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Product versus Non-product Oriented Social Media Platforms: Online Consumer Opinion Composition and Evolution

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Abstract

This article examines how different social media platforms affect opinion composition and evolution. We differentiate between product and non-product oriented outlets as they differ in the salience of social cues, thus resulting in distinct user behaviours. We extend prior research in several ways. First, comparing between comments from different types of social media platforms, we show that the product oriented outlets display a tendency to attract polarized opinions. Second, we find that similarity of online comments increases over time, suggesting opinion convergence. Lastly, product oriented outlets facilitate faster assimilation of opinions within the site compared to non-product oriented outlets.

Keywords: social media, sentiment analysis, opinion evolution, text mining

1. Introduction

As pointed out by Mabry and Porter [1], a distinct stream of research explores how consumers interact and behave on social platforms. They explain that the way consumers interact with traditional websites is different from their interactions with social platforms, which facilitate individual connectivity and the spread of word of mouth. Marketers can also benefit from this line of research as it helps them to rethink marketing tactics and better leverage this new medium. For example, the level of diversity in consumer postings may be used as a guide to whether managers should disclose more taste related product information to reduce consumer uncertainty [2]. At the current stage, our knowledge is limited when it comes to questions about user behaviours across social media outlets. In an attempt to alleviate this gap, the present study makes contributions to the literature by examining the following research questions: 1) Does the composition of consumers who post comments on social media sites vary across different social media platforms? If so, how do they

vary? 2) In what ways do social media comments evolve over time?

Research conducted to date seldom compare comments from different social media outlets. For example, Godes and Silva [3] studied the sequential and temporal dynamics of online ratings from Amazon.com. Moe and Schweidel [4] also gathered their data from one consumer ratings site to investigate the likelihood of consumers posting online and how these comments evolve over time.

Past research, however, has shown that different social media outlets serve different purposes [5], which suggests that user behaviours is likely to differ across outlets. For example, when one wants to post or read product evaluations, s/he is likely to visit online discussion boards and forums [6]. Likewise, when one wishes to converse with friends, social networking platforms like Facebook™ is the more likely outlet [7]. Social media platforms are not equal as they serve different functions. In this current study, we go beyond a single type of social media to examine whether and how the behaviors of users vary while using different types of social media platforms.

Methodologically, this study differs from most prior social media studies in two ways. First, we employ text-mining techniques to measure the sentiment embedded in social media comments. The sentiment expressed in the content of online comments, also known as the valence of online comments, reflects the consumer's attitude towards the product or service. It is a continuum with two extremes indicating either absolute positive or negative attitude. Without using text mining for sentiment analysis, one will naturally exclude consumer posts in social media outlets like forums and microblogs (that generally do not have rating scales) which now represents an overwhelming proportion of social media activity. Second, to compare across social media sources, we have to consider online comments from "live" feeds such as Twitter. Social media outlets like Twitter are highly dynamic and transitory. To ensure that we capture all relevant, time sensitive data, we maintain a constant

“live” connection to such social media outlet and continuously track the information at source for a year.

In this study, we chose cinematic movies as the context for the study. As highlighted by Godes & Mayzlin (2004), word of mouth effects are particularly important for entertainment goods and in influencing movie selection by consumers. Moreover, movies tend to receive significant public interest and attention, hence active communication about movies is quite prevalent [8]. Empirically, as common and standardized hedonic goods, movies also pose the ideal context to study social media comments. The number of movies released per year is manageable, making it possible to design a sampling schema that is representative of the industry yet practical for data collection efforts.

2. Literature review

2.1. Opinion composition

There has been a stream of research investigating the opinion and contributor composition. This research yields one interesting and important insight: online posts may not be representative of the entire population[e.g. 9] due to self-selection biases. This self-selection phenomenon is similar to the “exclusion bias” in the political science literature, which refers to the inequality found in opinion polling – that a certain subset of the population (e.g. the economically disadvantaged) is underrepresented [10]. Similarly, Moe and her colleagues [11] pointed out that online opinions represent the voice of only a small segment of the consumers, and do not reflect the opinions of a representative sample of the general customer base. Indeed, posting online is an act of consumers’ own free will, which is out of the control of researchers. Therefore no measure can be imposed to ensure the representativeness of online posts.

Prior research also investigates the factors that may affect the consumer’s decision to express their opinions online, focusing on the extent to which the level of satisfaction with the product is related to the likelihood of posting [12-14]. Although researchers have not arrived at a consensus about which group of consumers engage in greater word of mouth when comparing consumers with higher versus lower level of satisfaction, theoretical arguments suggest that consumers with polarized opinions are more likely to express their satisfaction or dissatisfaction [12, 15]. One camp argues in favour of a positive relationship between consumer satisfaction and word of mouth [13, 16-20], due to 1) concerns for other people’s

needs and welfare, 2) reduction of cognitive dissonance rising from the excitement in the experience with the product or service, 3) desire to improve image, and 4) the wish to help the company [15, 16, 21]. Empirical evidence is found to support this relationship. For example, in a survey on new car buyers, Swan and Oliver [22] showed that consumer satisfaction was one motive for favorable word of mouth communications. Hennig-Thurau and his colleagues [21] also found support that consumer satisfaction linked to an increase in the number of online posts.

On the other hand, other researchers contend that dissatisfied consumers are more likely to spread the word [14, 23-25]. Their reasons for communicating with others include 1) the wish to reduce anxiety and frustration, 2) to give a friendly warning to other consumers, 3) to gain sympathy from others, and 4) to take revenge [12, 15, 21, 23]. Zeelenberg and Pieters [23] used questionnaires to assess participants’ feelings and behavioural responses in relation to an experience with a dissatisfying service delivery. Results indicated that dissatisfaction reinforced consumers’ tendency to engage in word of mouth. This finding is consistent with the work of Sundaram et al. [15], which also attested to the relationship between consumer dissatisfaction and word of mouth. Hence, it is theoretically argued and empirically supported that consumers at both higher and lower ends of the spectrum in their levels of satisfaction are inclined to speak out.

What is needed to supplement this area of research is for research to further differentiate whether these findings apply to word of mouth effects online, and whether the findings apply equally to all online platforms to which consumer comments are posted. In the context of social media comments, there is documented evidence that there exists self-selection effect in online posts. For example, Li and Hitt [26] showed that book buyers exhibit self-selection behaviour in posting reviews on Amazon.com, and early postings displayed a positive bias. For consumer comments about movies, Dellarocas and Narayan [27] reported a higher inclination for consumers at higher or lower level of satisfaction to speak out. However, these studies typically collect data from a single type of social media platform (consumer ratings websites), when exploring the self-selection phenomenon [3, 4, 26, 27].

One crucial difference between online and offline word of mouth is that offline word of mouth is usually limited to verbal communication, while online word of mouth can be transmitted via a variety of outlets such as discussion forums and microblogs. We argue that social media platforms serve different purposes predefined by users, thus affecting consumers’ choice of outlet when they want to post comments about products. In other words, some social media outlets may be considered to

be more effective channels to communicate with other consumers, therefore attracting consumers who intend to create a bigger impact on others. Current research is limited in terms of our understanding about how consumers choose among social media outlets to make comments on products. Our research adds to the literature by exploring how the composition of the online posts may vary across social media platforms.

2.2. Opinion evolution

Another related research stream on online posts is to explore the evolution of online opinions. Prior research suggested that early reviews influence later comments, thus resulting in a sequential pattern [4, 28]. Moe and Trusov [28] decomposed product ratings into two components, one capturing the socially unbiased product evaluation, and the other reflecting the social influence impacting the consumer. This is consistent with research that has shown that one may strategically adjust communicated message when s/he has social concerns. It is common that people convey messages that do not truly reflect their beliefs, attitudes or values in order to manage the impressions or achieve interpersonal goals [29].

Research has shown that trends of posted opinions have a path dependent feature. In an experiment setting, Schlosser [30] showed that publicly expressed opinions will be adjusted downwards when existing reviews are negative. He explained that the fact that the comments will be accessible to the public may trigger social concerns about how others' perceptions of the post would affect one's image. Since negative evaluators are generally considered to be more intelligent compared to positive ones [31], the presence of negative reviews remind one to lower his/her rating in order to appear intelligent to others. In contrast, positive reviews do not cause ratings to fall because they do not heighten concerns with one's image. Moe and Schweidel [4], on the other hand, reviewed studies in offline settings and found a competing theory that predicts an upward trend, due to the bandwagon effect. For political campaigns, bandwagon effect is said to occur when voters rally for the party that is doing well [32]. Moe and Schweidel [4] found evidence on bandwagon effect, showing that some consumers adjust their ratings upwards when the existing ratings are positive. These two studies, together, show that early reviews influence later comments, and the direction of influence is could be either positive or negative, depending on the context.

While prior studies provide interesting insights about opinion evolution for online comments, they are silent on whether and how social media platforms affect the evolution of online opinions. As noted above, consumers revise their posts because of contextual cues that prompt them to think about enhancing their images. Different social media platforms that emphasize different contextual cues is thus expected to inevitably impact consumers' perceived need to adjust their posts, which will ultimately have an influence on the evolution pattern of online opinions. Given that social media platforms are predefined by users to serve different purposes [5, 33], the salience of contextual cues will probably vary, resulting in different levels of motivation for adjusting online posts. The current study thus aims to advance our understanding about how differences in social media platforms may affect opinion evolution by modifying consumers' adjustment behaviour.

2.3. Comparing between social media platforms

Due to the proliferation of Web 2.0 technologies, consumers are given the opportunity to choose from a variety of social media channels to interact with others [1]. The function of a social media platform is determined not only by its technological features and limitations, but also users' perception of the platform - an important key to characterizing user behaviours.

In this study, we categorize social media platforms into product and non-product oriented platforms so as to reflect the difference in users' perception regarding what the platform is designed for. The key difference between the two is the salience of contextual cues that remind users that the platform is dedicated to discussions relating to a specific product or service. We make this distinction because we argue that the self-selection effect and adjustment effect in consumers' posting behaviors are moderated by contextual cues of the platforms. By processing the contextual cues, consumers can compare and pick the most appropriate and effective social media platform to accomplish their purpose. We elaborate on these two types of social media platforms below.

As consumers increasingly look to peers for information about products and services, there are now many product oriented¹ sites available that serve as a forum for consumers to interact and share their experiences for a particular product [33]. The success of product oriented sites such as Eopinions.com, Ecomplaints.com and Tripadvisor.com show that consumers value a place for them to share product reviews and consumption experiences. Such websites

¹ Subsequent references to product-oriented sites refer to both product and service-oriented sites.

represent word-of-mouth networks where “individuals with an interest in a product category interact for information such as purchase advice, to affiliate with other likeminded individuals, or to participate in complaint or compliment interactions” [33, p. 3]. We classify such online discussion forums as product oriented social media platforms.

In contrast, microblogs is a representative example of non-product oriented social media platforms. Microblogging is a relatively new form of communication in which users send short messages (usually less than 200 characters), and the messages are sent to receivers by instant messages, mobile phones, email or the web [7]. Twitter, for example, is the most popular form of microblog in US, Europe and parts of Asia. We consider microblog to be non-product oriented platform in that such microblogs usually do not specify a key area of focus, hence messages sent via microblogs tend to be much less directed and not limited to certain themes or subjects. They are typically used for maintaining relationship with friends or professionals, and broadcasting information, rather than distributing product related information or evaluations [34].

We argue that it is important to compare product and non-product oriented platforms because they create different environments that invoke distinct behavioural codes. Ajzen and Fishbein [35] proposed that one decisive factor behind behaviours is subjective norms, which refer to perceptions of appropriate and expected behaviour in a particular social environment. As discussed earlier, product oriented social media platforms encourage users to conform to the behavioural norm of sharing product related knowledge or experience [33]. On the other hand, the main reason that people use social network sites like Twitter is to maintain offline relationships and digitalize personal life [5, 7, 34]. Such sites primarily serve social purposes and are not organized by topic. The difference in subjective norms of product and non-product oriented platforms has implications for people who post and/or read online posts. Consumers are likely to follow different behavioural norms across platforms, which subsequently lead to different patterns in posting and adjusting online comments.

3. Hypothesis development

3.1. Opinion composition across platforms

We speculate that there are more extremely positive and negative comments in product oriented social media platforms than non-product oriented

social media platforms. As noted before, consumers who post comments online do not represent the general consumer base [11]. The majority of consumers choose to remain silent, whereas those who post online represents the minority. Extremely satisfied and extremely dissatisfied consumers are more likely to express their opinions than those who are moderately satisfied [27], because they have strong motivations to share their opinions, as discussed above [12]. Hence, these consumers are more goal-directed, and they post comments online with deliberate intentions to exert influence on the rest of the consumers. Given that product oriented social media platforms are perceived as forums for discussions of products, consumers with polarized opinions are more likely to choose product oriented platforms as the suitable outlet to express their opinions, so that their voice can reach a larger audience and create a greater impact.

On the other hand, we expect the silent majority to be more likely to share their views on products in non-product oriented outlets. As they do not have strong opinions about the product, they do not have a strong motivation in complying with the subjective norms as in product oriented outlets to contribute evaluative and informative product related information. If they want to voice their opinions about product, they would prefer non-product oriented social media platforms, in which online posts can be casual chatter. The perceived “pressure” to proffer insightful advice to other consumers is reduced in non-product environments. Taken together, we expect that the composition of online posts is different for product versus non-product oriented social media platforms, and the proportion of extreme comments is higher in the former compared to the latter:

Hypothesis 1a: the proportion of extremely positive comments is larger in product oriented social media platforms than non-product oriented social media platforms.

Hypothesis 1b: the proportion of extremely negative comments is larger in product oriented social media platforms than non-product oriented social media platforms.

3.2. Opinion evolution across platforms

We predict that the sentiment reflected in online comments will converge over time, reflecting less disagreement amongst consumers who post comments, due to anchoring effects. First introduced by Tversky and Kahneman [36], anchoring effect refers to the cognitive bias that people’s assessment reflects an influence from an implicit reference point, namely the anchor. Research has also found that it is very difficult to adjust people’s assessment to eliminate the influence of an anchored reference point [37, 38].

For those who decide to post a comment, their postings involuntarily incorporate the influence from existing posts. When given an anchor, people are prone to consider the anchor to be plausible and pay more attention to information that is in line with the anchor, bringing about the anchoring effect [37]. In this context, the anchor ought to be the consumers' impression about the average product evaluation. Consumers often read more than one online comment, so it is more practical to predict that they anchor their evaluation to the general tone of recent postings. Following this argument, every time consumers skim through recent comments, they sub-consciously synthesize opinions expressed in them and set the anchor based on the average product evaluation. These earlier opinions get assimilated into consumers' own comments because of anchoring effect. Gradually, the similarity of the comments within the site would increase. Therefore, we hypothesize that:

Hypothesis 2a: The variance in the valence of new comments posted on product oriented social media platforms tends to decrease over time.

Hypothesis 2b: The variance in the valence of new comments posted on non-product oriented social media platforms tends to decrease over time.

Moreover, the anchoring effect is anticipated to be higher in product oriented social media platforms than non-product oriented social media platforms. As reviewed previously, research has suggested that publicly expressed opinions might be modified because consumers are susceptible to social influence and concerned about social outcomes [28-30]. When consumers are made aware that their comments will be accessible to others, they are prompted to consider the potential social consequences. And they may make necessary changes to their posts to attain social goals such as approval seeking and image maintenance [30]. We predict that the incidence of adjusting online comments also hinges on the type of social media platforms to which consumers post.

Anchoring effects are more likely to be present in product oriented outlets, due to two main reasons. First, reference points are readily available and accessible for consumers who post in product oriented outlets. In forums or discussion boards, consumers gather to share their viewpoints on similar products types in a particular thread [6, 33, 39]. A constant stream of consumer chatter is kept up in product oriented platforms, easily accessible to new posters, thus laying down the precondition for anchoring effect to exist. Second, consumers are likely to read existing comments, which triggers the anchoring effect. Consumer evaluations and discussions are well organized by topic, and the atmosphere encourages active participation in sharing

opinions about products [6]. Because the subjective norms dictate that postings should be product-related, and sought by people with a predetermined purpose, namely, to learn about the opinions of the product. Therefore consumers are expected to skim through posted comments, establishing a reference point in assessment of the product.

On the contrary, we argue that adjustment of one's comments due to the influence of existing comments tends to be less significant in non-product oriented social media platforms. First, non-product oriented social media platforms have limited availability and accessibility to product related opinions. Unlike product oriented outlets, which have a heavy concentration of consumer comments, non-product oriented outlets are not designed for sharing product evaluations [5, 7]. Product related snippets are broadcasted, and interspersed with other postings. It is therefore less convenient to create a general impression (i.e. setting the anchor) about the recent product related opinions. Also, to serve as an anchor, a particular comment can only exert a limited impact, because it would probably vanish quickly as a result of the overwhelming amount of new posts irrelevant to the product. Therefore, the precondition for anchoring effect to exist is less well established due to the relatively poor availability and accessibility to the anchor (i.e. product related chatter). Taken together, we hypothesize that:

Hypothesis 2c: The variance in the valence of new comments posted on product oriented social media platforms decreases faster over time than that posted on non-product oriented social media platforms.

4. Research method

4.1. Data collection

Our data collection covered 239 major US cinematic movies released from October 2010 to October 2011. We exclude documentaries, movies released directly to DVDs, and movies that were screened only in film festivals. We omitted these movies for consistency as they have limited market coverage and online comments, and are not equally accessible to the entire US market.

We adopted two main strategies to collect the data that is required. First, for product oriented social media comments, we developed an online automated agent to trawl the Internet based on pre-specified search parameters (details later). Second, for non-product social media comments (e.g. Twitter, Plurk), we partnered a social media monitoring and management company, which helped us to collect the comments.

Product oriented social media comments. These refer to information and comments mainly generated via

online forums, discussion boards, and consumer ratings websites. These comments are posted on websites for all to read and for search engines to index and search. Each week, we generate a movie keyword list based on the names of movies in the sample and collect the information for this class of reviews. The movie keyword list is created by using the movie title in its entirety. To ensure comprehensiveness, we included parts of the titles omitting non essential parts such as punctuations, articles, pronouns, prepositions and conjunctions whenever necessary. For example, the keywords for the movie “Transformers: Dark of the Moon” include the full movie title, as well as the phrase “Dark of the Moon” and “Transformers 3”.

Non-product oriented social media comments. Posts on Twitter, Plurk and Facebook constitute the major sources of non-product oriented social media comments at the time of data collection. Both Twitter and Plurk are generally subscription based – i.e. only those who subscribe to the feeds provided by an individual will receive the information s/he sends. We maintain a constant “live” link to the platform provider, monitoring and archiving all relevant traffic. Every week, we input the movie keywords (as described earlier) into a tool developed by a social media management company. The tool will monitor all feeds from Twitter, Plurk and Facebook (if the user makes his/her posts accessible to the public), and capture feeds that include words matching the list of keywords.

4.2. Measures

Valence of Online Comments. In prior studies, it is a common practice to measure the valence of a review using the self reported numerical ratings of a review [40–43]. However, this practice often results in a great loss of data because it is common that ratings are unavailable. Additionally, research has pointed out the value of textual comments, which cannot be replaced by ratings [e.g.44]. In Godes and Mayzlin [45], they drew a sample of peer reviews and have them manually coded as positive, negative, neutral, mixed, and irrelevant. The correlation between self reported ratings and manually coded data is approximately 0.1, suggesting a weak relationship. To accurately measure the sentiment of a comment, we developed a working sentiment analysis tool adapted from the algorithm, LIBSVM developed by Chang and Lin [46]. This tool gives us an estimate of the probability that a given text is positive, ranging from 0 to 1, with 0 meaning absolutely negative and 1 meaning absolutely positive. To ensure that our sentiment measurement

is robust, we triangulate our sentiment classification (i.e. positive or negative) against the sentiment classification provided by a social media management company’s propriety sentiment analysis tool. We found relatively high inter-rater (computerized classification) reliability of 0.822 and 0.926 for product and non-product social media comments respectively.

4.3. Data analysis and results

We grouped the observations by movie title and chose random effects generalized least squares (GLS) regression to test our hypotheses. The equation used in this research is:

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

where Y denotes dependent variables, i denotes the movie, and t denotes the number of weeks since release. X is the vector of variables including key independent variables and control variables. u_i represents the movie level stochasticity, ε represents stochasticity and β represents estimated parameters. Multicollinearity is not a significant problem since the VIF values for all independent variables are less than 5.

Extr_positive. To test H1a, we use the proportion of extremely positive opinions as the dependent variable. The following are the steps taken to calculate the figures. We first pool together all comments from product and non-product oriented social media platforms accumulated across time. Then we 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 this cutoff value are considered extremely positive. For each day, we calculate the proportion of extremely positive opinions appearing for product and non-product oriented social media platforms respectively.

Extr_negative. This variable is similar to that of Extr_positive, except that Extr_negative refers to the proportion of comments whose sentiment score falls below the 10th percentile of all comments.

We used random effects instead of fixed effects to estimate our model because various control variables employed in the model are invariant across the movie titles. These variables include the leading artists’ popularity, budget, genre and MPAA ratings. The model also considered the average valence of product (i.e. PO_valence) and non-product (i.e. NPO_valence) oriented social media comments for previous week, and the number of product (i.e. PO_volume) and non-product (i.e. NPO_volume) oriented social media comments for previous week. Two sets of analysis were conducted to test all hypotheses.

For the first set of hypotheses, the dependent variables are proportion of extremely positive (top 10%)

and negative (bottom 10%) social media comments. We use a dummy (i.e. PO_dummy) to differentiate product (coded as 1) and non-product (coded as 0) oriented social media platforms. Therefore, a positive and significant coefficient for PO_dummy would suggest a difference in the proportion of extreme comments between platforms. Results are shown in Table 1.

Table 1. Random effects estimation (H1a~H1b)

Dependent Variable:	Extr_negative		Extr_positive	
	Coefficient	SE	Coefficient	SE
PO Dummy	0.066***	0.003	0.164***	0.002
(N)PO_valence	-0.453***	0.013	0.248***	0.010
(N)PO_volume	0.001	0.001	0.002***	0.001
Weeks since release	10 ^{e-10}	10 ^{e-10}	10 ^{e-10}	10 ^{e-10}
Budget	-0.007*	0.003	10 ^{e-10}	0.003
Lead artist's ranking	-0.004	0.002	0.001	0.002
2nd Lead artist's ranking	-0.001	0.002	10 ^{e-10}	0.002
MPAA-PG	-0.001	0.012	-0.005	0.010
MPAA-R	-0.012	0.007	0.005	0.007
Drama	-0.010*	0.007	0.002	0.008
Thriller	-0.002	0.008	-0.010	0.008
Comedy	-0.006	0.008	-0.014	0.007
Intercept	0.566***	0.064	-0.160**	0.060
R ²	0.2135		0.2914	

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.

To test the second set of hypotheses, we use the standard deviation of the valence of daily comments (i.e. SD_valence) for product and non-product oriented platforms as the dependent variable. Hence, the unit of analysis is the daily comments for either product or non-product oriented platform (i.e. there will be two records each day, one representing the standard deviation of the valence of daily comments for product oriented platforms, and the other representing the standard deviation of the valence of daily comments for non product oriented platforms. In order to examine whether the difference of comment valence decreases over time, we include number of weeks since movie release (i.e. Weeks) in the model. If Weeks is negative and significant, then the result supports H2a and H2b, as it shows that the variation in new comments posted decreases over time. To compare whether the decrease in the standard deviation of the valence of daily comments is faster for product versus non-product oriented social media platforms, as hypothesized by H2c, we

introduce the product of Weeks and PO_Dummy (i.e. PO_dummy *Weeks) to the model. If its coefficient is significant, then there is a significant difference in the pace of opinion convergence over time for the two platforms. Table 2 tabulates the estimates of our regression analysis and Figure 1 depicts the social media platform differences in terms of opinion evolution.

Overall, the results suggested good model fit and explanatory power, and provided support for most of the hypotheses. After considering all the control variables, the results attest to the platform difference in opinion composition and evolution.

Table 2. Random effects estimation (H2a~H2c)

Dependent Variable: SD of Valence		
	Coefficient	SE
Weeks since release	-0.001***	10 ^{e-10}
PO_dummy	0.081***	0.002
PO_dummy *Weeks	-0.006***	10 ^{e-10}
(N)PO_valence	-0.152***	0.008
Budget	0.004	0.002
(N)PO_volume	0.014***	10 ^{e-10}
Lead artist's ranking	-0.002	0.001
2nd Lead artist's ranking	-0.006***	0.001
MPAA-PG	-0.008	0.006
MPAA-R	-0.001	0.004
Drama	-0.005*	0.004
Thriller	0.020***	0.005
Comedy	0.003	0.004
Intercept	0.188***	0.038
R ²	0.2323	

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.

Figure 1. Social media platform differences in Daily standard deviation of comment valence

4.4. Findings

We first examine how the opinion composition varies across platforms. Table 1 shows that the proportion of positive comments is higher ($\beta = 0.066$, p -

value <0.001) for product oriented social media platforms, which confirms H1a. The results also lend support to H1b in that there are more negative posts ($\beta = 0.164$, p -value <0.001) in product oriented social media platforms. All these suggest that for the product oriented environments, there are on average 6.6% (16.4%) more extreme positive (negative) comments compared to a non-product oriented environment. In all, we find evidence that product oriented social media platforms tend to attract polarized opinions, and there is no significant change in this tendency over time.

Next, we examine how online opinions evolve over time and across platform. Table 2 shows that the standard deviation of comment valence is larger in product oriented social media platforms ($\beta = 0.081$, p -value <0.001). Over time, however, the standard deviation of comment valence decreases as time elapses ($\beta = -0.001$, p -value <0.001), and it decreases at a faster pace in product oriented social media platforms ($\beta = -0.006$, p -value <0.001). This provides support for H2a, H2b, and H2c. In other words, opinion convergence is observed for both product and non-product oriented social media platforms, suggesting a decrease in opinion diversity as time passes by. And the opinions in product oriented social media platform converge at a comparatively faster pace. Interestingly, in spite of the evidence for a larger decrease in opinion divergence in product oriented platform, the results show that opinions are still more diverse in product oriented platforms.

5. Discussion and conclusion

Several implications can be drawn from our analysis. First, our results show that the posting population is different across outlets, with product oriented social media platforms attracting more polarized individuals. We found that there are more extremely positive and negative posts in product oriented social media platforms compared to non-product oriented social media platforms. This is in line with our hypotheses, which is premised upon the argument that when extremely satisfied or dissatisfied consumers intend to influence other consumers, they choose product oriented platforms over non-product oriented platforms. One possible reason is that former is perceived to have an environment which encourages consumer interaction and product related opinion sharing.

Second, our results show that while the opinions in product oriented social media platforms are more diverse, they converge faster than the opinions reflected in non-product oriented social media platforms. Given that there are more extreme

comments in product oriented social media platforms, the valence diversity ought to be greater. For both social media platforms, we observe opinion convergence over time, which is consistent with our argument that there exists an anchoring effect. Furthermore, we find evidence that opinions converged faster in product oriented social media platforms where consumer chatter is concentrated. As hypothesized earlier, the anchoring effect tends to be magnified in product oriented social media platforms due to greater availability and accessibility of the anchor. In the subsequent sections, we discuss the significance of our findings to research and practice.

5.1. Implications for research

Our results point to the importance of differentiating between different social media platforms. Findings from prior literature are typically based on data collected from a single type of social media platforms, and our study furthers the understanding by showing that consumers' behavior varies across different social media platforms. Consumers at higher or lower levels of satisfaction tend to post in platforms such as discussion boards and forums. By contrast, non-product oriented social media platforms like Twitter do not tend to attract polarized opinion, but instead, represent the views of more moderate consumers.

Another contribution lies in our effort to explore whether and how online opinions evolve differently across social media platforms. Previous investigations find that preceding posts affect subsequent posts. We contribute to this body of work by studying how existing posts impact opinion evolution in terms of how opinion convergence differs across social media platforms. We found evidence that consumers anchor their evaluations to what has been already posted in the site, leading to a gradual decrease in the diversity of comments. This anchoring effect is further intensified in product oriented social media platforms.

5.2. Implications for practice

Our research informs marketers that different social media platforms are not equivalent. They differ not only in what the posting population is comprised of, but also in terms of the opinion evolution pattern. Based on the results of this study, we recommend marketers to differentiate social media platforms when they try to interpret and act on what is posted online. Acknowledging platform difference helps marketers to develop a more proper understanding of actual consumers' sentiments. They can monitor different

social media platforms to get an overall idea about how consumers evaluate their product. In addition, our results show that changes in comment sentiment might be a reflection of or reaction to posted opinions. Therefore, we caution marketers against taking all postings literally because what is posted might not truly mirror individual consumer opinions.

6. Limitations

Although our study is conducted in the context of cinematic movies, we believe that the findings will be applicable to most experience goods which experience similar cost, demand and consumption patterns. There are, nonetheless some worthwhile issues that we leave for future research. First, our study focused on social media comments and did not include offline conversations. The objective of our research is to compare social media comments from different platforms, future research can extend our work by juxtaposing online and offline comments to gain more insights into the similarity and dissimilarity between the two. Additionally, researchers can study to what extent the whole population posting across social media platforms represents the general customer base. In this way, we can better translate social media comments into how consumers actually evaluate the product.

7. References

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