Opinion Convergence versus Polarization: Examining Opinion Distributions in Online Word-of-Mouth

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We examine how opinion distributions (i.e., opinion polarization and convergence over time) differ across product salient platforms (product platforms) versus product non-salient platforms (non-product platforms). Drawing on the theory of impression management, we hypothesize and explain when and why consumers choose to post their comments on different platforms, and how their behavior will be affected when they choose to post on online platforms. To test the hypotheses, we collected and text-mined online posts from product platforms such as review aggregator sites, discussion forums, and consumer rating websites, and non-product platforms such as microblogs. The results showed that product platforms have more polarized opinions, and exhibit more convergence in opinion across time, compared with non-product platforms. Our findings advise researchers and practitioners to pay attention to the characteristics of online platforms, and how users' perceptions of the purpose of the online platform may affect their online posting behavior.

Introduction

Modern consumers depend significantly on online opinions when making purchase decisions (Huang, Boh, & Goh, 2017). Platforms are also increasingly likely to help consumers make sense of the word-of-mouth (WOM) information available by providing the dispersion of the WOM information. The access to widespread online WOM information thus enables consumers to assess not only the opinions of others about the focal product or service, but also to ascertain the extent to which the opinions are consistent or dispersive (He & Bond, 2015). Prior research has shown that the distribution of online WOM opinions play an important role in consumers' decision making. Feng, Liu, and Fang (2015), for example, highlighted that high variance in user reviews may lead potential buyers to conclude that the product did not match their needs and preferences and exclude the focal product from further consideration in certain cases. In other cases and niche products, variance in user reviews can elicit a sense of uniqueness and enhance consumers' purchase intentions. Prior research has generally concluded that online opinion dispersion has a non-trivial influence on consumers, but the effects tend to be mixed and rather nuanced (Kiron, 2012).

With consumers often encountering a mixture of both positive and negative opinions about the same product or service, there is an increasing need and a long-standing call for researchers to contribute to a greater understanding of opinion dispersion (He & Bond, 2015). Although prior research has focused on examining the effects of online WOM dispersion on consumer attitudes (Feng et al., 2015; Kiron, 2012), another important question that remains unanswered is whether and how the use of different online platforms affects opinion distribution. Prior research has attributed opinion dispersion to product or individual taste differences (Bhattacharya, Phan, Bai, & Airoldi, 2015). Opinion dispersion attributed to products reflects inconsistent product performance and can be perceived to be

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negative. Opinion dispersion attributed to consumer characteristics, on the other hand, often result from taste and personality dissimilarity across individuals (Rozenkrants, Wheeler, & Shiv, 2018). One factor that has yet to be considered in this literature stream is whether the technology platform itself might influence the dispersion of consumers' opinions.

Theory building in the IS domain stresses the importance of considering how technological characteristics influence consumers' use of an IT artifact. Although we have built a rich tradition of understanding how technological characteristics influence the use and adoption of organizational information systems (Singh, 1997; Steensma & Corley, 2000), there is limited research on how different technological platforms influence consumers' online posting behaviors. Prior research tends to study consumer reviews from a single site, or a limited number of sites (Godes & Silva, 2012; Moe & Schweidel, 2012), and has not examined whether different online platforms exhibit differences in opinion polarization or opinion convergence. Our study thus aims to guidance about how one should interpret and regard comments sourced from different online platforms. Specifically, our research answers the following research question: In what ways do opinion distributions (i.e. opinion polarization and convergence) differ across different types of online platforms, and over time? In so doing, we provide an understanding of when and why opinion polarization and opinion convergence happens across different online platforms.

We focus on two dimensions of opinion distributions: opinion polarization and convergence. Opinion polarization refers to the extent to which consumers exhibit extremely positive and extremely negative comments online. Prior research has shown that consumers may pay special attention to agreement of extreme comments between themselves and other reviewers (Gershoff, Mukherjee, & Mukhopadhyay, 2003). Further, extreme comments may lead to bimodal distributions, which is more desirable for consumers looking for self-expression or who value uniqueness (Rozenkrants et al., 2018). It is thus important to examine whether differences in online platforms may result in a greater extent of extreme comments. Convergence, on the other hand, reflects the amount of dispersion in the sentiment reflected in online comments. The dispersion in sentiment reflects the level of consensus in opinions among consumers and can provide potentially valuable social information and information about the emerging social dynamic as reflected in the online WOM (Rozenkrants et al., 2018). As highlighted above, opinion dispersion can have significant influence on consumer decision making and attitudes about the product.

Our findings provide various theoretical and practical implications. Theoretically, we extend the knowledge of opinion distribution in the online context. Because of proliferation of various online outlets, opinion distribution is now observable and influences consumer decision making (He & Bond, 2015). Recent years have witnessed burgeoning interests on distribution characteristics of online WOM (Moon, Bergey, & Iacobucci, 2010; Sun, 2012). However, prior research has not examined whether different online platforms exhibit differences in opinion polarization or opinion convergence (Moe & Schweidel, 2012). Methodologically, we combined various online sources to develop a data set for research on platform differences, and using text-mining techniques, we analyzed online posts on cinematic movies from multiple sites such as review aggregator sites, discussion forums, consumer rating websites, and microblogs. Unlike prior studies, which focus on reviews from a single platform (Shen, Zhang, & Zhao, 2016), our research considers a wide spectrum of online platforms and outlets and provides a comprehensive view of the online WOM activities surrounding a product (i.e. movies).

Practically, our research helps marketers design targeted marketing tactics for different platforms and advise consumers to take heed of platform differences when making inferences based on online opinion distribution. As companies increasingly rely on online posts to gauge consumer opinions (Davis & O'Flaherty, 2012), they need to understand how various platforms differ in reflecting consumer opinion distributions and the extent to which they can rely on online posts in different online platforms to predict consumer actions.

Differentiating Online Platforms

Past research demonstrates that the characteristics and context of online platforms influence user attitudes, communication, inferences, and behaviors (Brambilla & Gusatti, 2016). From the perspective of website design, online platforms are cognitive landscapes, which provide cues to facilitate sense-making and user involvement (Rosen & Purinton, 2004). Inferential cues embedded in the online context help users to acquire an understanding of the purpose served by the online platform (Tan & Wei, 2006). Whether a platform provides salient cues regarding specific products or services, we propose, has significant implications for the way users post comments online, and helps to establish a social norm dictating online posting behaviors. As noted by Ajzen and Fishbein (2005), one decisive factor behind behaviors is behavioral norms, which refer to perceptions of appropriate and expected behavior in a particular social environment. Therefore, differences in behavioral norms of online platforms will have implications for people who post and/or read online posts, which subsequently lead to different patterns in online posting.

In the current study, we differentiate product salient platforms from product non-salient platforms. Specifically, a product salient platform (henceforth named product platform for short) is an online platform dedicated to discussions on a specific product or service. A product non-salient platform (henceforth named non-product platform for short) refers to a platform facilitating online WOM intended for diverse audiences without constraints on topic. The concentration of product reviews on product platforms provides salient cues reminding users that the platform is intended for a specific product or service, highlighting that

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individuals in product platforms are expected to follow behavioral norms (Ajzen & Fishbein, 2005) of providing information pertinent to the focal product. Examples include Tripadvisor.com for travel related products and experiences, IMDB.com for movies, and Rollingstone.com for music. Non-product platforms, on the other hand, facilitate general online discussion and are not restricted to products or services. On such platforms, posts may pertain to multiple domains, ranging from the latest news, to sharing of individual actions or thoughts, to latest rumors and happenings—conversations that are not limited to certain themes or subjects. In other words, behavioral norms in non-product platforms do not prompt users to post consumption related comments. We focus on microblogs as a specific and widely used example of non-product platform. As empirical evidence demonstrates a direct link between the volume and valence of microblog comments about a product to the sales of the product (Asur & Huberman, 2010), we expect microblogs to constitute a significant source of public comments on products and services that influence potential consumers. Table 1 summarizes the differences between the two types of platforms.

Theoretical Arguments and Hypotheses

Online Impression Management

Prior research in IS has shown that impression management forms a critical aspect of individuals' considerations as they actively participate in online communication (Marwick & Boyd, 2011). In the era of Web 2.0, individuals pay attention to their self-presentation in the Internet and have online personae characterized by what they post (Lampel & Bhalla, 2007). Researchers have shown that individuals leverage opportunities to engage in impression management online, and carefully think through how they should strategically manage their self-presentations to convey the desired impressions (Ellison, Heino, & Gibbs, 2006). This is because people are concerned with the impressions that others form of them, even when such impressions might not have any immediate or future outcomes (Gardner & Martinko, 1988).

TABLE 1. Differences between product and non-product platforms.

	Product platforms	Non-product platforms
Topicality	Products or services	No constraints
Target audience	Prospective or existing consumers of specific products/services	General population
Contextual cues to prompt product-related posts	Salient	Not salient
Perceived norm for posting	Providing information about purchase or consumption experience	Casual chatter, not limited to a certain topic
Concentration of product related information	High	Low
Examples	Tripadvisor.com for traveling, IMDB.com for movies, and Rollingstone.com for music	Twitter

In a thorough review of the impression management literature, Leary and Kowalski (1990) identified two distinct components—impression motivation and impression construction. Impression motivation refers to when and why individuals might be motivated to engage in impression management and describes conditions under which individuals have the desire to manage their public impressions and control how they are seen by others. Impression construction refers to how individuals go about achieving their goal of impression management and describes the tactics individuals often use to create desired impressions. We draw on the arguments relating to impression motivation to explain when individuals tend to be more attracted to post their comments on product versus non-product platforms, thus resulting in opinion polarization in product platforms. We then draw on the arguments relating to impression construction to explain why individuals tend to be affected by existing comments in product platforms, thus leading to greater opinion convergence.

Opinion Polarization

We expect that consumers with extreme opinions will be more likely to have a directed goal of having their voices heard and exerting influence on other consumers. Satisfied customers engage in WOM because of concerns for other people's needs and welfare, to improve their own image, to help the company, and to reduce cognitive dissonance arising from the excitement in using the product or service (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Dissatisfied consumers engage in WOM to reduce anxiety and frustration, to give a friendly warning to other consumers, to gain sympathy, and to take revenge (Anderson, 1998; Hennig-Thurau et al., 2004). Hence, extremely satisfied or dissatisfied consumers are more motivated to engage in impression management.

Because of stronger motivations to engage in impression management, we predict that consumers with polarized opinions would prefer to post comments on product platforms. People have greater motivation to engage in impression management when the impressions they make are particularly relevant to the fulfillment of their goals, and if the value or importance of their desired goals is high (Leary & Kowalski, 1990). Prior research has highlighted that people who make online postings are attentive to whom their audiences are, and they make sense of their audiences based on the technological affordances and immediate social context (Marwick & Boyd, 2011). We thus expect highly satisfied and dissatisfied consumers to seek online platforms wherein the audience would value extreme comments, and where they would have the most significant influence.

Product platforms are perceived as forums for discussing products (Brown, Broderick, & Lee, 2007), whose audiences are potential consumers showing an interest in product evaluations and are susceptible to influence

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(Anderson, 1998). Therefore, posting comments in product platforms improves the communication efficiency for consumers with polarized opinions, allowing their voice to reach an audience who seek product related information (Tetlock & Manstead, 1985). Further, prior research has shown that reviews of average valence are perceived to be less helpful than highly positive or negative reviews (Danescu-Niculescu-Mizil, Kossinets, Kleinberg, & Lee, 2009), Li, Huang, Tan, and Wei (2013) also finds that comments explicit about the performance of products or services increase the effectiveness and efficiency of purchase decision making, thus are perceived to be more helpful. Following this vein, consumer evaluations with extreme opinions are welcome in product platforms as they offer clear advice, and thus better satisfy the needs of consumers with extreme opinions to engage in impression management.

Prior research has advocated that reviewers have the motivations to influence others (Wu & Huberman, 2008). Because consumers with moderate opinions do not adopt a strong attitude about the product, they have a poor motivation to comply with norms in product platforms to contribute evaluative and informative product related information. Because of the reduced perceived pressure to offer insightful advice to other consumers on non-product platforms, the latter serves as an attractive platform for consumers with moderate opinions. Hence, we expect the proportion of extreme comments would be comparatively higher in product platforms:

> **Hypothesis 1a:** *The proportion of extremely positive comments is larger in online product platforms than online non-product platforms.*

> **Hypothesis 1b:** *The proportion of extremely negative comments is larger in online product platforms than online non-product platforms.*

Opinion Evolution: Social Influence Effects on Online Posting

Impression management theory highlights that in constructing the desired impressions, individuals pay attention to the environmental norms and context, and adjust their impression management tactics accordingly. In considering environmental norms, people conform to the perceived values and preferences of others whose impressions they are trying to manage (Leary & Kowalski, 1990). The characteristics of the audience, together with environmental cues, serve as stimuli that are selectively perceived and interpreted, guiding actors to select tactics that will create the required impressions (Gardner & Martinko, 1988).

Based on theory about impression management construction, we highlight that people will pay attention to existing reviews in their attempts to manage the impressions of others. Prior research suggests that the social context of online WOM make reviewers conscious that others are drawing conclusions not just about the products evaluated but also about the reviewers. Goes, Lin, Yeung, and Chingman (2014) found that consumers who are concerned about projecting impressions upon others are prone to the influence from prior posts, as consumers' opinions are a function of both their unbiased personal product evaluation as well as social influence that they face from existing product reviews and ratings(Moe & Schweidel, 2012). Ma, Khansa, Deng, and Kim (2013) identified a similar trend in the form of social influence from existing ratings, showing that one may strategically adjust communicated messages when she has social concerns, or wishes to manage the impressions of others.

We expect that product platforms have clear norms and well-defined target audiences that have distinct expectations and preferences, thus resulting in greater ease in which the impression management tactic described above—considering the values and preferences of the target audience—will be achieved. First, social norms on product platforms dictate that postings should be product-related, allowing consumers to learn about other consumers' opinions of the product. As consumers skim through posted comments, they are likely to gain a perspective on the current sentiment of the target audience. The awareness of the existing sentiment will likely cause consumers to factor in current views, to conform to the preferences of the target audience. The ready accessibility of all other consumer comments in forums or discussion boards, as a constant stream of consumer chatter on the same product, increases the ease with which the sentiment of existing contributors are accessed (P. Huang, Lurie, & Mitra, 2009). With greater ease of ensuring that one's opinions expressed online is in line with the preferences of the target audience, we predict that individuals will be more likely to express comments that are consistent with existing sentiment of the target audience. Hence, we expect the online posts in product platforms would converge over time, reflecting less disagreement among consumers who are posting comments, compared with non-product platforms.

On the contrary, non-product platforms do not provide a conducive environment for a person to factor in current sentiment of the target audience. First, non-product platforms provide limited accessibility to product related opinions (Boyd & Ellison, 2007). Product related snippets are dispersed and mingled with other postings. It is therefore less convenient to create a general impression based on recent product related opinions. For example, product-related posts in Twitter would probably be obliterated as a result of the overwhelming number of new posts irrelevant to the product. Therefore, the relative poor availability, saliency and accessibility to product related chatter restrict the access to the opinions of their target audience and increase the difficulty to effectively execute the impression management tactic of incorporating others' opinions in their remarks. Hence, we predict that individuals are less likely to effectively anchor their new comments on the sentiment reflected in existing messages for non-product platforms, thus resulting in less opinion convergence. Taken together, we hypothesize that product platforms will see greater convergence of the online posts, relative to non-product platforms:

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Hypothesis 2: *The variance in the sentiment of new comments posted on online product platforms decreases faster over time than that posted on online non-product platforms.*

Research Methods and Analysis

Data

Our data collection covered 214 major US cinematic movies released from October 2010 to October 2011. For each movie, we tracked daily online posts for as long as they were screened in cinemas. The rest of this section details how we combined various online data sources to develop a data set that allows us to test our hypotheses.

Comments from Product Salient Platforms refer to comments generated via online forums, discussion boards, and consumer rating websites targeted at movies. Each week, we generate a movie keyword list based on names of movies and collect information from the major movie comments/review aggregator sites, discussion forums, and consumer rating websites. The movie keyword list is created by using the movie title in its entirety, as well as parts of the titles omitting non-essential parts such as punctuations, articles, pronouns, prepositions and conjunctions whenever necessary. For example, keywords for the movie "Pirates of the Caribbean: On Stranger Tides" include the full movie title, as well as the phrase "On Stranger Tides" and "Pirates of the Caribbean 4."

Comments from Product Non-salient Platforms refer to posts on Twitter and Plurk, which we use as key examples of non-product platforms. The challenge of collecting these comments is that they can be short-lived and not all comments remain searchable publicly on the Internet over time. Hence, we maintain a constant "live" link to the platform provider, monitoring and archiving all relevant traffic for approximately one year. Every week, we input the movie keywords (as described earlier) into a tool developed by an online media management company to monitor and capture feeds with words matching our keywords from Twitter and Plurk. Most of the comments in this study originated from Twitter. We ran two sets of analysis, one with only Twitter data and the other with data from both sources and found statistically similar results.

Valence of online comments.. The valence of online comments refer to how positive or negative is the sentiment communicated in the comments. Most research relies on self-reported numerical ratings of a review as a proxy for the valence of the review (Chevalier & Mayzlin, 2006; Lee, Hosanagar, & Tan, 2015). The shortcoming is that many online comments do not include numerical ratings, resulting in a potential loss of data. Further, review ratings convey limited information and consumers often read the review text and do not depend solely on the ratings (Chevalier & Mayzlin, 2006). Prior research, recognizing that ratings may provide inappropriate or limited information, have used textual analysis to capture the valence of online posts (Archak, Ghose, & Ipeirotis, 2011).

To measure the sentiment of unrated comments, we developed a sentiment analysis tool adapted from the algorithm, LIBSVM developed by Chang and Lin (2011). This tool estimates the valence of a given text by scoring it from 0 to 1, with 0 and 1 representing negative and positive sentiment, respectively (Details in Appendix A). To ensure robustness, we triangulated our sentiment classification (i.e. positive or negative) against a separate sentiment classification provided by the online media management company's propriety sentiment analysis tool. We found relatively high inter-rater reliability of 0.822 and 0.926 for product and non-product platforms, respectively.

Data Analysis and Results

We constructed a panel data set with average daily comments in each online platform as the unit of analysis. For each day and each movie, we may have two observations, one from product platforms and the other from non-product platforms. We represent the functional form for our analysis as follows:

$$Y_{it} = \alpha + X_{it}\beta + u_i + \varepsilon_{it}$$

where Y represents three different dependent variables (Models 1 to 3) for three different estimation procedures (see details below), i denotes the movie, and t denotes the number of days since release. X is the vector of variables including key independent variables and control variables. u represents the movie level stochasticity, ε represents stochasticity across movie and time and β represents estimated parameters. Multicollinearity is not a significant problem because the VIF values for all independent variables are less than 5. As the data set is panel data, we estimated both fixed and random effects and found that the random effects estimators are inconsistent compared with the fixed effects estimators for the three models (Hausmanχ^2_{Model1} = 48.53, p-value <0.001; Hausmanχ^2_{Model2} = 406.00, p-value <0.001; Hausmanχ^2_{Model3} = 122.40, p-value <0.001). We report Huber–White standard errors to minimize estimation biases because of possible heteroscedasticity in the data. We further computed the Durbin Watson statistic to test for possible auto-correlation in the panel data. We found auto-correlation was not present in Models 1 and 2 but is present in Model 3. We hence presented the estimators with AR(1) disturbance for Model 3 and the non-AR(1) results for models 1 and 2. The results remain the same.

Dependent Variable 1 (Model 1): Proportion of Extreme Positive Comments (Extreme +). To test H1a, we use the daily proportion of extremely positive opinions as the dependent variable. We first pool all comments from both product and non-product platforms for each movie accumulated across all time periods and rank them in ascending order of their sentiment scores. The sentiment score at the 90th percentile is marked as the cutoff value. Sentiment scores above the cutoff

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value are considered extremely positive.[1] Each day, we calculate the proportion of extremely positive opinions appearing in product and non-product platforms separately.

Dependent Variable 2 (Model 2): Proportion of Extreme Negative Comments (Extreme –). This variable represents the daily proportion of extremely negative opinions and is used to test H1b. The calculation is like that of *Extreme +*, except that extreme negative comments are defined as the proportion of comments whose sentiment score falls below the 10th percentile for all comments, pooled across platforms and time. [1]

Dependent Variable 3 (Model 3): Standard Deviation of Daily Comments Valence (Valence Stdev). This variable, used to test H2, represents the standard deviation of the valence of daily comments for product and non-product platforms. As our unit of analysis is the daily comments for the two types of platforms, there will be two records each day, representing the standard deviation of the valence of daily comments for product platforms, and for non-product platforms.

Independent Variable 1: Product Platform. We use a dummy to differentiate between product platform (coded as 1) and non-product platform (coded as 0).

Independent Variable 2 – Weeks Since Release (ln(Weeks)). To examine whether the variance of comment valence decreases over time, we include number of weeks since movie release (*ln (Weeks)*) in the model to test H2. To compare whether the decrease in the standard deviation of the valence of daily comments is faster for product salient or non-salient platforms (H2), the product of *ln(Weeks)* and *Product Platform* was added to the model. A significant coefficient will suggest a difference in the pace of opinion convergence over time for the two platforms. Descriptions of all variables are provided in Table 2, and variable descriptive statistics and correlations are given in Table 3.

TABLE 2. Description of variables.

Variable	Description
Dependent Variable	
Extreme +	Proportion of extremely positive opinions, i.e. top 10%
Extreme -	Proportion of extremely negative opinions, i.e. bottom 10%
Valence Stdev	Daily standard deviation of comment valence within product or non-product platforms
Key Independent Variables	
Product Platform	A dummy to differentiate comments from product platforms (coded as 1) and those from non-product platforms (coded as 0)
Weeks since release	Number of weeks since movie release
Controls	Note: Citations indicate the prior studies that included that control variable.
Product Valence	The average sentiment of online comments from product platform for previous week
Product Volume	The number of online comments from product platform for previous week
NonProduct Valence	The average sentiment of online comments from non-product platform for previous week
NonProduct Volume	The number of online comments from non-product platform for previous week
Ratio Consumption	Daily ratio of comments emphasizing consumption experience to total number of comments. For product platforms, it is calculated as the number of comments from consumer ratings discussion threads to the number of comments from consumer ratings discussion threads and generic discussion forums. For non-product platforms, it is calculated as the number of posts with movie related hashtag to the number of posts from Twitter.
Budget	Movie budget
Lead Rank	The popularity ranking of the leading artist
2nd Lead Rank	The popularity ranking of the 2nd leading artist
MPAA-PG	Movie is rated PG in MPAA ratings
MPAA-R	Movie is rated R in MPAA ratings
Drama	Movie genre is Drama
Thriller	Movie genre is Thriller
Comedy	Movie genre is Comedy

Findings

Tables 4–6 report both fixed and random effects model estimates. Although we provide the random-effects model with all the commonly applied controls for comparison purposes, we discuss our findings based on the fixed effects model as the random effects estimators are inconsistent compared with the fixed effects estimators based on Hausman tests. Qualitatively similar conclusions can be drawn from both models. We first examine how the proportion of extreme comments varies across platforms. Table 4 shows that the proportion of positive comments is higher (β = 0.183, *p*-value <0.001) for product platforms, which confirms H1a. This result suggests that product platforms have, on average, 18.3% more extreme positive comments compared with non-product platforms. The results in Table 5 also lend support to H1b in that there are more negative posts (β = 0.027, *p*-value <0.05) in product platforms. The results suggest that on average, product platforms have about 2.7% more extreme negative comments compared with non-product platforms. The results also show that the previous week's online comment valence and volume do not affect the percentage of extreme opinions, with one exception that the valence of non-product platform comments has a positive relationship with the percentage of extremely positive comments (β = 0.041, *p*-value <0.05).

Table 6 tabulates the estimates for examining whether online opinions tend to converge or diverge over time and across platform. Table 6 shows that the standard deviation of comment valence is larger in product platforms (β = 0.028, *p*-value <0.001). This is consistent with our findings in Table 4 and Table 5, which found that product platforms tend to attract more extreme comments. Over time, however, Table 6 shows that the standard deviation of comment valence decreases at a faster pace in product platforms (β = –0.018, *p*-value <0.001), providing support for H2.

Figure 1 plots the relationships between the weeks elapsed since movie release with the daily online comments

[1] Sensitivity tests conducted by varying the cut-off from 85% to 95% for extreme positive comments, and from 5% to 15% for extreme negative comments (for each percentage point – for example, 85%, 86%) provided qualitatively similar results.

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TABLE 3. Correlation of variables.

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Extreme+	0.070	0.161																	
2 Extreme-	0.104	0.186	−0.108																
3 Valence Stdev	0.180	0.112	−0.037	0.271															
4 Product Platform	0.213	0.410	0.446	0.095	0.107														
5 ln(Weeks)	1.644	1.014	−0.198	−0.069	−0.217	−0.432													
6 Product Valence	0.752	0.112	0.103	−0.195	−0.053	−0.052	0.089												
7 Product Volume	1.668	2.37	0.224	0.061	0.251	0.466	−0.644	−0.049											
8 NonProduct Valence	0.692	0.125	0.114	−0.348	−0.138	−0.030	0.059	0.242	−0.035										
9 Product Volume	3.906	2.054	0.042	0.008	0.354	0.02	−0.264	0.089	0.424	0.005									
10 Ratio Consumption	0.241	0.327	0.279	0.061	0.164	0.633	−0.317	−0.013	0.448	−0.002	0.191								
11 ln (Budget)	17.218	1.307	−0.035	−0.048	0.129	−0.032	0.12	0.047	0.047	0.069	0.162	0.013							
12 ln (Lead Rank)	4.560	1.895	0.015	−0.012	−0.155	0.059	−0.125	−0.032	−0.039	−0.019	−0.236	0.007	−0.49						
13 ln (2nd Lead Rank)	5.434	1.789	0.03	0.003	−0.165	0.061	−0.134	−0.014	−0.032	−0.042	−0.228	0.019	−0.519	0.615					
14 MPAA-PG	0.137	0.344	0	−0.036	−0.047	0.006	0.036	0.066	−0.041	0.062	−0.034	0.013	0.273	0.107	−0.043				
15 MPAA-R	0.329	0.470	−0.004	−0.002	−0.008	−0.012	−0.045	0.036	−0.018	−0.062	−0.038	−0.021	−0.326	0.146	0.134	−0.278			
16 Drama	0.486	0.500	0.041	−0.057	−0.095	−0.027	−0.065	0.107	−0.066	0.126	−0.043	−0.018	−0.391	0.085	0.139	−0.29	0.101		
17 Thriller	0.317	0.465	−0.034	0.04	0.14	−0.014	0.004	−0.093	0.049	−0.079	0.13	−0.018	0.127	−0.141	−0.098	−0.217	−0.033	−0.124	
18 Comedy	0.383	0.486	−0.008	−0.015	−0.057	0.029	0.026	−0.018	−0.037	0.021	−0.102	0.002	0.067	0.176	0.009	0.285	0.093	−0.292	−0.417

Note. Correlation values greater than 0.018 indicates that it is significant at p-value<0.05.

valence for product and non-platforms. The figure shows that there is more convergence over time for product platforms, indicating that although product platforms attract more extreme comments, the spread of these comment's valence decreases more rapidly over time.

Overall, all regression estimations suggest good model fit, explanatory power, and provided support for all the hypotheses. Hence, the results attest to the platform difference in opinion polarization and opinion convergence for product vs non-product platforms.

Additional Analysis

Although we differentiate between product vs non-product platforms, we note that some product platforms allow users to post ratings, which provide more evaluative information to

TABLE 4. Random effects and fixed effects estimation (DV = extreme positive comments).

	Random effects				Fixed effects			
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
ln(Weeks)			−0.003	0.002			−0.003	0.002
Product Platform			0.183***	0.010			0.183***	0.009
Product Valence	0.042	0.030	0.040	0.027	−0.017	0.038	−0.022	0.033
Product Volume	0.010***	0.001	0.000	0.001	0.010***	0.001	0.000	0.001
NonProduct Valence	0.062***	0.018	0.066***	0.016	0.031	0.019	0.041*	0.016
NonProduct Volume	−0.006***	0.001	0.001	0.001	−0.006***	0.001	0.001	0.001
RatioConsumption	0.117***	0.009	−0.008	0.008	0.114***	0.008	−0.008	0.008
ln(Budget)	−0.006	0.004	−0.003	0.004				
ln(Lead Rank)	0.000	0.002	−0.000	0.002				
ln(2nd Lead Rank)	−0.001	0.002	−0.002	0.002				
MPAA-PG	0.011	0.010	0.007	0.010				
MPAA-R	0.002	0.008	0.005	0.008				
Drama	0.013*	0.007	0.015*	0.006				
Thriller	−0.010	0.007	−0.015*	0.007				
Comedy	−0.009	0.007	−0.017*	0.008				
Intercept	0.072	0.074	0.017	0.069	0.038	0.032	0.021	0.028
AIC	−16753.24		−19112.96		−17414.42		−19808.61	
BIC	−16629.28		−18973.5		−17367.93		−19746.63	

Note. ***represents p-value<0.001; **represents p-value<0.01; *represents p-value<0.05. All F-statistics are significant at the p-value<0.001.

TABLE 5. Random effects and fixed effects estimation (DV = extreme negative comments).

	Random effects				Fixed effects			
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
ln(Weeks)			−0.002	0.002			−0.001	0.002
Product Platform			0.031**	0.012			0.027*	0.012
Product Valence	−0.102*	0.044	−0.099*	0.044	0.076	0.051	0.075	0.052
Product Volume	0.001	0.001	−0.001	0.001	0.001	0.001	−0.001	0.001
NonProduct Valence	−0.212***	0.034	−0.209***	0.034	−0.054	0.028	−0.052	0.029
NonProduct Volume	−0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001
RatioConsumption	0.032***	0.008	0.011	0.009	0.033***	0.008	0.015	0.009
ln(Budget)	−0.007	0.005	−0.007	0.005				
ln(Lead Rank)	−0.003	0.004	−0.003	0.004				
ln(2nd Lead Rank)	−0.001	0.003	−0.001	0.003				
MPAA-PG	−0.009	0.015	−0.010	0.014				
MPAA-R	−0.007	0.011	−0.006	0.011				
Drama	−0.026**	0.010	−0.026**	0.010				
Thriller	0.001	0.013	−0.000	0.012				
Comedy	−0.003	0.012	−0.005	0.011				
Intercept	0.481***	0.130	0.473***	0.132	0.074	0.046	0.073	0.046
AIC	−12893.4		−12939.47		−13748.9		−13793.07	
BIC	−12769.44		−12800.01		−13702.41		−13731.08	

Note. ***represents *p*-value<0.001; **represents *p*-value<0.01; *represents *p*-value<0.05. All *F*-statistics are significant at the *p*-value<0.001.

TABLE 6. Random effects and fixed effects estimation (DV: std. dev. of valence).

	Random effects				Fixed effects				Fixed effects with AR(1)			
	Null model		Full model		Null model		Full model		Null model		Full model	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
ln(Weeks)			−0.020***	0.002			−0.023***	0.002			−0.023***	0.002
Product Platform			0.027***	0.006			0.021**	0.006			0.028***	0.005
Product Platform *ln(Weeks)			−0.023***	0.005			−0.020***	0.005			−0.018***	0.003
Product Valence	0.015	0.020	0.023	0.019	0.050	0.027	0.051*	0.025	0.091***	0.012	0.121***	0.013
Product Volume	0.006***	0.001	−0.000	0.001	0.006***	0.001	−0.000	0.001	0.006***	0.001	−0.000	0.001
NonProduct Valence	−0.055***	0.015	−0.053***	0.014	−0.024	0.016	−0.021	0.016	0.013	0.011	0.024*	0.011
NonProduct Volume	0.010***	0.001	0.009***	0.001	0.010***	0.001	0.008***	0.001	0.006***	0.001	0.003***	0.001
RatioConsumption	0.028***	0.005	0.016***	0.005	0.027***	0.005	0.018***	0.005	0.013***	0.003	0.004	0.003
ln(Budget)	0.003	0.003	0.004	0.003								
ln(Lead Rank)	−0.002	0.002	−0.003	0.002								
ln(2nd Lead Rank)	−0.006***	0.002	−0.007***	0.002								
MPAA-PG	−0.014	0.008	−0.016*	0.008								
MPAA-R	0.002	0.005	0.000	0.006								
Drama	−0.016**	0.006	−0.018**	0.006								
Thriller	0.023***	0.006	0.024***	0.006								
Comedy	0.001	0.006	0.001	0.006								
Intercept	0.139*	0.061	0.173*	0.069	0.104***	0.022	0.158***	0.020	0.065***	0.006	0.098***	0.006
AIC	−30467.43		−31122.36		−32426.54		−33106.9		−32699.79		−33115.76	
BIC	−30343.46		−30975.15		−32379.79		−33036.78		−32653.13		−33045.76	

Note. ***represents *p*-value<0.001; **represents *p*-value<0.01; *represents *p*-value<0.05. All *F*-statistics are significant at the *p*-value<0.001.

consumers. We therefore further differentiate between product platforms providing ratings (i.e., evaluative platforms) and those do not (i.e., non-evaluative platforms), resulting in three types of platforms: evaluative platform (denoted as “Eval”), non-evaluative platforms (denoted as “NonEval”) and non-product platforms (denoted as “NonPro”). The analysis results are available in Appendix B. The results supported our earlier hypotheses and further indicated that evaluative product platforms appear to contribute more to opinion polarization and convergence, as extreme negative comments tend to show up in evaluative product platforms rather than non-evaluative product platforms, and evaluative product platforms also tend to show greater opinion convergence compared with non-evaluative product platforms.

Discussion and Conclusion

Our study contributes to existing research on online WOM by examining how opinion distributions differ across product versus non-product platforms. First, our results show that

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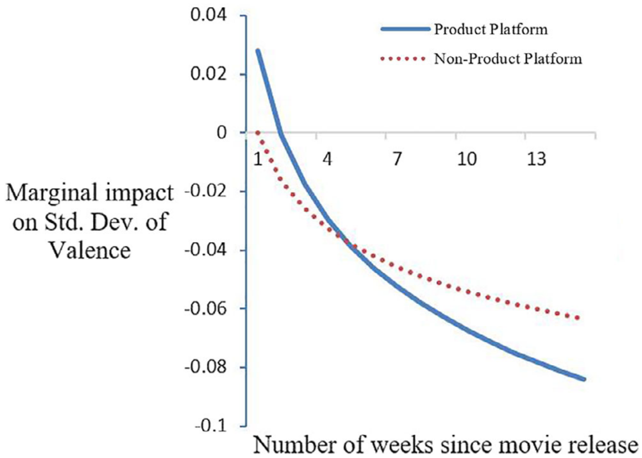

FIG. 1. Interaction of weeks since movie release and online platform differences. [Color figure can be viewed at wileyonlinelibrary.com]

product platforms tend to attract more polarized (i.e., extremely positive and negative) comments. In contrast, non-product platforms like Twitter represent the views of more moderate consumers. Second, we show that although product platforms attract extreme opinions, opinions also converge at a faster rate than those reflected in non-product platforms. Our arguments and hypotheses are further bolstered by our additional findings, which show that evaluative product platforms are even more likely to attract extreme negative comments and show greater convergence than non-evaluative product platforms. These results highlight that the impression management tendencies tend to be magnified in such evaluative product platforms.

Implications for Research

This research provides several contributions to research. First, we contribute to the debate on opinion diversity (polarization) vs opinion convergence, by highlighting that opinion polarization and opinion convergence differ on different online platforms. Our results highlight that future research needs to consider the characteristics of online platforms, and how users' perceptions of the purpose of the online platform will affect their usage behavior. This concurs with research that has examined the affordance of technology, or how technology characteristics both shape and constrain technology usage and perceptions (Markus & Silver, 2008). Although this earlier work tends to take a more qualitative approach towards examining how technology characteristics may influence technology use, our study contributes to the literature by using a quantitative approach to show that the characteristics of different technologies affect the way users perceive and use different types of online platforms.

Second, our research draws on impression management theory to explain when and why opinion polarization and opinion convergence tends to occur, showing the applicability of impression management theory in explaining consumers' behaviors online. In so doing, we contribute to the opinion dispersion literature by giving a glimpse into insights of why opinion dispersion might happen, and how online platforms might make a difference in influencing opinion dispersion. We show that the characteristics of the online platform influence the extent to which impression management influences consumers' online posts. Our findings imply that users pay significant attention to the impression that they create on others, as they post comments online, and that consumers pay attention to the characteristics of the online platform when considering how they should make online posts. This highlights that current research examining opinion dispersion should consider the characteristics of the online platform as they seek to gain a greater understanding of the topic.

Implications for Practice

Marketers are paying more attention to online marketing – using various online platforms to listen in on consumers' online conversations about the company, brand, products or services, and also to actively interact with consumers. Companies are thus relying on the sentiment reflected in online comments as a barometer for consumers' sentiments about products, reactions to a marketing campaign, and even as a leading indicator for future sales (Davis & O'Flaherty, 2012). It is thus critical for marketers to understand how consumers may be attracted to different online platforms, or how their posting behaviors differ across platforms. Our research informs marketers that online platforms are not direct counterparts of each other. They differ not only in what types of consumers are attracted to post in each type of platform, but also the extent to which online posts will be affected by existing comments.

Specifically, our results show that microblogs tend to be less susceptible to impression management by consumers posting online comments, implying that marketers should pay attention to the comments on microblogs if they wish to obtain a more moderate view of consumers' sentiment on specific products. On the other hand, marketers should pay more attention to consumers views reflected on online forums dedicated to product centered discussions, and even more so to evaluative product platforms, for more controversial issues surrounding their products and services, especially if the company wishes to seek ideas for improving their product or service, and to moderate the impact of highly polarized opinions by responding to them. Additionally, our results show that the interactions on online platforms are complex. Marketers might interpret increasing similarity in the sentiment of online posts as a signal that consumers have reached a consensus over the product, provoking strategic response from marketers. Our results, however, imply that marketers should factor in some expected convergence in opinion when evaluating consumer opinions on product platforms and react only when there are distinct and obvious trends exhibited in consumer opinions.

Limitations

Our study is not without limitations. First, our study examined cinematic movies; hence our results may not generalize to other products and services. Nevertheless, we believe that the findings will be applicable to experience

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goods that have similar demand and consumption patterns. Second, the strength of our research approach lies in the comprehensiveness of the data collected around the same set of movies. In comparing across different online platforms, we aggregated the sentiment reflected in the online posts for all sites. There could be differences in the extent to which different types of product salient platform sites may attract extreme comments or may exhibit sentiment convergence over time. Hence, it is worthwhile for future studies to further expand our research to examine whether site level differences—either on product or non-product platforms—may further cause individual online comments to differ. Third, although we use the theory of impression management to explain why we expect differences in opinion distributions across the two types of platform, we are unable to provide direct evidence showing motivations of consumers' online posting behavior. This is thus an area worthwhile for future research. Fourth, one should note that automated sentiment analysis generally achieves moderate levels of accuracy in sentiment coding, and it presents a natural limitation in the current state of natural language processing technologies. Nevertheless, it still provides an efficient and effective way of analyzing large quantities of data. Further, this study compares sentiments across platforms using a common sentiment analysis tool, and given that the errors are exogenous, we can conclude that any difference in the effects is because of the difference in the independent variable (i.e., platform difference).

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