates of significance using heteroscedasticity-consistent (HC3) standard errors (for Poisson models) or clustered standard errors (for mixed models.)

Model V0 includes control variables along with the focal content variables. More affective content is associated with a reduced number of likes ($\beta = -0.030$, $p < 0.01$). More concrete content is also associated with a reduced number of likes ($\beta = -0.145$, $p < 0.001$). More extreme content is associated with a greater number of likes ($\beta = 0.151$, $p < 0.001$). Creating WOM on the mobile platform is related to differences in the content (Affective, Concrete, and Extreme); in the control model, these difference are associated with reduced consumption of that content.

4.2.2. Creation Platform Even after controlling for the observable review, reviewer, and restaurant characteristics, does creation platform affect review value? We propose that simply knowing that content was created on a mobile device may change its value beyond effects of differences in content. Model V1 adds the platform of creation as an additional explanatory variable and finds that mobile content is associated with reduced value ($\beta = -0.409$, $p < 0.001$.) On average, mobile content is associated with 40% fewer likes; however, this average effect masks heterogeneous effects that we examine further. Before investigating these sources of heterogeneity, we consider a number of possible alternative explanations for this continued difference.

Table 5 Consumption of Mobile Reviews versus Non-Mobile Reviews

	Model V0	Model V1	Model V2	Model V3	Model V4
Intercept	-3.317^{***}	-2.985^{***}	-0.097^{***}	-0.151^{***}	-0.136^{***}
	(0.068)	(0.067)	(0.010)	(0.011)	(0.011)
Reviewer (fixed effects)				yes	yes
Restaurant (fixed effects)			yes		yes
Age (ln, days)	0.436^{***}	0.396^{***}	0.050^{***}	0.054^{***}	0.061^{***}
	(0.012)	(0.011)	(0.002)	(0.002)	(0.002)
Review Sequence (ln)	-0.092^{***}	-0.099^{***}	0.027^{***}	-0.021^{***}	0.029^{***}
	(0.009)	(0.009)	(0.001)	(0.002)	(0.001)
Length (/100, ln)	0.196^{***}	0.150^{***}	0.046^{***}	0.041^{***}	0.046^{***}
	(0.012)	(0.013)	(0.002)	(0.002)	(0.002)
Complexity (ln)	0.009	0.002	0.002	0.002	0.002
	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)
Reviewer Reviews (ln)	-0.041^{***}	-0.049^{***}	-0.016^{***}		
	(0.004)	(0.004)	(0.001)		
Reviewer Popularity (ln)	0.452^{***}	0.435^{***}	0.263^{***}		
	(0.016)	(0.015)	(0.003)		
Restaurant Reviews (ln)	0.109^{***}	0.105^{***}		0.005^{**}	
	(0.008)	(0.008)		(0.002)	
Restaurant Popularity (ln)	1.131^{***}	1.116^{***}		0.502^{***}	
	(0.010)	(0.010)		(0.002)	
Site Engagement (avg)	0.138^{***}	0.174^{***}	0.148^{***}	0.194^{***}	
	(0.018)	(0.018)	(0.003)	(0.004)	(0.004)
Text metrics	yes	yes	yes	yes	yes
Affective (ln)	-0.030^{**}	-0.014	0.003^{*}	0.001	0.003^{*}
	(0.010)	(0.009)	(0.001)	(0.001)	(0.001)
Concrete (ln)	-0.145^{***}	-0.079^{*}	-0.003	0.004	0.001
	(0.031)	(0.032)	(0.004)	(0.004)	(0.004)
Extreme (ln)	0.151^{***}	0.156^{***}	0.043^{***}	0.036^{***}	0.045^{***}
	(0.011)	(0.011)	(0.002)	(0.002)	(0.002)
Mobile		-0.409^{***}	-0.058^{***}	-0.075^{***}	-0.076^{***}
		(0.013)	(0.002)	(0.002)	(0.002)
Log Likelihood	-289,066.9	-287,253.6	-172,938.9	-161,680.9	-167,224.4
Akaike Information Criterion	578,185.7	574,561.3	345,931.7	323,415.8	334,500.8

Poisson regressions (V0, V1) using likes or linear mixed models (V2, V3, V4) using natural log of likes (adding 1 to avoid taking the natural log of 0) as dependent variables for 275,362 reviews. Heteroscedasticity-consistent (HC3) standard errors in parentheses (V0, V1). Fixed effects for day of week included. All models include all text metrics (Past, Perception, Personal, Informal, Cognitive, One-sided, Social; see Table 9 in the Appendix for the complete table.) $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Alternative modeling choices To begin, the continued effect of creation platform may be due to modeling choices. Model V2 includes restaurant fixed effects; Model V3 includes reviewer fixed effects; and Model V4 includes both restaurant and reviewer fixed effects. All models continue to find a significant negative relationship ($\beta = \{-0.409, -0.058, -0.075, -0.076\}$, $p < 0.001$) between mobile platform and consumption value.

Sampling alternatives Table 6 considers sampling alternatives using Poisson models. Heavily-liked reviews could be more influential; Model S1 excludes the top 25% of reviews by number of likes. Similarly, reviews without any likes could drive the results; Model S2 excludes reviews without any likes. Mobile reviewers may differ in unobservable ways from non-mobile reviewers; Model S3 considers only reviews where the reviewer reviewed at least four times on each platform and includes reviewer fixed effects. Similarly, some restaurants may attract reviewers with unobservable characteristics; Model S4 considers only reviews where the restaurant was reviewed at least four times on each platform and includes restaurant fixed effects. In all samples, reviews created on mobile devices continue to have lower perceived value ($\beta = \{-0.271, -0.087, -0.116, -0.199\}$, $p < 0.01$ in all models and $p < 0.001$ in many of these).

Matching models We also examine models that, for each mobile review, find a similar non-mobile review. Because content cannot be matched exactly, we use coarsened exact matching (Iacus et al. 2015). Table 7 describes the details of the matching process. We match on content attributes, valence, and other review / reviewer characteristics. We match three different ways: (M1) allowing the observations to vary, (M2) enforcing the same number of matches of each type, and (M3) matching on reviewer characteristics as well while allowing the number of observations to vary. The matching process results in a substantial reduction in both mean difference and imbalance ($\mathcal{L}_1$) along every dimension. However, this matching comes at a cost of reduced sample size. For example, because of excluded reviews for which no close match was found, the number of reviews drops from 275,362 to 14,776 in the M1 matching. However, the benefit is that for each mobile review that is retained, the sample contains a closely matching non-mobile review. We again find that creation on a mobile platform is associated with a decrease ($\beta = -0.052$, $p < 0.001$) in the perceived value of reviews (measured by the natural log of the number of likes and continuing to control for all other variables [i.e., review age, reviewer reviews, reviewer popularity, restaurant reviews, restaurant popularity, sequence, and site engagement]). Although the matching models do not establish a causal relationship, they provide additional evidence that the observed relationship is related to the creation platform rather than other observed characteristics.

Table 6 Consumption of Mobile versus Non-Mobile Reviews (Sampling Alternatives)

	Model S1	Model S2	Model S3	Model S4
Intercept	-3.457^{***}	-0.225^{***}	-3.410^{***}	-3.529^{***}
	(0.056)	(0.056)	(0.285)	(0.132)
Reviewer (fixed effects)			yes	
Restaurant (fixed effects)				yes
Age (ln, days)	0.282^{***}	0.140^{***}	0.546^{***}	0.526^{***}
	(0.009)	(0.009)	(0.038)	(0.023)
Review Sequence (ln)	-0.020^{*}	-0.049^{***}	-0.093^{**}	0.012
	(0.008)	(0.007)	(0.028)	(0.009)
Length (/100, ln)	0.035^{***}	0.101^{***}	0.316^{***}	0.161^{***}
	(0.010)	(0.011)	(0.042)	(0.017)
Complexity (ln)	0.023^{**}	-0.012	-0.003	-0.009
	(0.008)	(0.008)	(0.029)	(0.015)
Reviewer Reviews (ln)	0.010^{**}	-0.058^{***}		-0.023^{***}
	(0.003)	(0.003)		(0.006)
Reviewer Popularity (ln)	0.557^{***}	0.231^{***}		0.241^{***}
	(0.011)	(0.010)		(0.013)
Restaurant Reviews (ln)	0.071^{***}	-0.041^{***}	0.015	
	(0.008)	(0.007)	(0.026)	
Restaurant Popularity (ln)	0.810^{***}	0.618^{***}	0.836^{***}	
	(0.009)	(0.010)	(0.037)	
Site Engagement (avg)	-0.075^{***}	0.190^{***}	-0.038	0.387^{***}
	(0.016)	(0.013)	(0.098)	(0.030)
Text metrics	yes	yes	yes	yes
Affective (ln)	-0.004	-0.012	0.007	0.018
	(0.008)	(0.008)	(0.029)	(0.014)
Concrete (ln)	-0.106^{***}	0.004	0.032	-0.057
	(0.024)	(0.026)	(0.092)	(0.049)
Extreme (ln)	0.025^{*}	0.112^{***}	0.182^{***}	0.238^{***}
	(0.010)	(0.009)	(0.030)	(0.016)
Mobile	-0.271^{***}	-0.087^{***}	-0.116^{**}	-0.199^{***}
	(0.011)	(0.010)	(0.041)	(0.019)
Observations	240,627	77,061	21,026	19,051
Log Likelihood	-108,609.7	-146,411.1	-17,331.8	-22,848.4
Akaike Information Criterion	217,273.3	292,876.3	36,057.6	45,748.8

Poisson regressions using likes as the dependent variable. Heteroscedasticity-consistent (HC3) standard errors in parentheses. Fixed effects for day of week included. All models include all text metrics (Past, Perception, Personal, Informal, Cognitive, One-sided, Social, Affective, Concrete, Extreme). Log-transforms are of the variable + 1 to avoid taking the log of 0. Model S1 excludes reviews with the 25% greatest likes; Model S2 excludes reviews without any likes; Model S3 includes reviewer fixed effects and excludes any reviewer without at least 4 non-mobile and 4 mobile reviews; Model S4 includes restaurant fixed effects and excludes any reviewer without at least 4 restaurant and 4 restaurant reviews. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Sensitivity Our study is not based on randomized assignment of platform for review creation. As a result, despite efforts to control for alternative explanations, bias remains in our analysis. In particular, platform choice is endogenous to the decision to write a review. Therefore we analyze the sensitivity of our results to this bias. We first match reviews created on mobile platforms with

Table 7 Coarsened Exact Matching

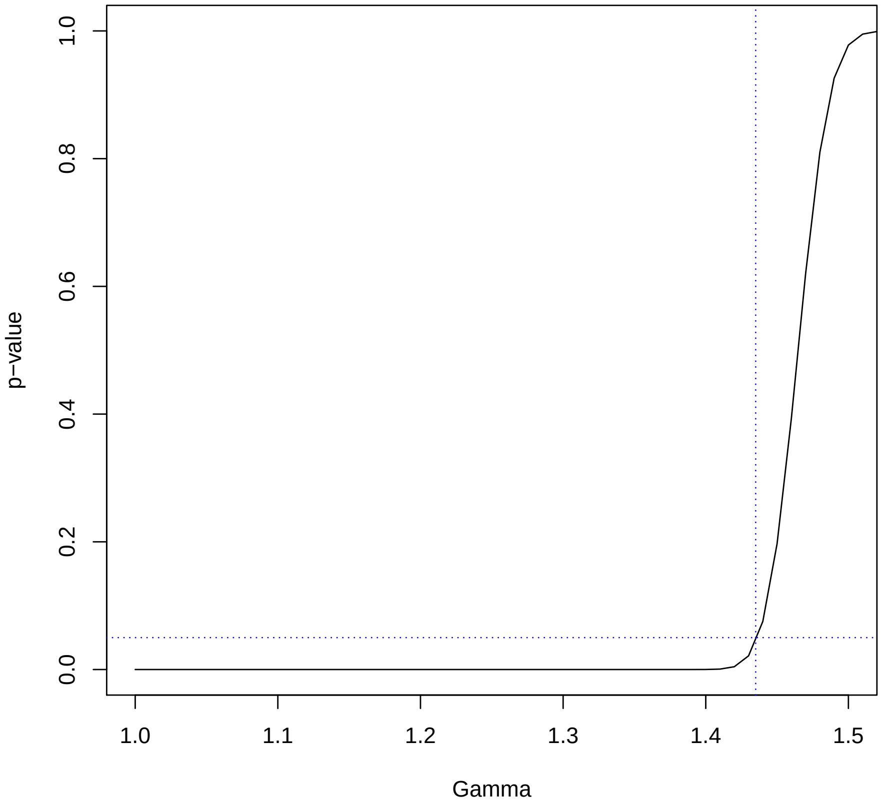
Attribute	Mean Difference Before	M1	M2	M3	Imbalance ($\mathcal{L}_1$) Before	M1	M2	M3
Length (/100, ln)	0.818	0.003	0.003	−0.002	0.000	0.000	0.001	0.001
Complexity (ln)	0.454	0.002	0.002	0.006	0.000	0.000	0.000	0.000
Past (ln)	0.318	0.000	0.000	0.000	0.229	0.000	0.000	0.000
Perceptive (ln)	0.198	0.000	0.000	0.000	0.234	0.000	0.000	0.000
Personal (ln)	−0.030	−0.001	−0.001	0.000	0.117	0.000	0.000	0.000
Informal (ln)	−0.015	0.000	0.000	0.000	0.108	0.000	0.000	0.000
Cognitive (ln)	0.306	−0.002	−0.002	0.000	0.143	0.000	0.000	0.000
One-Sided (ln)	−0.026	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Social (ln)	0.378	−0.001	−0.001	0.001	0.205	0.000	0.000	0.000
Affective (ln)	−0.256	−0.002	−0.002	0.002	0.021	0.000	0.000	0.000
Concrete (ln)	−0.276	0.001	0.001	0.002	0.011	0.000	0.000	0.000
Extreme	0.055	0.000	0.000	0.000	0.055	0.000	0.000	0.000
Reviewer Reviews (ln)	0.436			0.001	0.028			0.000
Reviewer Popularity (ln)	0.159			−0.001	0.170			0.006
Multivariate					0.999	0.859	0.888	0.883
Observations								
Non-Mobile					155,482	6,064	5,587	827
Mobile					119,880	8,712	5,587	1,003
Total					275,362	14,776	11,174	1,830
Common Support						6.8%	5.8%	6.6%
Average linear effect on Likes (ln)								
Mobile						-0.052^{***}	-0.046^{***}	-0.084^{***}
						(0.007)	(0.008)	(0.021)

Comparison of means and imbalance, before and after coarsened matching. M1 uses unbalanced matching; M2 uses balanced k-to-k matching; M3 includes reviewer characteristics with unbalanced matching. Linear models estimate average effects and include unreported coefficients for age, reviewer characteristics, restaurant characteristics, day of week, sequence, and site engagement (standard errors in parentheses).

reviews created on the non-mobile platform (Sekhon 2011). Then, we quantify the amount of bias, Γ, that would be required to qualitatively change the conclusions (Rosenbaum 2005). Figure 4 illustrates the change in significance that results from changes in bias, Γ. We find that the 95% confidence interval remains below zero until Γ is greater than 1.43. To attribute the reduction in perceived value to an unobserved covariate rather than the mobile platform, that unknown covariate would need to produce at least a 143% increase in the likelihood of selecting the mobile platform and directly reduce review value. Although guidelines for Γ in social science research lack consensus, $\Gamma = 1.5$ indicates substantial insensitivity and $\Gamma = 1.2$ is around average (Sen 2014).

Display Order Users are likely more inclined to "like" a review if the website displays the review higher on the webpage. As a result, if platform (non-mobile versus mobile) affected the

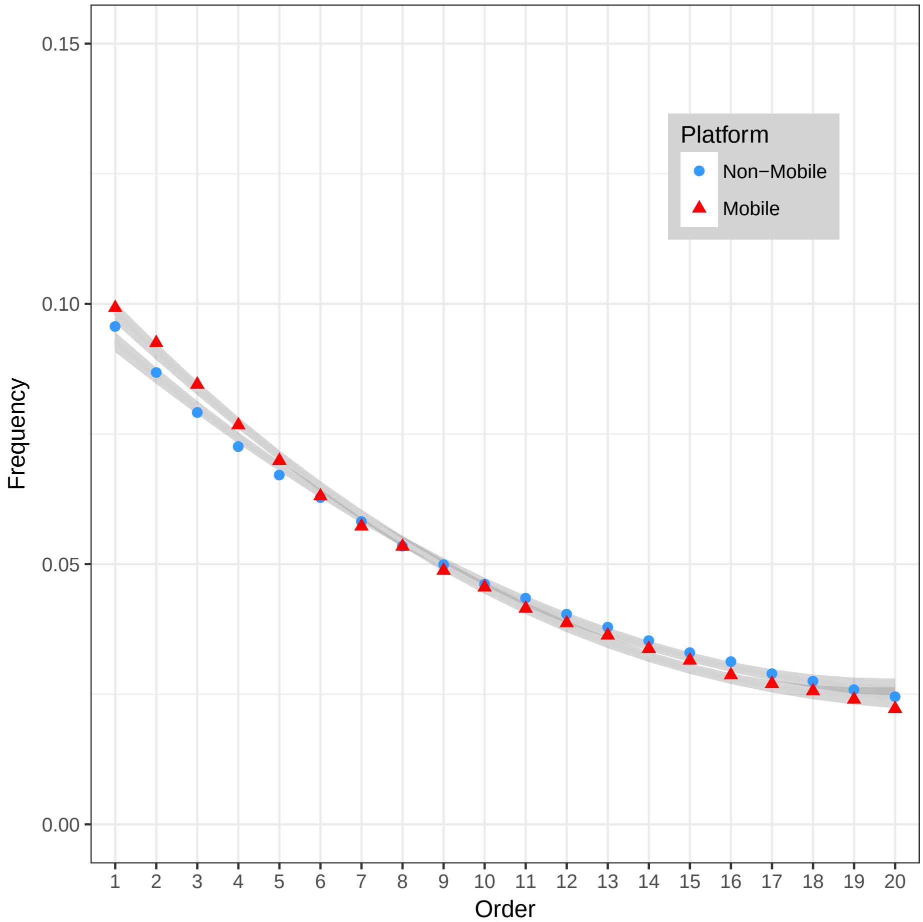
Figure 4 Rosenbaum Sensitivity



display order, then the results we observe could be related to this order of presentation and not the platform itself. However, we do not have information about the order in which each user saw reviews when indicating (or not indicating) that they liked a particular review. Instead, to assess differences in ordering, using the Internet Archive's Wayback machine, we collected a new data sample of 66,257 Urbanspoon restaurant pages up until January 2015 (before the acquisition by Zomato) that contained both non-mobile and mobile reviews. These pages contain 1,309,063 reviews with up to 20 reviews per page.

Figure 5 displays the percentage frequency of review order position by platform. While we do not know the exact ordering for each user at the time they did or did not like a review, we do not see evidence of a sizable systemic difference in the ordering of mobile versus non-mobile reviews.

Figure 5 **Display Order by Platform**



Note.

4.3. Platform Learning

We use the introduction of the mobile platform to further examine how the mobile platform affects consumption value and how it changes over time as consumers learn about mobile platform content quality. The fundamental idea behind this analysis is that the introduction of the new mobile platform in the middle of the study period allows comparison of reviews before and after the introduction of the mobile platform. In this analysis, non-mobile reviews after the introduction of mobile help control for general changes in creation and consumption. The analysis uses the dual platform subsample from reviewers who contributed at least 4 mobile and 4 non-mobile reviews.

Table 8 shows the relationship between platform and WOM value over time. Model T0 contains control variables, text metrics, and indicator variables for each quarter. Model T1 interacts these quarterly indicator variables with mobile platform creation. Initially (in quarters 8 and 9), mobile WOM value is equal or greater than non-mobile value. However, starting in quarter 10, the association with mobile is negative and significant; the magnitude of coefficients generally grows as time progresses, consistent with consumers learning about the relative value of the new platform.

Model T2 introduces linear and quadratic time trends (scaled by dividing by 365 for presentation) instead of quarterly indicator variables. In aggregate, Model T2 finds a negative quadratic effect ($\beta = -0.11.702$, $p < 0.001$) trend of value of all reviews. Model T3 finds this trend does not significantly change for all reviews after the introduction of mobile.

Model T4 separates the post-mobile trend for the mobile and non-mobile reviews using an interaction. The non-mobile trend does not significantly change ($\beta = \{57.562, 30.632\}$, $p > 0.05$) but the trend for mobile reviews is negative ($\beta = -29.814$, $p < 0.01$). Model T5 interacts all variables with the time trend to lend support to the idea that these effects are not being driven by other changes in review content, restaurants, Urbanspoon popularity, or reviewers over time. Together, these results indicate that, over time, consumers valued mobile reviews less than non-mobile reviews.

Figure 6 illustrates the changes in consumption valuation over time, relative to quarter 7 of our study period (quarter 2 of 2008.) After the initial introduction of the mobile platform, the valuation of mobile reviews was significantly greater than non-mobile reviews. However, as the quarters progressed, the valuation of mobile content decreased while that of non-mobile reviews was stable.

5. Conclusion

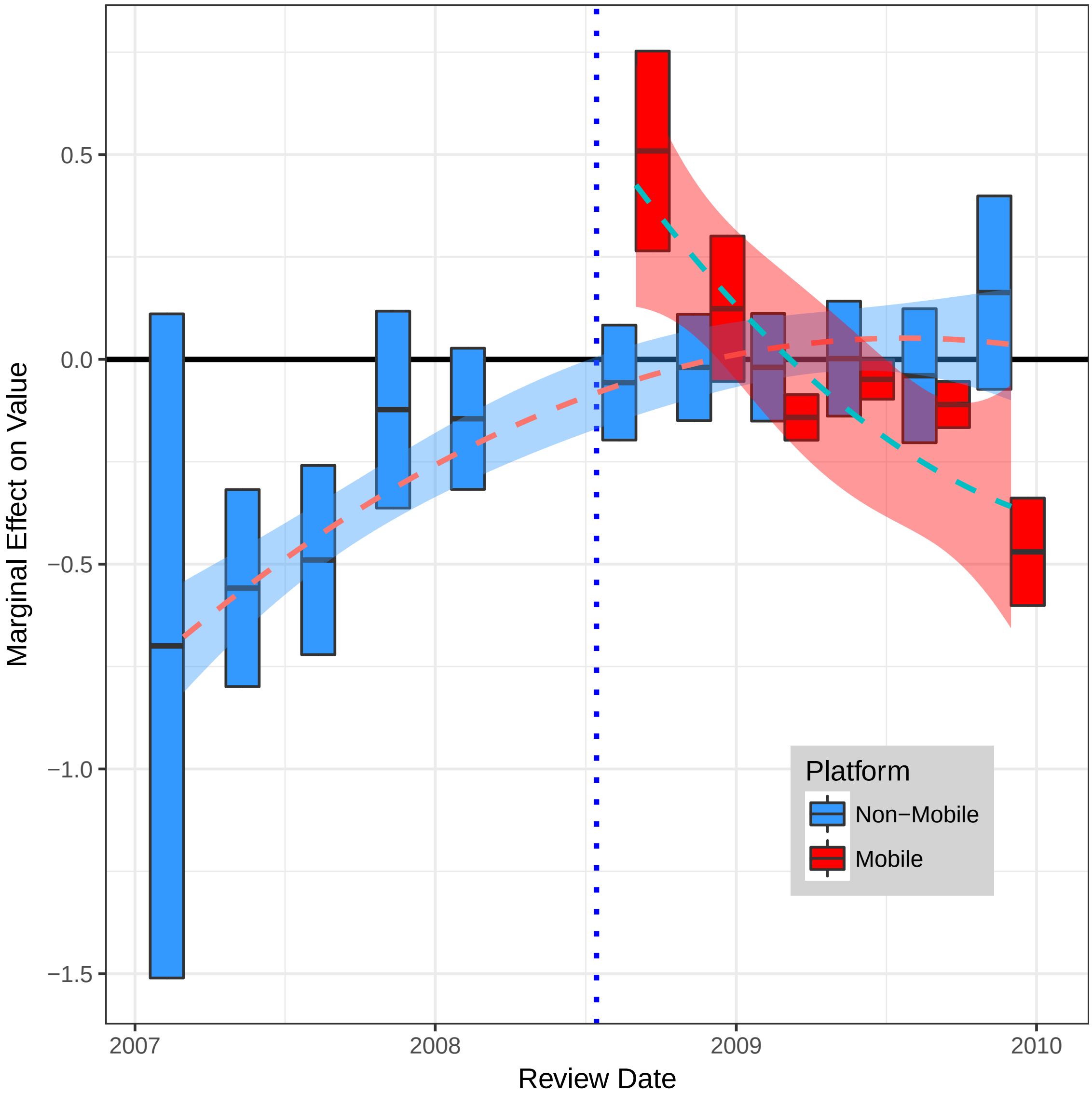
We propose that: 1) The real-time creation process associated with mobile WOM should indirectly affect WOM consumption by changing WOM content, 2) knowing that a review was created on a mobile platform should directly affect WOM consumption through associations between the mobile label and information quality, and 3) this direct relationship should grow stronger as consumers learn about the association between platform and information quality. We test these ideas using a unique data set that identifies whether reviews were created on mobile versus non-mobile platforms and allows us to examine reviews written by the same people on both platforms.

Table 8 Platform Learning Effects on Consumption of Mobile vs. Non-Mobile Reviews over Time

	Model T0	Model T1	Model T2	Model T3	Model T4	Model T5
Intercept	-3.793^{***}	-3.833^{***}	-3.523^{***}	-4.528^{***}	-4.693^{***}	-4.017
	(0.372)	(0.368)	(0.273)	(0.764)	(0.768)	(4.031)
Age (ln, days)	0.474^{***}	0.483^{***}	0.405^{***}	0.471^{***}	0.500^{***}	0.285
	(0.045)	(0.044)	(0.040)	(0.057)	(0.058)	(0.819)
Sequence (ln)	-0.040^{*}	-0.040^{*}	-0.038	-0.041^{*}	-0.041^{*}	-0.032
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.023)
Length (/100, ln)	0.192^{***}	0.177^{***}	0.191^{***}	0.193^{***}	0.187^{***}	0.198^{***}
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.032)
Complexity (ln)	0.013	0.013	0.016	0.014	0.017	0.045
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.025)
Reviewer Reviews (ln)	0.057^{***}	0.052^{***}	0.060^{***}	0.059^{***}	0.058^{***}	0.067^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Reviewer Popularity (ln)	1.134^{***}	1.134^{***}	1.133^{***}	1.135^{***}	1.136^{***}	1.161^{***}
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.029)
Restaurant Reviews (ln)	-0.006	-0.006	-0.007	-0.005	-0.005	-0.014
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)
Restaurant Popularity (ln)	0.996^{***}	0.995^{***}	0.998^{***}	0.998^{***}	0.998^{***}	0.990^{***}
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Text metrics	yes	yes	yes	yes	yes	yes
Quarter (fixed effects)	yes	yes				
Quarter 8 × Mobile		0.509^{*}				
		(0.244)				
Quarter 9 × Mobile		0.124				
		(0.136)				
Quarter 10 × Mobile		-0.142^{**}				
		(0.048)				
Quarter 11 × Mobile		-0.049				
		(0.042)				
Quarter 12 × Mobile		-0.110^{*}				
		(0.048)				
Quarter 13 × Mobile		-0.470^{***}				
		(0.109)				
Post Mobile			0.003	0.698	0.725	1.049
			(0.127)	(0.686)	(0.686)	(0.765)
Time (/365 days)			-9.079	-56.298	-54.603	-316.252
			(6.308)	(48.392)	(48.398)	(662.654)
Time^2 (/365 days)			-11.702^{***}	-27.819^{*}	-27.645^{*}	-30.353
			(3.065)	(13.801)	(13.803)	(21.971)
Time × Post Mobile				52.211	57.562	86.019
				(48.448)	(48.490)	(58.720)
Time^2 × Post Mobile				29.516	30.632	48.821
				(16.944)	(17.212)	(35.988)
Time × Post Mobile × Mobile					-29.814^{**}	-28.685^{*}
					(11.250)	(12.094)
Time^2 × Post Mobile × Mobile					30.811^{*}	30.001
					(15.230)	(15.746)
Time (interacted with all)						yes
Log Likelihood	-41,827.6	-41,772.7	-41,842.2	-41,838.3	-41,826.8	-41,758.8
Akaike Information Criterion	83,729.1	83,631.4	83,740.4	83,736.6	83,717.6	83,629.6

Poisson regression using likes as the dependent variable for 45,766 reviews. Log-transforms are of the variable + 1 to avoid taking the log of 0. Heteroscedasticity-consistent (HC3) standard errors in parentheses. Fixed effects for day of week included. All models include all text metrics (Past, Perception, Personal, Informal, Cognitive, One-sided, Social, Affective, Concrete, Extreme.) $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure 6 **Changes in Consumption Value by Platform over Time**



In support of the idea that the real-time creation process reduces reflection, is focused on the present, and increases the likelihood that consumers engage in word-of-mouth about neutral, as well as very positive and negative experiences, we find that content created on mobile devices is more affective, involves more concrete language, and is less extreme. These content differences are associated with lower perceived value. However, once source platform is considered, only extremeness is consistently associated with perceived content value.

Even after controlling for differences in the content of mobile and non-mobile word-of-mouth, reviewer, and restaurant characteristics, we find that mobile word-of-mouth is less valued. An analysis of how WOM value changed after the introduction of the mobile application shows that, although mobile WOM initially had equal or greater consumption value, over time, it became significantly lower than non-mobile WOM; presumably as consumers developed stronger negative associations between the mobile platform and its quality as a source of information.

Some of these results are somewhat different from those of prior research. For example, Chen and Lurie (2013) find that the presence of temporal contiguity cues–words such as "just got back" linking service experiences to review writing increases the value of positive (but not negative) reviews. To the extent that the real-time nature of mobile reviews is associated with higher value value for positively valenced reviews, by increasing the presence of temporal contiguity cues, or that the mobile label itself serves a temporal contiguity cue, our results show that these positive associations are overwhelmed by the negative associations of the mobile platform.

5.1. Is Mobile Different?

We find differences in mobile versus non-mobile content in every model we try. Despite the consistency of our findings, they are descriptive; not conclusive. In our context, the process of selecting the platform and writing the review are co-mingled. A sensitivity analysis suggests that the results are relatively insensitive to this endogeneity but we cannot completely rule it out.

Our results should be interpreted as indicators of potential platform effects interesting enough to warrant future research that cleanly identifies (a) the selection of platform, (b) the effect the platform on content, and (c) the perception of value attributable to platform only. One potential avenue is randomized experiments. At the same time, antecedents, such as restaurant experience, or creation platform are difficult to randomize without resorting to hypothetical scenarios that may lack validity and lead to demand effects. Other sources of identification, such as instrumentation through mobile outages, also introduce variation in propensity to review.

5.2. Theoretical Implications

Our research adds to the growing literature on how mobility affects behavior and contributes to data-driven theory development on mobile marketing (Lamberton and Stephen 2016). We add to research examining consumer response to mobile coupons from marketers (Fong et al. 2015, Zubcsek et al. 2015), differences in search costs and clickthrough on mobile devices (Ghose et al. 2012), data usage patterns (Ghose and Han 2011), and use of mobile platforms for habitual purchase (Wang et al. 2015) to examine how the mobile platform affects the content that consumers create. We draw on psycho-linguistic analysis (Brysbaert et al. 2014, Pennebaker et al. 2015) to provide insights into psychological differences in mobile WOM.

Our study is one of the first to examine how the mobile platform is associated with consumption value and how this changes over time. Some of our results are consistent with prior research while others add important nuance. For example, results showing that less extreme ratings are less valued are consistent with the findings of Mudambi and Schuff (2010). However, results showing that more affective content is less valued contrasts with research showing that arousing content is more likely to be shared (Berger and Milkman 2012). Our results showing that the relative value of mobile WOM diminishes over time adds to research on the dynamics of WOM content and ratings (Li and Hitt 2008, Moe and Schweidel 2012). Our study thus contributes to prior research on the creation, effects, and dynamics of WOM (e.g., Berger et al. 2010, Chen and Lurie 2013, Godes and Mayzlin 2004, Li and Hitt 2008, Toubia and Stephen 2013).

5.3. Managerial Implications

Our results support the idea that mobile word-of-mouth is created in real-time using devices that are more accessible than traditional desktop or laptop computers. This leads to differences in content. Furthermore, while estimates vary by model, mobile reviews are associated with a 10%-40% reduction in the number of likes a review receives. Understanding these differences is important to managers who seek insights from mobile word-of-mouth and who wish to determine how to best respond to mobile users.

Two important managerial implications that our research raises, but does not completely resolve, is 1) whether to encourage people to write mobile reviews, 2) whether mobile reviews should be marked as such. Our results show that mobile reviews have lower consumption value and that the negative relationship increases over time. This argues for discouraging mobile reviewing. At the same time, the act of writing reviews may be therapeutic and help consumers make sense of their experiences (Berger 2014)—raising value for review writers—if not for those who read reviews. Although real-time user attitudes may not persist, their word-of-mouth will. Managers may attempt to address these concerns by encouraging review writing sufficiently after service experiences.

5.4. Limitations and Future Research

While our analysis includes many measures, the creation platform may affect content variables that our analysis does not measure. There is a need for research to understand additional ways in which mobile content differs from non-mobile. Other research could examine how platform affects word-of-mouth creation and content over time (Moe and Schweidel 2012). Future research could also use examine how platform affects actual purchase behavior.

Although examining the subset of reviewers who write both mobile and non-mobile reviews helps control for individual differences that may be associated with platform choice, we are unable to isolate platform effects from contextual (such as consumption platform, März et al. 2017) and psychological state variables that may drive the observed effects. Additionally, our data comes from a single company and other companies' experiences and management of mobile may differ. Additionally, we focus on the early period of mobile adoption. Mobile has changed significantly since that time and further study is warranted. However, our study identifies important differences in mobile content and value that could become stronger over time as consumers gain experience with the mobile platform. However, as new technologies continue to change the user experience, and the ways in which users communicate these experiences to others, managers will face new opportunities to gain insights as well as challenges to meet consumer needs. Our study may be applicable as other new platforms emerge.

Acknowledgments

This research was supported by grants from the Marketing Science Institute, the Wharton Customer Analytics Initiative, and the Connecticut Information Technology Institute.

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Appendix. Appendix

For brevity, Table 5 does not include all text characteristics in the output. Table 9 describes these fully.

Table 9 Consumption of Mobile Reviews versus Non-Mobile Reviews (Full)

	Model V0	Model V1	Model V2	Model V3	Model V4
Intercept	-3.317^{***}	-2.985^{***}	-0.097^{***}	-0.151^{***}	-0.136^{***}
	(0.068)	(0.067)	(0.010)	(0.011)	(0.011)
Reviewer (fixed effects)				yes	yes
Restaurant (fixed effects)			yes		yes
Age (ln, days)	0.436^{***}	0.396^{***}	0.050^{***}	0.054^{***}	0.061^{***}
	(0.012)	(0.011)	(0.002)	(0.002)	(0.002)
Review Sequence (ln)	-0.092^{***}	-0.099^{***}	0.027^{***}	-0.021^{***}	0.029^{***}
	(0.009)	(0.009)	(0.001)	(0.002)	(0.001)
Length (/100, ln)	0.196^{***}	0.150^{***}	0.046^{***}	0.041^{***}	0.046^{***}
	(0.012)	(0.013)	(0.002)	(0.002)	(0.002)
Complexity (ln)	0.009	0.002	0.002	0.002	0.002
	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)
Reviewer Reviews (ln)	-0.041^{***}	-0.049^{***}	-0.016^{***}		
	(0.004)	(0.004)	(0.001)		
Reviewer Popularity (ln)	0.452^{***}	0.435^{***}	0.263^{***}		
	(0.016)	(0.015)	(0.003)		
Restaurant Reviews (ln)	0.109^{***}	0.105^{***}		0.005^{**}	
	(0.008)	(0.008)		(0.002)	
Restaurant Popularity (ln)	1.131^{***}	1.116^{***}		0.502^{***}	
	(0.010)	(0.010)		(0.002)	
Site Engagement (avg)	0.138^{***}	0.174^{***}	0.148^{***}	0.194^{***}	
	(0.018)	(0.018)	(0.003)	(0.004)	(0.004)
Past (ln)	-0.004	0.0001	-0.002	-0.003^{***}	-0.001
	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Perception (ln)	0.0002	-0.002	-0.001	-0.002	-0.001
	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Personal (ln)	0.041^{***}	0.045^{***}	0.006^{***}	0.005^{***}	0.005^{***}
	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
Informal (ln)	-0.010	-0.006	-0.003	-0.002	-0.002
	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
Cognitive (ln)	-0.069^{***}	-0.066^{***}	-0.012^{***}	-0.011^{***}	-0.010^{***}
	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
One-sided (ln)	-0.031	-0.047	-0.004	0.006	0.001
	(0.025)	(0.025)	(0.004)	(0.004)	(0.004)
Social (ln)	0.026^{***}	0.017^{**}	0.001	0.002^{*}	0.001
	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Affective (ln)	-0.030^{**}	-0.014	0.003^{*}	0.001	0.003^{*}
	(0.010)	(0.009)	(0.001)	(0.001)	(0.001)
Concrete (ln)	-0.145^{***}	-0.079^{*}	-0.003	0.004	0.001
	(0.031)	(0.032)	(0.004)	(0.004)	(0.004)
Extreme (ln)	0.151^{***}	0.156^{***}	0.043^{***}	0.036^{***}	0.045^{***}
	(0.011)	(0.011)	(0.002)	(0.002)	(0.002)
Mobile		-0.409^{***}	-0.058^{***}	-0.075^{***}	-0.076^{***}
		(0.013)	(0.002)	(0.002)	(0.002)
Log Likelihood	-289,066.9	-287,253.6	-172,938.9	-161,680.9	-167,224.4
Akaike Information Criterion	578,185.7	574,561.3	345,931.7	323,415.8	334,500.8

Poisson regression using likes (V0, V1) or linear mixed models using natural log of likes (V2, V3, V4) as dependent variables for 275,362 reviews. Heteroscedasticity-consistent (HC3) standard errors in parentheses (V0, V1). Fixed effects for day of week included. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$