Posting behaviour of consumers and the impact of social media on product sales

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**POSTING BEHAVIOUR OF CONSUMERS AND
THE IMPACT OF SOCIAL MEDIA ON PRODUCT
SALES**

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ABSTRACT

As social media permeates daily life, it attracts attention from both researchers and practitioners. Prior research has demonstrated the relevance of social media mainly by studying its impact on product sales in various settings. However, little is known regarding differences in social media across sources, time and platforms. In order to fill this gap, this dissertation conducts two studies differentiating social media opinions in research on purchasing and posting behaviour.

The first study investigates the relationship between the sentiment embedded in online comments (i.e. valence), the quantity of comments (i.e. volume) available on a movie and box office receipts. The results show that the persuasive effect of different online sources fluctuates as time evolves. Our findings suggest that online opinions are strong predictors of sales, but the different sources of online opinion are not equal in impacting product sales. This study demonstrates that online opinions are not always persuasive and useful, and our findings yield insights into when consumers are likely to pay attention to online opinions.

The second study examines how different social media platforms influence 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.

In addition, product oriented outlets facilitate faster assimilation of opinions within the site compared to non-product oriented outlets.

Empirically, the two studies are different from most social media research which focuses on single source and relies on self-reported ratings to measure comment valence. To compare online opinions across sources and platforms, we tracked over 1500 sources of online expert and consumer reviews for cinematic movies released for an entire year and continuously monitored major social media sites (e.g. Twitter and Plurk) for comments. To avoid data loss due to the lack of self-reported ratings, we text mined the comments to elucidate the sentiments and analyzed the data.

These two studies caution researchers and practitioners against treating online opinions from different sources as the same, and highlight that what is posted online may not truly mirror consumer opinions. Study 1 shows that influence of online opinions on cinematic movie box office is dynamic and varies across sources and platforms. The importance to appreciate platform difference is again illustrated in Study 2, which finds that online posts in some social media platforms are relatively polarized, and become more assimilated over time.

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CHAPTER 1.

INTRODUCTION

Owing to developments in communication technology, channels for information propagation have been diversified and the volumes of consumer generated content are rising unprecedentedly fast. Electronic media is gaining power to enlarge audience base with more mediums and increase the odds to shape their attitudes towards the product. In recent years, the importance of electronic media is further highlighted with the advent of social media, which is defined as “the broad and evolving set of online technologies and related practices for social engagement and interaction” (Du & Wagner, 2007, p. 50).

The proliferation of social media has attracted great interest among academics and practitioners alike. Considerable effort has been devoted to acquire understanding about the impact of social media on product sales. Unfortunately, previous inquiries do not provide a holistic picture capturing the dynamics between social media and product sales across platforms, and little is known regarding the trends and content of social media comments per se.

First of all, prior inquiries seldom compare social media comments even though they are sourced from various platforms. It is common that consumers consult external websites which are different from where they made their purchases (Gu, Park, & Konana, 2012). Gu and his colleagues (2012) further showed that the impact of consumer comments from external websites can be even more important compared to those on internal retailer-hosted websites. Focusing on comments from a particular site is not sufficient to obtain the complete picture of how consumers are affected by comments

online. It is thus necessary and meaningful to capture a greater breadth of comments from various sources and sites available to consumers via social media.

Secondly, there is inconsistency in the empirical findings regarding the relationship between the sentiment expressed in social media comments and product sales. One of the probable explanations is that prior studies make a questionable assumption that there are no differences between early and late consumers. In Li and Hitt (2008)'s work, a positive bias is observed in the early consumer reviews, and the average product rating tends to decline over time. It is possible that early consumers are different from late consumers systematically, who might follow a different behavior pattern and consult different sources, resulting in fluctuating levels of persuasiveness over time.

Thirdly, it remains an unanswered question that in what way the differences in social media platforms affect opinion composition and evolution over time, i.e. who contribute online posts to social media and what trend online opinions follow (Toubia & Stephen, 2012). Prior literature mainly demonstrates the relevance of social media comments by investigating their impact on the external like product sales, research is lacking regarding social media comments per se (Wu & Huberman, 2008). Both researchers and practitioners can benefit from a more proper understanding of the nature of social media comments (Sobkowicz, Kaschesky, & Bouchard, 2012), as it is fundamental knowledge of social media, helping us make valid interpretations and inferences, and produce appropriate responses based on changes observed in them.

Prior research on social media comments is usually limited to a single site (e.g. Moe & Schweidel, 2012), and little is known about whether and how people react to platform differences. Firstly, there are studies into consumers' decision to provide

comments, but our understanding is limited about how consumers choose social media platform when they decide to post comments. The answer to this question enhances our understanding of social media use. Given that prior research has found social media outlets are used to accomplish different purposes (Blackshaw & Nazzaro, 2004), it is probable that user interactions with social media platforms follow different patterns. The second study therefore develops and tests hypotheses on consumers' selection of social media platform based on research on posting motivations.

In addition, research is needed regarding opinion evolvement across platforms, which reveals how social media platform may interfere with posting behaviours. We usually consider social media as a tool for us to communicate ideas, this study shows that social media is not as "passive" as we thought, but may induce adjustment behaviours in posting. Study 2 not only provides empirical evidence that social media opinions deviate from actual consumer opinions, but also shows how different social media platforms "distort" consumer attitudes. The comparison of social media platforms yields fresh insights about how posting behaviours are moderated by new forms of information technology

The remainder of this dissertation will be organized as follows. Chapter 2 provides a preview of the two empirical studies, explains how these studies relate and contribute to the literature. Chapter 3 describes the first study that compares the impact of online comments on movie box office across source, time and outlet. Chapter 4 describes the second study which investigates how opinions composition and evolution vary across social media platforms.

CHAPTER 2.

PREVIEW OF THE TWO STUDIES

Online media has become one of the biggest contributors in interpersonal communications with respect to propagation speed, volume, and variety in channel. In recognition of its growing importance, there is an abundance of research devoted to explore it and its effects. Unfortunately, prior studies have not fully appreciated the fact that social media is a general name for a variety of sources of consumer generated information (Blackshaw & Nazzaro, 2004), which as we argue and empirically show, differ in aspects so that ultimately induce different user behaviours in purchasing and posting. Drawing upon models of communication, this section explains the motivations behind the two empirical studies and their connection to the literature.

Since social media is only a part of communication, we revisit research on communications to gain a full picture so that we can better understand its relation to other components. The initial model of communication (as shown in Figure 2-1) was comprised of information source, channel, and receiver (Shannon & Weaver, 1949). But it has been criticized for weaknesses such as neglect of the different communication purposes and context, isolation of information source and receiver, and the indifference to the social nature of the channel which have implications for the communication (Chandler, 1994). We argue that most previous studies on social media suffer from similar weaknesses, which this dissertation intends to overcome.

Figure 2-1. Initial model of communication

Firstly, researchers typically focused on one source (e.g. experts or peers) of electronic media information in examining its influence on the purchase behaviour of consumers (i.e. receivers). For example, empirical evidence has been accumulated that information and reviews from experts (e.g. Basuroy, Chatterjee, & Ravid, 2003; Reinstein & Snyder, 2005; Sawhney & Eliashberg, 1996) or peers (e.g. Chevalier & Mayzlin, 2006; Forman, Ghose, & Wiesenfeld, 2008; Liu, 2006) have significant impact on product sales, but they seldom compare the impact of different sources. However, Prior research has shown that consumers are likely to consult multiple sources instead of relying on a single source (Gu et al., 2012). Research is therefore needed to compare online comments across sources so that we could extend our knowledge of the potential differences among online comments.

Secondly, social media is a collection of channels which are not direct counterparts of one another. Some social media channel might be considered as a more appropriate or efficient communication tool in sources' and receivers' eyes. Firstly, from the perspective of sources, we argue that social media platforms are not identical to each other, and fulfill different functionalities defined by sources. We propose that the determinants of the function that a social media channel will carry out include not only its technological features and limitations, but also users' perception of the platform, which is no less important and ultimately key to characterizing user behaviours.

When sources want to communicate a message, they choose from the collection of social media channels to best serve their purposes. For example, consumer discussion forums encourage users to sharing product related knowledge or experience (Brown, Broderick, & Lee, 2007). On the other hand, the main reason that people use social media

sites like Twitter is to maintain offline relationships and digitalize personal life (Ellison, 2007; Java, Song, Finin, & Tseng, 2007; Trusov, Bucklin, & Pauwels, 2009). Social media channels differ in terms of the perceived functionality, which subsequently affect sources' posting behaviours.

Furthermore, we predict that social media channels are different from the standpoint of information receivers (i.e. consumers who browse online comments for information). Generally speaking, online comments reach information receivers because they are pulled by information receivers from websites (e.g. consumer ratings websites, online forums, and discussion board), or pushed to information receivers (e.g. microblogs) (Hermans, 1998). It is a basic approach to classify social media channels into push-based and pull-based channels (Kendall & Kendall, 1999). We argue that how online comments are delivered might vary the level of persuasiveness and impact thereof.

In addition to downplaying the diversity in sources and social media channels, previous studies tend to assume that information receivers are homogeneous. We believe characteristics of information receivers affect how they are influenced by electronic opinions. Evidence is gathered that early consumers are different from later consumers in terms of dispositions (e.g. Van den Bulte & Stremersch, 2004). In the first study, we differentiate early from late adopters of products to study whether and why they may prefer different source or information delivery mechanism. Taking this consumer heterogeneity into consideration, we find an opportunity to reconstruct the dynamic process via which consumers consult online comments before they make a purchase.

Moreover, there is a dearth of research into the nature and temporal evolution of social media opinions. One reason for researchers and practitioners pay attention to social

media is that it is influential and less subject to manipulation (Angelis, Bonezzi, Peluso, Rucker, & Costabile, 2011). Unfortunately, research has shown that social media opinions are by their very nature biased (Kapoor & Piramuthu, 2009; Moe, Schweidel, & Trusov, 2011). In order to better leverage this new and prevailing medium, research is needed to yield insights about questions like how social media comments might be different from the opinions of the overall population, and how they evolve over time (Gao, Greenwood, McCullough, & Agarwal, 2013; Wang, Zhang, & Hann, 2010; Wu & Huberman, 2008).

Lastly, we have limited understanding about the dynamic impact of electronic comments on information receivers (in the present case, consumers' purchase decision). Empirical findings are not consistent regarding the significance of the impact of electronic comments on purchase behaviour. Some studies documented a positive relationship between electronic opinions and product sales (Dellarocas, Zhang, & Awad, 2007; Gu et al., 2012), while others observe an insignificant relationship (Dhar & Chang, 2007a; Li & Hitt, 2008; Liu, 2006).

It is probable that certain electronic media opinions do have an influence on receivers, but their impact concentrates at a certain point of time. When aggregating the observations, one might fail to observe a significant relationship. Consumer heterogeneity in information seeking is the reason for us to consider the possibility that the impact of electronic opinions is subject to change over time.

We argue that the overall population of consumers can be divided into segments on the basis of the source which consumers find most persuasive compared to other sources. To rephrase the point, a certain segment of consumers may find type A electronic comments persuasive, while a second segment prefers type B. As mentioned previously,

consumers have different information seeking habits. Consumer segment which consults type A might be more active than consumer segment persuaded by type B when searching for electronic opinions. In this way, type A electronic comments would appear impactful at an earlier point of time compared to type B. Therefore consumer heterogeneity somehow determines when electronic media opinions “can” affect receivers’ purchase decision, varying the impact of electronic media comments over time. Figure 2-2 shows how the aforementioned research gaps in current empirical studies related to the communication model, and Table 2-1 summarizes the corresponding unanswered questions and how this dissertation addresses them.

Figure 2-2. Electronic media facilitated communication

Table 2-1. Research questions

Component in the communication model	Research question	How is the research question addressed
Source	Whether and how the impact of comments from different sources differs	Study 1 juxtaposes comments from different sources (experts vs peers)
Receiver	Whether and how consumer heterogeneity affects information seeking	Study 1 develops a typology to segment consumers based on their information seeking
Source-Channel	How social media channels	Study 2 differentiates social

	differ in sources' eyes when they want to post a comment	media channels based on their perceived functionality
Receiver-Channel	How social media channels differ in receivers' eyes when they want to consult before purchase	Study 1 differentiates social media channels based on their information mechanism
The dynamics of communication	Whether and how the relationship between electronic media comments and product sales changes over time?	Study 1 formulates hypotheses about when electronic media comments are impactful
	How social media comments evolve over time?	Study 2 investigates opinion convergence across platform

As shown in Table 2-1, two studies were conducted in an attempt to bridge the gaps. To be specific, study 1 examines how the sentiment embedded in online comments (i.e. valence) and the quantity of comments (i.e. volume) available on a movie influence the movie's box office receipts across time. It extends prior research in several ways. Firstly, the results show that online opinions are strong predictors of sales, but the different sources of online opinion are not equal in impacting product sales. Moreover, comparing between comments from different types of online comments, we find evidence that the persuasive effect of different online sources fluctuates as time evolves. The findings suggest we should not treat online comments as the same, but differentiate between the source of the online comments and how the comment is delivered (i.e. pull versus push) when we study their effect on product sales over time. This study demonstrates that online comments are not always persuasive and useful, and the findings provide insights into when consumers are likely to pay attention to online comments.

In study 2, we examined how comments differ in composition and opinion evolution across social media platforms. It is one among the first to explore how social media platform difference may affect posting population composition (i.e. opinion

composition) and the pattern in opinion change over time (i.e. opinion evolution). The results show that the composition of posting population actually differs, supporting our argument that social media outlets are defined by users to fulfill different functionalities, therefore attracting different groups of consumers to post. Moreover, as the traceability of opinions is enhanced, anchoring effect comes into play, causing online comments become assimilated gradually. Evidence is documented that there is platform difference in the pace of opinion convergence, which again cautions researchers against treating social media platforms as they are the same.

To sum up, both Study 1 and Study 2 centre upon the impact of social media platform differences, with the former trying to project a more comprehensive picture of the relationship between online comments and the external, namely movie box office, and the latter exploring social media comments themselves. Together, the two studies contribute to the literature by demonstrating the importance to differentiate social media platforms when we carry out research related to consumer generated content.

CHAPTER 3.

STUDY 1-A TEMPORAL STUDY OF THE EFFECTS OF ONLINE OPINIONS: INFORMATION SOURCES MATTER

Introduction

Online media (sometimes termed social media) has become an important source of information that affects consumers' decision making when purchasing products and services. There are now more channels through which users can communicate their opinions and views of products, events, people, and issues. Consumers can conveniently post their comments via different outlets (e.g. blogs, online discussion forums, online communities, etc.), read comments from unknown peers, friends or experts, and exchange opinions with other consumers. With improved information dissemination in terms of propagation speed, breadth, and volume, there are now more channels through which opinions and ideas of others can disseminate and impact the purchasing intentions and decisions of consumers.

Past literature documents the enthusiasm of researchers towards online media and its commercial impact (e.g., Dewan & Ramprasad, 2009; Duan, Gu, & Whinston, 2008; Godes & Mayzlin, 2004). While these studies enrich our understanding of the effects of online media, previous inquiries tend to focus on one particular medium of online media, or focus on examining how the product reviews from one site affect sales of the product in the same site. For example, research has shown that information and reviews from retailer sites (e.g. Amazon.com and Barnesandnoble.com) have significant impact on product sales in the same sites (Chevalier & Mayzlin, 2006).

As highlighted by Gu, Park, & Konana (2012), consumers often conduct searches through various external websites that are different from where they made their purchases. They further showed that consumer comments on external websites can have an even more significant effect than those on internal retailer-hosted websites. This highlights that consumers often search broadly for information on the internet, and given the multiple channels of information propagation available for any product, it is too limiting to examine only the reviews from a single source. In focusing on comments from only one source, prior research has not accurately captured the breadth of opinions from various sources and sites available to consumers via the social media, and has not considered how distinct information sources, based on the source characteristics, would influence product sales differently. In this paper, we go beyond a single type of online media to examine how product comments from different sources of online media affect product sales. By comparing how different sources of information influence product sales, we seek insights into the ways in which social media influence individuals' decision making.

Our research also aims to provide an understanding of how the effects of time would change the influence of online opinion, arguing that consumers who make purchases early versus late in the product life cycle are fundamentally different in what sources of information they pay attention to. Prior research has shown that the reviewers who post comments early versus late are clearly not randomly distributed, but rather, exhibit certain biases and trends. For example, Li and Hitt (2008) found that the average rating for a product tends to decline over time and early consumer reviews demonstrate positive bias due to a self-selection effect. Acknowledging that the content posted at different points in time of a product life cycle is different, prior research has also

examined how the influence of online comments¹ differs at different points in time of a product life cycle. Building upon previous work, we further our understanding of how the effects of online comments differ not only over time but also over different information sources, by examining the overall research question of how different sources of information impact consumers' decision making via the sales of the product at different points in time.

By providing a comparison of how different sources of information influences box office receipts over time, our study differs from prior research in the comprehensiveness of the data collected and of the insights drawn from the data. The comparison of different sources of information across time allows us to present a theoretically derived model of different types of imitators who exhibit different information processing behaviors. To provide adequate comparison, our empirical data collection is more comprehensive than published studies to date, as we collected different types of online comments, and we used multiple sites to collect each source of information.

In order to provide a comprehensive comparison of the impact of online opinion over time, our study also differs methodologically from most prior social media studies in two ways. First, we employ text mining techniques to present a holistic view of the relationship between online opinions and movie box office receipts. Our study is not limited to comments with self reported ratings, which constitute a small proportion of all posted online comments. Here we see compelling reasons to use text mining because using only online comments and reviews with self-reported rating scale results in a tremendous loss of data, and a natural biased censoring of the data. Without using text

¹ We use online comments and online opinions interchangeably in this paper.

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. This exclusion undermines the goal to acquire a comprehensive understanding of the effect of online comments across sources. 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; over time not all tweets are always publicly searchable and such data might not be easily captured after the information generating event. 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 posts for over a year.

Our results reveal that the persuasiveness of online comments differs not only across different source but also over time, showing the importance of comparing across different sources of online opinion.

Context of the Study

We chose cinematic movies as the context for this study. As highlighted by Godes & Mayzlin (2004), word of mouth effects are particularly important for entertainment goods and in influencing movie selection by consumers (Bayus, 1985). Moreover, movies tend to receive significant public interest and attention, hence active communication about movies is quite prevalent and online opinions about movies, in particular, have been shown to affect movie box office receipts (Dellarocas et al., 2007).

Empirically, movies also provide the ideal context to examine the effects of online opinion on sales, due to various reasons. First, movies are common and standardized

hedonic goods. The movie industry is a vital part of the American economy (Mohr, 2007). As an affordable entertainment option, movie theatres continue to draw more consumers than other forms of entertainment (McDonald, 2009). Second, various information aggregators constantly monitor the daily box office receipts, making it possible to obtain daily sales data for movies. Third, it is feasible to design a sampling schema that is representative of the industry yet practical for data collection efforts as the number of movies released per year is a manageable number to track. Moreover, it is feasible for us to comprehensively retrieve online comments about movies, as the dispersion of comments on each movie tends to be concentrated in the period around its release. This allows us to quite comprehensively collect most comments about a movie within a relatively short time period. In a nutshell, the context of movies provides an appropriate context to conduct our study of comparisons between different sources of online opinion.

Literature Review

The information processing literature has shown that independent of message content, messages from different sources influence a person's attitude differently (e.g., Chaiken & Maheswaran, 1994; Forman et al., 2008; Kang & Herr, 2006; Pornpitakpan, 2004). Given that online comments can be sourced from multiple outlets, there is a need for research to compare whether the online comments from various outlets influence consumers in the same way. In particular, we examine the online comment obtained from experts versus peers, and further differentiate peer comments that are available via forums and discussion boards to search and browse, versus comments from microblogs that are pushed to consumers. The diversity in the ways that these platforms are used influence how the information reaches and gets digested by consumers. Hence, we believe that it is

important for research on the influence of online media to progress by comparing the effects of information sourced from multiple platforms.

Comparing between Experts and Peers

Both Forman et al. (2008) and Godes and Mayzlin (2004) have demonstrated that reviewer characteristics affect the way people process messages from online media. In particular, expertise is a key aspect of a message source that influences the persuasiveness of a message (Wilson & Sherrell, 1993). It is, however, not always the case that a message from an expert is more persuasive than that from a non-expert. Fitzsimons and Lehmann (2004), for example, found that unsolicited expert recommendations can backfire, resulting in consumers deliberately ignoring or even contradicting them. In our study, we thus distinguish between online opinions that are representative of expert reviews versus peer reviews. Expert reviews are written by critics, defined as “persons usually employed by newspapers, television stations or other media who screen newly released movies and provide their subjective views and comments on the movie for the public’s information” (Cones, 1992, p. 120). Prior research has found that it is common for experts and consumers not to agree in their reviews. Prior research found that experts and consumers differ in their preferences and tastes for aspects like movie genres and artistic acting, and they also differed in their evaluations for many movie characteristics, including sensory experiences conveyed by the movie (Holbrook, 1999; Wang, 2008).

Since experts and peers tend to disagree with each other, which source would have a greater influence on movie sales? Donnavieve et al. (2005) examined when people used peer versus editorial recommendations for online purchases and found that a consumer’s preference depends on whether his or her shopping goal is more utilitarian or hedonic in

nature. Prior research differentiates between purchases made for utilitarian purposes – of functional products that are used in an instrumental manner, versus purchases for hedonic purposes – for experiential consumption, fun, pleasure, and excitement. Microwaves, detergents, home security systems, or personal computers are examples of purchases made for utilitarian consumption, while flowers, designer clothes, music, and luxury watches are examples of purchases made for hedonic consumption (Holbrook & Hirschman, 1982; Wertenbroch & Dhar, 2000). Both Donnavieve et al. (2005) and Wang (2008) found that peer opinions are valued for hedonic or experiential products, while expert opinions are valued more for utilitarian products. This may be because experts tend to focus on technical features of a product and evaluate functional attributes in their reviews, while peers tend to offer their subjective experiences and feelings of using a product based on their own idiosyncratic usage situations. Hence, readers may find peer reviews more useful for hedonic products that are more usually more experience based, or products for which the quality can often only be determined after consumption (Bansal & Voyer, 2000; Klein, 1998).

Based on the above line of argument, one would expect expert opinion not to matter for hedonic goods such as movies. Several studies, however, have found evidence that experts or critics review have significant impact on explaining box office receipts (Basuroy et al., 2003; Boatwright, Basuroy, & Kamakura, 2007; Reinstein & Snyder, 2005; Sawhney & Eliashberg, 1996). This provides significant contradictory evidence to the argument that peers rather than experts are expected to influence the purchase of hedonic products. Our study thus aims to reconcile this contradictory evidence and to build the theoretical arguments about when experts versus peer reviews are expected to

influence consumer purchases for hedonic purchases. We do so not by assuming that expert opinions do not matter for hedonic products, but rather, by examining when expert opinion matters based on underlying arguments of which types of consumers are influenced by experts versus peers.

Comparing between Peer Platforms

While prior research has compared the effects of expert versus peer opinion, prior studies have not differentiated between peer opinions originating from different platforms. The increasing proliferation of technologies provides opportunities for more ways through which consumers can obtain information from peers online. A basic approach to classify platforms providing peer opinions is to differentiate between push-based versus pull-based platforms (Kendall & Kendall, 1999).

Pull-based platforms. As consumers increasingly look to peers for information about products, there are now many websites available that serve as a forum for consumers to interact and share their experiences for a particular product (Brown et al., 2007). The success of internet sites such as Epinions.com, Ecomplaints.com and Tripadvisor.com show that consumers value a place for them to share product reviews and consumption experiences. Such websites 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” (Brown et al., 2007, p. 3). We classify such online discussion forums as pull based peer comments, as the information from such channels reach other consumers only if the consumers search for and browse the content in the online discussion forums.

Push-based platforms. In contrast, microblogs represent a push based approach of distributing information. Microblogging is a form of communication in which users send short messages (usually less than 200 characters), and the messages are sent to the receivers by instant messages, mobile phones, email or the web (Java et al., 2007). Twitter, for example, is the most popular form of microblog in US, Europe and parts of Asia. Individuals predominantly receive messages from sources that they have elected to follow. Following a source implies that the short messages generated by the source would be automatically pushed onto the Twitter pages of all his or her followers (Kaplan & Haenlein, 2011).

We argue that it is important to compare the persuasiveness and impact of messages that consumers receive from these two sources because they not only represent different ways in which consumers receive information about a product, but the messages also influence the message recipient via different underlying persuasion mechanisms.

Understanding Valence and Volume

We conducted a thorough review of the literature that has examined the effect of online comments on the sales of hedonic products like movies, songs and books. Table 3-1 provides a summary of the key articles in this domain. Based on our review of the articles, we conclude that empirical support so far corroborate the role of online comments as an effective tool that affects consumer purchasing decision and product sales of hedonic goods.

Table 3-1 Previous Empirical Research Examining the Impact of Online Comments on Hedonic Product Sales

Study	Dependent Variables	Key Independent Variables	Source of Reviews	Key Findings
Sawhney and	Movies weekly	Valence of	Variety, Baseline	The valence of expert reviews

Study	Dependent Variables	Key Independent Variables	Source of Reviews	Key Findings
Eliashberg (1996)	box office receipts	expert reviews	Movie Guide	correlates with box office receipts
Eliashberg and Shugan (1997)	Movies weekly box office receipts	Valence of expert reviews	Variety	The valence of expert reviews correlates with later weeks and with cumulative box office receipts
Basuroy, et al. (2003)	Movies weekly box office receipts	Valence and volume of expert reviews	Variety	The valence of expert reviews correlates with box office receipts
Elberse and Eliashberg (2003)	Movies opening week box office receipts	Valence of expert reviews	Entertainment Weekly	The valence of expert reviews correlates with box office receipts
Reinstein and Snyder (2005)	Movies opening weekend box office receipts	Valence of expert reviews	Two critics: Gene Siskel and Roger Ebert	Valence of expert reviews correlates with box office receipts
Liu (2006)	Movies weekly box office receipts	Valence and volume of peer comments	Yahoo Movies	Only volume of peer comments correlates with box office receipts
Zhang and Dellarocas (2006)	Movies weekly box office receipts	Valence and volume of expert and peer comments	Yahoo Movies	Volume of expert/peer reviews has no effect; valence of expert reviews correlates with box office receipts in the early stage; valence of peer comments correlates with box office receipts
Boatwright et al. (2007)	Movies weekly box office receipts	Valence of expert reviews	Variety	The valence of expert reviews correlates with box office receipts
Dellarocas, et al. (2007)	Movies weekly box office receipts	Valence of expert reviews, Valence and volume peer comments	Yahoo Movie	Valence of expert reviews, Valence and volume peer comments correlate with box office receipts
Duan, et al. (2008)	Movies daily box office receipts (first 2 weeks)	Valence and volume of peer comments	Yahoo Movie	Only volume of peer comments correlates with box office receipts
Asur and Huberman (2010a)	Movies weekly box office receipts	Valence and volume of peer comments	Twitter	Valence and volume of peer comments correlate with box office receipts
Chevalier and Mayzlin (2006)	Books sales rank	Valence and volume of peer comments	Amazon and Barnesandnoble	Valence and volume of peer comments correlate with book sales rank
Chen, et al. (2008)	Books daily sales rank	Valence and volume of peer comments	Amazon	Valence and volume of peer comments correlate with book sales rank
Forman, et al. (2008)	Books monthly sales rank	Valence and volume of peer comments	Amazon	Full support for the effect of volume but only partial support for the valence of peer comments
Li and Hitt (2008)	Books weekly sales rank	Valence and volume of peer comments	Amazon	Valence and volume of peer comments correlate with book sales rank
Dewan and	Songs weekly	Valence of peer	Amazon	No significant effect

Study	Dependent Variables	Key Independent Variables	Source of Reviews	Key Findings
Ramaprasad (2007)	album sales	comments		
Dhar and Chang (2007b)	Songs weekly album sales rank	Valence and volume of expert and peer comments	Amazon, Pitchfork Media, PopMatters, Stylus Magazine, Rolling Stone, Entertainment Weekly, Allmusic, and Technorati	Full support for the effect of volume of peer comments but the results for the rest are not consistent
Clemons, Gao et al. (2006)	Craft beer sales growth	Valence and volume of peer comments	Ratebeer.com	Valence but not volume of peer comment has an effect
Zhang, et al. (2010a)	Stock market indicators (i.e. Dow Jones, NASDAQ, and S&P 500)	Valence of peer comments	Twitter	Valence of peer comments has an effect
Zhang, et al. (2010b)	Page views of a restaurant webpage	Valence and volume of peer comments, valence of expert reviews	Dianping.com	Valence and volume of peer comments, valence of expert reviews all have a significant effect, but the valence of expert reviews has an unexpected and negative effect
Zhu and Zhang (2010)	Monthly video game sales for PlayStation 2 and Xbox Games	Valence and volume of peer comments	GameSpot.com	Both Valence and volume of peer comments have an effect

Table 3-1 shows that prior empirical research usually examines the influence of online opinion on a product via the valence and volume of the online comments. Valence refers to the sentiment expressed in the content of the comment. It is a continuum with two extremes indicating either absolute positive or negative attitude. The higher the valence, the more favorably the product is perceived by the consumer. Volume of online reviews refers to the quantity of comments, which reflects the frequency that individuals encounter information about a product.

Prior research has shown that the volume of online opinion influence consumers by way of creating awareness about a product – what has been termed the “informative” effect, whereas the valence of online opinion influence consumers by way of changing

individuals' attitudes about a product – what has been termed the “persuasive” effect (Liu 2006; Duan, Gu, & Whinston 2008). The volume of online messages generate awareness because message repetition attracts individuals' attention to the topic of message (Cacioppo & Petty, 1989), and has been shown to generate awareness for product brands (Tellis, 1988), which is one of the preconditions that must exist before people will buy the product. Valence, on the other hand, influences consumers' attitudes because the sentiment embedded in online comments reveal information about product quality (Li & Hitt, 2008) or individuals' feelings about interacting with the product and the extent to which their expectations will be met (Chen & Xie, 2008).

Past empirical studies have provided mixed results regarding the relationship between consumer ratings or valence of online comments and product sales. Some of them document a positive relationship (Chen et al., 2008; Dellarocas et al., 2007; Zhu & Zhang, 2010), while others do not observe a significant effect of ratings on product sales (Dewan & Ramaprasad, 2012; Forman et al., 2008; Liu, 2006). Liu (2006) argues that this is because the link between attitude and behavior is weak. When it comes to products that are subject to impulse purchases like movies, the link is further weakened. However, this idea cannot explain why some studies document a significant relationship in the same class of products (Asur & Huberman, 2010b; Dellarocas et al., 2007; Zhang & Dellarocas, 2006). We believe that the influence of the valence of online comments on product sales are more nuanced and complex than a simple yes/no relationship. To reconcile these contradicting findings, we propose that it is important to examine the influence of the valence of online comments across different sources of online comments, and also across time, so as to examine the influence across early versus late purchasers of the product. In

so doing, we can unpack the complexities of the relationship between valence and product sales and reconcile the contradictory findings.

For volume of online comments, on the other hand, prior research has found the volume of online comments to significantly influence product sales. For example, Gruhl et al. (2005) found the volume of blog posts to influence book sales, whereas Zhu and Zhang (2010) found a positive relationship between the number of consumer reviews and video game sales. Prior research, however, has examined the volume of online comments in a single platform or website. We seek to further build on this literature and confirm the findings by conducting a broader based inquiry, comparing the volume of online comments across multiple platforms on a daily basis to examine whether the influence of the volume of online comments on product sales hold across different platforms.

Hypothesis Development

In order for us to examine how the valence and volume of online comments from different sources influence movies box office receipts at different points in time, we draw upon the underlying premise that there are fundamental differences between different groups of moviegoers, and these fundamental differences account for what sources of online comments these different groups of individuals tend to pay attention to. Prior research has established that there exist different segments of consumers. Advertising campaigns, for example, are often tailored to a targeted segment of consumers based on demographic characteristics – such as age, gender, ethnicity, and geographic location (McGuire, 1976). This is because different consumer segments are expected to have different information exposure habits (for example, they watch television at different times of the day) and different consumption styles (Kotler, 2009).

One approach of segregating moviegoers into different segments is to differentiate between the early and late moviegoers. The marketing literature has long recognized that there are differences between early and late buyers and this characteristic has driven the marketing strategies of many companies (Zhu & Zhang, 2010). The product diffusion literature (Bass, 1969; Rogers, 1995) also bases its theory and arguments on the differences between early and late adopters of new products. Prior research has shown evidence that consumers who make purchases early may have different dispositions compared to those who make purchases late in the product's life cycle (Li & Hitt, 2008; Van den Bulte & Stremersch, 2004).

In the classic work of Bass (1969), he grouped consumers into two categories – (1) innovators who are independent decision makers, willing to take risks and try out new products; and (2) imitators, whose decision to make purchases are influenced by others' purchases. Subsequent research has also confirmed this finding by showing that early adopters tend to lead the diffusion process, while the later adopters tend to learn by observing others (Susarla, Oh, & Tan, 2012; Zhang et al., 2010b; Zhu & Zhang, 2010). Those who lead the diffusion process tend to be the “influentials” who are more in touch with new developments and who “have no qualms about sharing and spreading their experiences among other consumers” (Blackshaw & Nazzaro, 2004, p. 7), thus affecting imitators through their opinions (Van den Bulte & Joshi, 2007). We would expect that the imitators would be the ones who would be affected by the opinions and comments about products available online.

We argue, however, that imitators can be further differentiated by their level of involvement. As highlighted by prior research, consumer behavior can be classified as

high or low involvement (Zaichkowsky, 1985). Involvement refers to the level of interest in or concern about an issue (Freedman, 1964; Mittal & Lee, 1989). The more involved a consumer is with regards a purchase decision, the more he or she would invest in an extensive search for information and a comprehensive evaluation of the choice alternatives. As prior research has shown, the hedonic value of a product, or its ability to provide emotional appeal, pleasure and affect influence the level of consumer involvement (Laurent & Kapferer, 1985). In addition, prior research has also shown that for the same product, consumers will exhibit different levels of involvement, depending on their personal interests and values, the attributes of the product (e.g. the movie itself), and the situation (a special situation that temporarily increases the relevance or interest in the product) (Zaichkowsky, 1985).

We also build draw upon the typology proposed by Moore (1991), who highlights that various segments of early versus late adopters differ in terms of psychological and social profiles, explaining differences in their timing of purchase. According to Moore (1991), both innovators and early adopters are comparatively adventurous, and have more enthusiasm for pioneering products and technologies. The early majority, however, are relatively risk adverse pragmatists who will only adopt a product when there are well-established references. The late majority and laggards, on the other hand, adopt products only when they become an established standard.

Based on the different levels of consumer involvement as well as the proposed psychological profile of early versus late adopters, we argue that “imitators” can be further segregated into three groups: (1) Active imitators: Highly involved enthusiasts who actively seek out information and are willing to process large amounts of information

about the product; (2) Passive imitators: Moderately involved movie goers who adopt a lukewarm attitude towards new products and would delay their purchase to wait for advice from other trusted consumers; and (3) Pragmatic imitators: Less involved movie goers, who are also the “late majorities”, who will be the last to watch a movie, and who are unwilling to spend much effort to process information about the product but look for cues to help them with the processing of information. Based on these three groups, we make arguments and hypotheses about what information sources and when they pay attention to and how that, in turn, influences box office receipts.

Effect of Peer Opinions on Active Imitators

We expect that the influence of peer opinion from pull-based platforms will have the greatest influence on active imitators, who will be among the first to patronage the movie theatre for new releases. Active imitators tend to be the most enthusiastic about the purchase as they are the ones who have the highest level of consumer involvement. Prior research has observed that early adopters of products such as books tend to be avid fans, who are sensitive to advanced and exciting characteristics of the product, perceiving product quality differently from the rest of the consumers who are relatively level-headed (Li & Hitt, 2008). These active imitators are thus likely to actively seek out information and comments of peers who are perceived to be similar to themselves. Research has found that similar experience or background leads to ideological similarity, which results in similar ways of thinking, beliefs and preferences (Burnkrant & Cousineau, 1975; Cialdini & Goldstein, 2004). Message recipients tend to speculate that they and ideologically similar people share more in common, and probably have similar attitudes and make similar decisions. Prior research has suggested that peer comments exert a persuasive

effect because of the perceived ideological similarity (Donnavieve et al., 2005; Mudambi & Schuff, 2010; Susarla et al., 2012; Wang, 2008). Following this vein, active imitators shall expect their own evaluations of the product to coincide with similar minds, i.e. peer consumers of the early movie goers. Therefore, we expect the active imitators to actively seek peer comments from pull based information sources, and the valence of peer opinion from such platforms are expected to have a positive effect on active imitators' purchase decision.

Active information seeking behavior signifies that consumers are interested in what the comment says and value the specific content and attitudes contained in it. Pull based websites like online forums, discussion boards and consumer ratings websites are organized by topic, whose atmosphere encourages active participation in sharing opinions about products. In forums or discussion boards, consumers gather to share their viewpoints of products (Blackshaw & Nazzaro, 2004; Brown et al., 2007; Huang, Lurie, & Mitra, 2009). Hence, we hypothesize that pull based peer comments influence box office receipts in the first few weeks of a movie's release through their influence on active imitators.

H1a: The valence of pull based peer opinions has a positive effect on movie box office receipts in the early stage of a movie's release.

As noted before, while the valence of online comments is expected to change individuals' attitudes toward a product, the volume of online comments about a product is expected to raise awareness of the product. While the sentiment of online comments is reflected in the valence of the comments, the volume of opinions will serve as a signal of the popularity and attention that a particular movie is generating. Given that active

imitators are willing to process a large amount of information, we argue that they will also pay attention to the volume of online comments from the pull based outlets. Hence, we argue that the volume of online comments from pull based outlets will also positively influence the movies' box office receipts in the early stages of a movie's release, through the influence on active imitators.

H1b: The volume of pull based peer opinions has a positive effect on movie box office receipts in the early stage of a movie's release.

Passive Imitators and Peer Opinions

Consumers who are classified as passive imitators, on the other hand, are expected to visit the cinemas only after the first couple weeks' of a movie's release, and we expect this group of consumers to be most influenced by peer opinions from push-based online comments. As their label suggests, passive imitators' lower level of involvement compared to the active imitators implies that they will not actively seek out information about the product. We thus expect this group of consumers to be influenced by push based peer comments rather than pull based peer comments, as they are influenced by comments that are pushed to them but they are not expected to actively seek information from pull based websites. The main reason that people use social network sites like Twitter (i.e. a typical push based outlet) is to maintain offline relationships and digitalize personal life (Ellison, 2007; Java et al., 2007; Trusov et al., 2009). Such sites primarily serve social purposes and are not organized by topic. Subjective norms do not prompt users to provide opinions regarding a product. People are free to touch on any topic, and they anticipate the viewing behavior to be more accidental and without the intention to gain knowledge about

certain products. Consumers therefore do not depend on such push based platforms to actively search for information.

In contrast, push based peer comments are automatically displayed as long as consumers log into their account. With moderate level of involvement, consumers will likely process the information available from such push based peer sources, especially since these are people whom they have chosen to follow. Hence, these peers are trusted individuals whom people feel they have certain rapport with arising from shared preferences and tastes (Donnavieve et al., 2005). Prior research has shown that shared attitudes influence perceived trustworthiness (Brock, 1965; Feick & Higie, 1992; Gilly, Graham, Wolfinbarger, & Yale, 1998). In shopping online, consumers often communicate with strangers and depend on their advice to make purchase decisions, making use of whatever information they can access to make trust inferences (McKnight, Choudhury, & Kacmar, 2002). Hence, in platforms such as twitter where individuals know and choose to follow the individuals making the comment, the level of trust of the person making the comment is significantly higher. Since passive imitators are subject to peer influence, but inactive to search for information, push based platforms are expected to be the information source that influences them. However, we expect push based platforms to have an effect on the passive imitators only after the early stage of a movie's release. Prior research finds evidence that the attractiveness of a movie, especially for blockbuster movies, is usually the highest during the first weeks of release (Clements et al. 2006). As the bulk of the push based comments will appear only after consumers have watched the movie, we thus expect push based peer comments to have an effect only after the early stage of a movie's release. Therefore:

H2a: The valence of push based peer opinions has a positive effect on movie box office receipts after the early stage of a movie's release.

In a similar vein, we expect the volume of push based peer comments to exert a positive influence on passive imitators (Asur & Huberman, 2010b). Push based comments are automatically displayed, which increases the frequency of a consumer being exposed to the product without request. Repeated exposure to product comments increases consumer's awareness of a product, increasing the availability and accessibility of the product in consumers' memory. After exposure to a product, subconscious psychological reactions can be provoked, increasing people's inclination to develop a preference for a product on account of familiarity (Cacioppo & Petty, 1989; Crano & Prislin, 2006). We thus expect that volume of push based peer online opinion would be positively associated with product sales.

H2b: The volume of push based peer opinions has a positive effect on movie box office receipts after the early stage of a movie's release.

Pragmatic Imitators and Expert Reviews

Finally, we expect that late movie goers, whom we call the "pragmatic imitators", will be influenced by expert reviews, rather than peer comments online. Pragmatic imitators are the least involved in the purchase decision, and are thus expected to be the least willing to expend the effort to sieve through large amounts of data to make a purchase decision. While a lot of information is available through peer reviews, especially by the time the movie has been on screen for some time, the information can be overwhelming to consumers who have limited cognitive capacity to process the abundant information (Mudambi & Schuff, 2010). Prior research shows that cues such as the

credibility of the message source are used to assist in the preservation of cognitive resources (Holbrook, 1978; Wang, 2008). In studies across various settings, results consistently show that messages from sources with high credibility induce more persuasion than those from sources with relatively low credibility (Basuroy et al., 2003; Harmon & Coney, 1982; Pornpitakpan, 2004; Wilson & Sherrell, 1993).

In particular, when movie goers have low involvement or low motivation to process large amounts of information, they are more likely to depend on heuristics and cues to help them to identify relevant information (Arndt, 1968; Wilson & Sherrell, 1993). Hence, they are more likely to pay attention to expert reviews, experts are expected to supply consumers with “correct” information to bring down the level of risk associated with purchase, which is much appreciated especially when the products are unfamiliar or unknown (Brown et al., 2007; Donnavieve et al., 2005). Moreover, as professionals, experts are anticipated to deliver unbiased, reliable and informative reviews to inform purchase decisions (Senecal & Nantel, 2004). Hence, we hypothesize:

H3: Valence of expert opinions has a positive effect on movie box office receipts during the later stage of a movie’s release.

We do not examine the volume of expert comments, as the number of experts available to review movies does not exhibit a significant enough variance, and thus is not of particular relevance in the movie setting. Table 3-2 provides a summary of our hypotheses, and Table 3-3 describes the consumer segments and information seeking pattern.

Table 3-2. Summary of Hypotheses

Weeks after a movie’s release:	Movies Box Office Receipts	
	Early stage	-----> Late stage

Peer comments from Pull based online platforms	Valence (H1a)	+		
	Volume (H1b)	+		
Peer comments from Push based online platforms	Valence (H2a)		+	
	Volume (H2b)		+	
Expert comments	Valence (H3)			+

Table 3-3. Customer segment characteristics

	Time of market entry	Involvement with the product	Information seeking	Preferred source
Active imitator	Early stage	High	Active	Pull based peer comments
Passive imitator	Middle stage	Moderate	Less active	Push based peer comments
Pragmatic imitator	Late stage	Low	Least active	Expert reviews

Research Method

Data Collection

We combined various online data sources to develop a dataset which allows us to test the hypotheses put forth. Broadly, three types of data are required. First, we need to differentiate between expert and peer comments; next for peer comments, we also need to differentiate between pull based peer comments and push based peer comments. We adopted two main strategies to collect the data that is required. First, for expert and pull based peer comments, we developed an online automated agent to crawl the Internet based on pre-specified search parameters (details later). Second, for push based peer comments (e.g. Twitter, Plurk), we partnered a social media monitoring and management company, which helped us to collect the comments from “live” feeds such as Twitter. Given the longitudinal nature of this study and as some social media comments are transitory; we conducted our data collection program from October 2010 to October 2011. What is unique about our data collection methodology is that we considered numerous forms of

social media content. Unlike prior research, which focus on reviews from a single platform (e.g. Amazon or Yahoo!), our research consider a wide spectrum of social media outlets. Gu et al. (2012) highlight the importance of both internal and external word-of-mouth in influencing consumers' purchase intentions; hence, we believe that our research design provides a comprehensive view of the social media activities surrounding any particular information good.

Expert Reviews. These refer to movie reviews provided by experts, usually affiliated with mainstream press such as a major newspaper or magazine (e.g. Entertainment Weekly), radio station, or website (e.g. eFilmCritic.com). We considered various websites that aggregate the movie reviews from different sources, which represent the majority of all expert reviews: IMDb (<http://www.imdb.com>), Rotten Tomatoes (<http://www.rottentomatoes.com>), MRQE (<http://www.mrqe.com/movies/>), Yahoo (<http://movies.yahoo.com/movie/>), Rolling Stone (<http://www.rollingstone.com/movies/>), and PopMatters (<http://www.popmatters.com/pm/>). We tested the robustness of our samples by randomly using Google search to test if the sample reviews are comprehensive. Our ad-hoc searches did not yield any new reviews within the first page of the search listing. Each week, we downloaded the reviewer's name, review post date, review content, title of the review and also the review rating (if any) of the movies released in the preceding week. Our dataset covers expert reviews from more than 1,500 websites. We process these expert reviews using a script to determine the valence of each expert review (details later), also removing any duplicate reviews that may have been cross-posted on different websites.

Pull Based Peer Comments. These refer to information and comments mainly generated via online forums, discussion boards, and consumer ratings websites, posted by consumers and moviegoers, not expert reviewers. To read these comments, users have to engage in active search on the internet for them or actively browse the websites containing these comments; hence they are considered pull based comments. 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 from the major movie comments/review aggregator sites (IMDb (<http://www.imdb.com/>), Rotten Tomatoes (<http://www.rottentomatoes.com/>), Yahoo (<http://movies.yahoo.com/movie/>), Rolling Stone (<http://www.rollingstone.com/movies/>)), discussion forums, and consumer rating websites. 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”.

Push Based Peer Comments. New posts on Twitter, Plurk and Facebook constitute the major sources of push based peer comments. 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 she sends. Thus information propagated via Twitter and Plurk is considered to represent information received from the parties we identify with or have interest in. The challenge of collecting push based comments is that they can be short-lived and not all comments remain searchable publicly on the Internet over time. Hence, to collect all relevant push based comments, we have to 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 or her posts accessible to the public), and capture feeds that include words matching the list of keywords.

We capture all comments for a movie for two weeks prior to its release, then throughout the time that it is screening in the cinemas, and for two weeks after the movie has been removed from the cinemas.

Dependent Variable

Box office receipts. Our data collection of major US cinematic movie box office receipts started from October 2010 to October 2011. We sampled our data systematically based on the following procedure. First, we obtained the population list of movies released during the said period from IMDb (<http://www.imdb.com>). IMDb is one of the most comprehensive online movie database that monitors movies worldwide. We triangulated this list with an alternative site: Rotten Tomatoes (<http://www.rottentomatoes.com>) to ensure further accuracy. We excluded documentaries, movies released directly to Videos/DVDs (i.e. not screened in theatres), and movies that were released and screened only in film festivals. We omitted these movies for consistency as they have limited market coverage and are not equally accessible to the entire US market. Such movies also in general have limited online comments and often lack daily box office records. Finally, we collected the daily box office information from the Box Office Mojo website (<http://www.boxofficemojo.com>, a subsidiary of IMDb). Based on the above criteria we

collected data for 239 movies in total and for each movie, we tracked the daily box office information and daily online comments for an average of 86 days.

Data Cleaning

Our data collection methodology is comprehensive as we cast a wide search for social media content, with a total of almost 10 gigabytes of *relevant* online comments in plain text format collected for the data collection exercise. The challenge, however, is that this resulted in a demanding data cleaning and preparation processes on various fronts. Specifically, there is a non-trivial amount of irrelevant data collected in the process especially when the keywords for a movie are generic (e.g. Source Code) Nevertheless, we believe this methodology provides a granular, yet comprehensive snapshot of the social media content. In order to filter out data that contains the keywords but does not concern the movie, we carried out the procedure described in Appendix A.

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 (Chevalier & Mayzlin, 2006; Dhar & Chang, 2007a; Duan et al., 2008; Liu, 2006). However, many reviews do not provide numerical ratings. Therefore this practice often results in the loss of data. In some cases, the review ratings may even distort the actual sentiment conveyed in the textual review as some websites provide a default rating of zero (when reviewers do not provide any ratings), even though the sentiment conveyed in the text of a review is obviously positive or negative. In Godes and Mayzlin's work (2004), 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. Review ratings also convey limited information about a reviewer's sentiment and consumers often read the review text and not depend solely on the summary statistics provided in the ratings (Chevalier & Mayzlin, 2006). Prior research, recognizing that review ratings may provide inappropriate or limited information, have begun to use textual analysis to capture the valence of online reviews (Ghose, Ipeirotis, & Li, 2009).

To accurately measure the sentiment of a comment, we adopted a machine learning method for sentiment classification as appeared in prior literature (Chang & Lin, 2011; Cortes & Vapnik, 1995; Schölkopf, Platt, Shawe-Taylor, Smola, & Williamson, 2001). The essence of this technique involves randomly selecting a sample of the messages that have prior sentiments attached to them by the authors of the messages. The sample of messages is then codified into a set of vectors for machine learning. Using these trained vectors, we predict the probabilities of which other messages are positive (or negative) by the similarity in the message structure. The assumption made here is that message with similar words are likely to have similar sentiment value. The theoretical basis of such a classification technique has been applied in similar IS research (Antweiler & Frank, 2004; Gu, Konana, Raghunathan, & Chen) whereby the authors used a Naïve Bayes algorithm to train a subset of messages to recognize the significance of particular words that will impact the sentiment of the entire message. 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 0.852, 0.822 and 0.926 for expert reviews, pull based peer comments and push based peer comments respectively. The correlation between expert ratings and the estimates from the tool reaches 0.821. Appendix B provides more details of the algorithm used.

Volume of Online Comments. We measured volume with the number of online comments concerning a particular movie. Volume figures are compiled on a daily basis for pull based peer comments and push based peer comments. These figures are subsequently aggregated as required by the empirical specification. We did not compute the volume of expert reviews as an independent variable here because most expert reviews appear within the first week of movie release and the volume does not vary much after that. Descriptive statistics for the volume and valence of online peer comments across time are provided in Table 3-4 and 3-5.

Table 3-4. Descriptive statistics for Pull based peer comments

	Valence				Volume			
	Average	Std	Max	Min	Average	Std	Max	Min
Week1	0.744	0.153	1	0.006	80.093	178.021	1987	0
Week2	0.733	0.177	1	0	52.476	104.196	1085	1
Week3	0.729	0.185	1	0	24.006	106.480	2261	0
Week4	0.722	0.215	0.999	0	12.195	67.831	1714	0
Week5+	0.742	0.238	1	0	1.071	9.922	254	0

Table 3-5. Descriptive statistics for Push based peer comments

	Valence				Volume			
	Average	Std	Max	Min	Average	Std	Max	Min
Week1	0.680	0.146	1	0.046	87.424	144.835	1968	0
Week2	0.687	0.156	0.995	0.036	44.808	68.880	543	0
Week3	0.699	0.159	0.999	0.015	28.711	50.811	564	0
Week4	0.704	0.161	1	0.030	20.095	38.820	393	0
Week5+	0.699	0.169	1	0.005	12.771	34.501	909	0

The detail descriptions of the variables used in the empirical model are shown in Table 3-6, and the correlations among the variables are given in Table 3-7.

Table 3-6. Description of Variables used in Empirical Model

Variable	Description
Dependent Variable	
Daily Sales	Daily box office receipts from North America market (in US\$)
Independent Variables	
Expert valence	The average sentiment of cumulative expert reviews
Pull valence	The average sentiment of pull based peer comments for current week
Push valence	The average sentiment of push based peer comments for current week
Pull volume	The number of pull based peer comments for current week
Push volume	The number of push based peer comments for current week
Days	Number of days since movie is release
Expert valence*Days	Product of Expert valence and Days. The coefficient shows how the impact of Expert valence changes over time.
Pull valence*Days	Product of Pull valence and Days. The coefficient shows how the impact of Pull valence changes over time.
Push valence*Days	Product of Push valence and Days. The coefficient shows how the impact of Push valence changes over time.
Pull volume*Days	Product of Pull volume and Days. The coefficient shows how the impact of Pull volume changes over time.
Push volume*Days	Product of Push volume and Days. The coefficient shows how the impact of Push volume changes over time.

Table 3-4 Correlation of Variables

Variables	1	2	3	4	5	6	7	8	9	10	11
1.Daily Sales	1										
2.Expert valence	0.1672	1									
3.Pull valence	0.1317	0.3944	1								
4.Push valence	0.0854	0.2120	0.1497	1							
5.Pull volume	0.4113	-0.0436	-0.0206	-0.0377	1						
6.Push volume	0.2881	0.1544	0.1377	-0.0182	0.3931	1					
7.Days	-0.5505	0.1487	0.0584	0.0617	-0.5812	-0.1990	1				
8.Expert valence*Days	-0.3154	0.6748	0.2719	0.1613	-0.4483	-0.0529	0.8114	1			
9.Pull valence*Days	-0.4199	0.3099	0.5022	0.1179	-0.5079	-0.1065	0.8832	0.8274	1		
10.Push valence*Days	-0.3872	0.2264	0.1220	0.5892	-0.4815	-0.1720	0.8303	0.7345	0.7680	1	
11.Pull volume*Days	0.2892	-0.0243	-0.0201	-0.0208	0.9347	0.3298	-0.3958	-0.3046	-0.3493	-0.3271	1
12.Push volume*Days	-0.0013	0.2312	0.1651	0.0087	-0.0132	0.8259	0.2772	0.3417	0.3173	0.2182	0.0523

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

Data Analysis and Results

We grouped the observations by movie and chose fixed effects model test our hypotheses. We conducted the Hausman's test to find out whether a random effects or fixed effects model is more appropriate. The result is $\chi^2(11)=85.84$, $p\text{-value}<0.0001$, which provides support for fixed effects model. Table 3-5 tabulates the results for IV/GMM estimation, calculated with fixed effects, auto-correlation consistent estimators, and taking care of heteroskedasticity. The results for the Sargan-Hansen test is $\chi^2(3)=7.22$, $p\text{-value}=0.065$, which suggests the instruments are valid and uncorrelated with the error term. The total number of observations is 15,161, and F-statistics is significant at the 0.001 level.

Table 3-5 IV/GMM estimation

	Coefficient	Std. Err
Expert valence	2.480***	0.251
Pull valence	1.735***	0.355
Push valence	-0.222	0.296
Pull volume	0.105***	0.021
Push volume	0.030	0.022
Days	-0.246**	0.086
Expert valence*Days	-0.373***	0.069
Pull valence*Days	-0.326***	0.097
Push valence*Days	0.262***	0.078
Pull volume*Days	-0.023***	0.006
Push volume*Days	0.015**	0.006
Intercept	4.097***	0.316

Note: ***represents $p\text{-value}<0.001$; ** represents $p\text{-value}<0.01$; * represents $p\text{-value}<0.05$. All $F\text{-statistics}$ are significant at $p\text{-value}<0.001$.

Findings

We first examine how the *valence and volume of peer opinions in pull based online platforms* influence the box office receipts of movies. Table 3-5 shows that the both the valence ($\beta = 1.735$, $p\text{-value} < 0.001$) and volume ($\beta = 1.105$, $p\text{-value} < 0.001$) of pull based

peer comments are positively associated with the movies box office receipts, their impact decreases over time ($\beta_{\text{Pull valence*Days}} = -0.326$, $p\text{-value} < 0.001$; $\beta_{\text{Pull volume*Days}} = 0.023$, $p\text{-value} < 0.001$). Therefore, pull based peer comment mainly affect movie box office during the early stage. This provides support for both H1a and H1b.

Next, we examine how the *valence and volume of peer opinions in push based online platforms* influence the box office receipts of movies. Table 3-5 shows that the relationship between valence of push based peer comments and movies box office receipts is not significant at first ($\beta = -0.222$, $p\text{-value} > 0.05$), but its impact increases over time ($\beta_{\text{Push valence*Days}} = 0.262$, $p\text{-value} < 0.001$). This provides support for hypothesis 2a. We observe a similar pattern for the impact of push based peer comment volume. Specifically, it does not have a significant impact on the movies box office receipts during the early stage ($\beta = 0.030$, $p\text{-value} > 0.05$), but its impact increases over time as well ($\beta_{\text{Push volume*Days}} = 0.015$, $p\text{-value} < 0.01$). This provides support for hypothesis 2b.

Finally, we examine how the valence of expert comments influence movies' box office receipts. Table 3-5 shows that the valence of expert reviews is positively and significantly associated with a movie's box office receipts in the early stage ($\beta = 2.480$, p -value < 0.001), but its effect wears off over time ($\beta_{\text{Expert valence} \times \text{Days}} = -0.373$, p -value < 0.001). Thus, it shows that the valence of expert reviews mainly influences the movies box office receipts in the early stage, which does not provide support for hypothesis 3, which hypothesized that expert reviews will influence movies box office receipts in the later stages of a movie's release.

Discussion and Conclusion

Several implications can be drawn from our analysis. Through a comprehensive data collection effort, we considered not only different types of online comments (peer vs expert), but also multiple sources of data for all types of reviews (e.g. we collected expert comments from more than 1,500 websites, pull based peer comments from 4 major movie aggregator sites, and various discussion forums, push based peer comments from the main sources of such comments: Twitter, Plurk and Facebook). Moreover, by segregating the influence of online comments by source, and by examining their influence on the movies' box office receipts across time, we are able to obtain detailed insights about the influence of both the valence and volume of online comments on box office receipts, thus resolving much of the conflicting results seen in prior literature that tends to focus on a single source of information.

First, our results show that the influence of online peer comments not only fluctuates across time, but the influence from different information sources kick in at different points in time after the release of a movie. This may serve to reconcile the

contradicting findings presented by prior literature. For example, in contrast to Liu (2006), Dellarocas et al. (2006) and Zhang and Dellarocas (2006) who examined peer comments only from Yahoo Movie, we considered peer comments from four large movie aggregator sites, and discussion forums. We found that both the volume and valence of pull based online comments influenced box office receipts in the early stage of a movie's release. This is consistent with our hypotheses, which is premised upon the argument that pull based online comments have the greatest influence on active imitators, who are most enthusiastic about making the purchase and would spend the most time looking for and processing information about a movie provided by peers.

On the other hand, the valence and volume of push based peer comments influence box office receipts more in the later stage of a movie's release. This is consistent with our expectations that movie goers are generally most active during the early stage of a movie's release, hence, these movie goers become the source of the push based comments that influence the subsequent movie goers. Interestingly, our results show that both the valence and volume of push based peer comments have an increasing impact on movie box office receipts. This may be because push-based peer comments are so pervasive that even late movie goers, or the pragmatic imitators are affected by them.

In addition, we observed that a downward trend in the impact of the valence of expert reviews on box office receipts, contrary to our hypotheses, which had expected an effect only in the later stages of a movie's release. Our results indicate that early movie goers pay more attention to the expert reviews, but the active and passive imitators tend to rely less on expert reviews. This attests to the significant influence of expert reviews on early box office receipts.

We provide fresh insights as to the effect of different sources, channels, and receivers. Based on the empirical analysis, both sources (i.e. experts and peers) are persuasive but inform consumer purchase decision at different points of time. This contributes to the literature as prior investigations seldom compare the two sources (e.g. Liu, 2006; Sawhney & Eliashberg, 1996; Zhu & Zhang, 2010), or are silent on how the persuasiveness of sources changes over time (e.g. Dhar & Chang, 2007a; Zhang et al., 2010b). Our results reveal that pull based peer comments and expert reviews are more persuasive at the earlier stage, while push based peer comments create more impact on late movie goers, enhancing our understanding of the impact of sources of online comments. This study is also one among the first to compare online outlets, which finds that push based sites have the most lasting effect on purchase. This not only highlights the relevance of platform differences in social media research, but also informs practitioners about what platform is more impactful and when different types of online comments may affect product sales. Moreover, our study attests to the existence of consumer heterogeneity. We show that consumers do follow different patterns in information search and retrieval. In the subsequent sections, we discuss the significance of our findings to both research and practice.

Implications for Research

From a theoretical point of view, this research contributes to the list of emerging work on social media with a focus on the dynamic influence of social media on economic outcomes. Extant literature has shown that the valence and volume of online opinions have a significant influence of product sales (e.g., Chen et al., 2008; Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Forman et al., 2008), providing evidence that online

opinions significantly affect consumers in their decision about purchases of products and services. There is, however, an unresolved question in the literature as to why there is inconsistency regarding the significance of comment valence. We propose that the contradicting results are mainly due to the focus on a single source of information and the lack of comparison across information sources. This piece of research thus deepens our understanding via comparing the effect of online comments across platforms and time, revealing a more comprehensive picture on the dynamics of online comments.

Our study provides a comprehensive understanding of how online comments influence box office receipts across time in several ways. First, we provide a comparison of how different sources of information influences box office receipts over time. To the best of our knowledge, we are one of the first studies to provide a comparison of the effects of push and pull based peer comments on the sales of hedonic goods. The comparison of different sources of information across time allows us to present a theoretically derived model of different types of imitators – active, passive and pragmatic – who have different levels of consumer involvement in the purchase decision and thus different search behaviors. We use this model to guide our hypotheses development and testing of the hypotheses. We believe that this theoretical model can be further expanded upon by future research to examine whether it can potentially explain other results regarding the influence of peer and other comments on consumer decisions.

Further, our results show the importance of comparing across different sources of online opinion. Our study shows that the persuasiveness of online comments differs not only across different sources but also over time. Pull based peer opinions and expert reviews are more impactful for the active imitators, who are typically early adopters. By

contrast, the passive imitators are influenced more by push based peer comments because they do not actively seek out information, but will process information that is pushed to them, usually later in the product life cycle. Understanding when and how online opinions persuade consumers increases our knowledge of the impact of information technology, and the ongoing digitalization of our lives.

Finally, our empirical data collection is the most comprehensive amongst published studies to date, as we collected different types of online comments, and we used multiple sites to collect each source of information. The comprehensiveness of the data collection provides us with more confidence that our findings are not influenced by the tendency of certain sites to attract certain types of consumers, and for us to conclude that online comments from different sites indeed have an influence of box office receipts.

Implications for Practice

Our research informs marketers that online opinions are not all equal. They differ not only in the extent to which they persuade or inform consumers, but also in terms of the points of time when they exert an influence. Based on the results of this study, we recommend marketers monitor the sentiment of pull based peer comments during the initial release period of a product. In the subsequent stages of a product's release, however, marketers would need to pay more attention to the more push based platforms for online comments. In addition, our results also show that despite the increased attention and affluence of the social media, expert reviews are still persuasive during the early stage of a movie's release. Hence, it is important for marketers to continue to monitor and ensure the availability of expert reviews for their products, and not neglect this group of reviewers in their pursuit of a marketing strategy focused on social media.

Limitations

Although our study is based on cinematic movies, we believe that the findings will be applicable to the context of most experience goods that have similar cost, demand and consumption patterns. There are, nonetheless some worthwhile issues that we leave for future research. First, we did not differentiate between comments that are more versus less influential. In addition to the source and information delivery mechanism, the influence of specific comments is likely to vary. In other words, some comments may be read by a lot more consumers and likely to make a greater impact. However, it is impractical for us to collect data on the number of views of a particular comment, given the scale of our data collection. This would thus be an interesting area for future research. Second, our study focused on online comments and did not include offline conversations. The objective of our research is to compare online comments from different outlets; future research can extend our work by juxtaposing online and offline comments to gain more insights into the relationship between the two and their effects on product sales. Lastly, while we believe our results are generalizable to similar experience goods, it is important for future research to replicate and extend our study to other context. As the popularity of social media is growing rapidly, the role of online comments becomes increasingly important. It is thus meaningful to explore whether and how consumers of different products react to online opinions.

CHAPTER 4.

STUDY 2-PRODUCT VERSUS NON-PRODUCT ORIENTED SOCIAL MEDIA PLATFORMS: ONLINE CONSUMER OPINIONS COMPOSITION AND EVOLUTION

Introduction

Most of the past research inquiries centre upon the impact of online comments on purchase behaviours (Chen et al., 2008; Chevalier & Mayzlin, 2006; Zhang & Dellarocas, 2006), but research regarding trends and the content of online comments per se is still in its primary stage. Past literature has established the relevance of social media comments by highlighting its commercial impact (Dewan & Ramprasad, 2009; Duan et al., 2008; Godes & Mayzlin, 2004). They improve our knowledge of the impact of social media comments, but our understanding of i) who makes comments online (i.e. opinion composition), and ii) how online comments evolve over time (i.e. opinion evolution) remain largely unexplored territories (Kapoor & Piramuthu, 2009; Wu & Huberman, 2008). Answers to these research questions bear both theoretical and practical relevance. Because they advance the understanding about the organicism of social media comments, which is essential knowledge needed to adequately interpret and respond to changes in these posted opinions (Sobkowicz et al., 2012; Toubia & Stephen, 2012).

As pointed out by Mabry and Porter (2010), a distinct stream of research emerges to explore how consumers interact and behave on social platforms. They explain that the way consumers interact with traditional websites is different from that with social platforms, which facilitate individual connectivity and the spread of word of mouth. We therefore cannot perfunctorily generalize the findings from research on traditional

websites to social media. Wu and Huberman (2010) also voiced the opinion that there is a dearth of research on the dynamic aspects of online posts, i.e. how online opinions are generated and change over time.

A second reason for research into user posting behaviours on social media is that it creates essential knowledge that one must have before he or she can make good use of this new medium. The commonly held assumption is probably false that social media comments truly reflect consumers' opinion about products. As a result of sequential exposure to information, the posted opinions are inherently biased and deviate from what consumers actually think of the product (Kapoor & Piramuthu, 2009). Social media opinions are dissimilar from actual consumer evaluations, if not distinct. It is therefore problematic to survey and act on social media opinions as if they were an accurate barometer of consumer attitudes. In view of the impact of social media, it behooves us to conduct research to investigate the nature and organicism of product-related social media comments, acquiring knowledge about how they are "distorted" from consumer opinions, and what inference can be made based on their evolvement/changes over time.

Furthermore, marketers and the social media monitoring industry can benefit from this line of research because it helps them to rethink marketing tactics and better leverage this new medium. Online opinions in social media are largely not subject to manipulation by companies, but play an increasingly influential part in consumer communication (Angelis et al., 2011). It is crucial to develop an understanding of the generation and transmission of social media comments. Proactively, appropriate mechanisms could be introduced to remove or alleviate bias or deleterious effects provided that we acquire deeper knowledge of how users interact with social media platforms (Kapoor &

Piramuthu, 2009). In addition, findings of this study are informative about what the social media monitoring industry can incorporate into their analysis. Although social media monitoring industry is aware of the fact that consumers access multiple platforms, the analysis report usually provides summary statistics for each platform and there is not much in-depth comparison across platforms (e.g. Nielsen, 2012). This piece of research intends to produce insights into social media platform differences germane to consumer opinion generation and evolution over time.

At the current stage, our knowledge is limited when it comes to questions about user behaviours across social media outlets. Research on social media opinions conducted to date seldom compares comments from different social media outlets, but tends to focus on one particular social media outlet. For example, Godes and Silva (2012) studied the sequential and temporal dynamics of online ratings from Amazon.com. Moe and Schweidel (2012) also gathered their data from one consumer ratings site to investigate the likelihood of consumers posting online and how these comments evolve over time. In order to further this stream of research, we need to take into account the fact that social media platforms are perceived differently by users, which ought to affect user interaction patterns.

Past research, has shown that different social media outlets serve different purposes, which imply that user behaviours will tend to differ across outlets (Ellison, 2007). When consumers want to post or read product evaluations, they visit Internet discussion boards and forums (Blackshaw & Nazzaro, 2004). To talk about daily routines or make a conversation with friends, one logs into social networking account (Java et al., 2007). Social media platforms are not equal as they perform different functions.

In an attempt to alleviate this gap, we go beyond a single type of social media to examine 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? In so doing, we are able to obtain deeper insights into differences in posting behaviour due to the specific role or function a particular social media outlet is supposed to fulfill from the users' perspective.

Literature Review

Opinion Composition

There has been a stream of research investigating opinion composition, or examining who are the consumers posting their comments online. This research yields one interesting and important insight: online posts may not represent opinions of the overall population. 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 (Berinsky, 2002). Similarly, Moe and her colleagues (2011) 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 (Anderson, 1998; Berndt &

Koekemoer, 2012; Wangenheim & Bayón, 2007). 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 (Anderson, 1998; Sundaram, Mitra, & Webster, 1998). One camp argues in favour of a positive relationship between consumer satisfaction and word of mouth (Arndt, 1968; Dichter, 1966; File & Prince, 1992; Holmes & Lett, 1977; Wangenheim & Bayón, 2007; Westbrook, 1987), due to concerns for other people's needs and welfare, reduction of cognitive dissonance rising from the excitement in the experience with the product or service, desire to improve image, and the wish to help the company (Dichter, 1966; Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Sundaram et al., 1998). Empirical evidence is found to support this relationship. For example, in carrying out a survey on new car buyers, Swan and Oliver (1989) showed that consumer satisfaction was one motive for favorable word of mouth communications. Hennig-Thurau and his colleagues (2004) 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 (Berndt & Koekemoer, 2012; Charlett, Garland, & Marr, 1995; Schlossberg, 1991; Zeelenberg & Pieters, 2004). Their reasons for communicating with others include the wish to reduce anxiety and frustration, to give a friendly warning to other consumers, to gain sympathy from others, and to take revenge (Anderson, 1998; Hennig-Thurau et al., 2004; Sundaram et al., 1998; Zeelenberg & Pieters, 2004). Zeelenberg and Pieters (2004) 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. (1998), which also attested to the relationship between consumer dissatisfaction and word of mouth. Hence, it is theoretically 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 (2008) 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 (2006) reported a higher proclivity for consumers at higher or lower level of satisfaction to speak out. However, these studies typically collect data from a certain type of social media platform (consumer ratings websites), when exploring the self-selection phenomenon in consumer postings (Dellarocas & Narayan, 2006; Godes & Silva, 2012; Li & Hitt, 2008; Moe & Schweidel, 2012).

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 consumers posting online may vary across social media platforms.

Opinion Evolution-Social Influence

Another related research stream on online posts is to explore the evolution of online opinions. Evidence is documented that early reviews influence later comments, thus resulting in a sequential pattern (Moe & Schweidel, 2012; Moe & Trusov, 2011a). In an experiment setting, Schlosser (2005) 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 (Amabile, 1983), the presence of negative reviews remind one to lower his or 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 (2012), 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 to the party that is doing well (McAllister & Studlar, 1991). Moe and Schweidel (2012) found evidence of the existence of bandwagon effect. They reported 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 could be either positive or negative. Moe and Trusov (2011a) 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 which has shown that people may strategically adjust communicated message when they have 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 (Fleming, Darley, Hilton, & Kojetin, 1990).

While prior research provides interesting insights about opinion evolution for online comments, prior research is 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 (Brown et al., 2007; Ellison, 2007), 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.

Opinion Evolution-Opinion Convergence

As reviewed above, opinion evolution of social media comments has a path dependent feature (Wang et al., 2010). Evidence is accumulated that future trends in the

valence of social media comments can be positive or negative, as they depends on what are already posted on the platform, attesting to the impact of social influence (Moe & Schweidel, 2012).

In addition to changing the tone of posted opinions, path dependency could have an effect on opinion diversity, which is of concern to practitioners. An increase in similarity in social media comments might be interpreted as a signal that consumers reach a consensus over the product, provoking strategic response from marketers. However, such response is justifiable only when the opinion convergence does reflect general agreement among consumers. As consumers' posts probably mirror previous comments (Kapoor & Piramuthu, 2009), a gradual decrease in opinion diversity is expected. It would then be imprudent to act on observed opinion convergence in social media comments. Therefore, there is a need to extend our knowledge of online opinion formation, which help us draw reasonable inferences from social media comments (Wu & Huberman, 2008).

Unfortunately, scant attention is devoted to investigate the dynamics of product related online chatter, although extensive research is conducted to study bias resulting from exposure to information in other context (Kapoor & Piramuthu, 2009). One exception is the work of Wang and his colleagues (2010), which conducted quasi-experimental studies on one website to explore the relationship between social influence and similarity in book ratings. They find that the relationship is moderated by factors like product popularity, user experience, and social network size. Their findings again echo our argument that adjustment behaviour in posting is volatile. Our research examines the moderator effect of platform difference, which is one primary factor determining the context, but neglected in most of previous social media research. Findings from this study

can reveal a realistic picture of how social media may “distort” consumer opinions, as the existence of platform difference would suggest need for caution against the idea that opinion evolution of social media comments is reliable barometer of consumer opinions about products.

Comparing between Social Media Platforms

In the current study, we categorize social media platforms into product and non-product oriented platforms based on the level of perceived salience of contextual cues that suggest the outlet is designed for discussion about product. Therefore discussion boards, forums and platforms alike are considered as product oriented, while microblogs and similar outlets serving social purposes are classified as non-product oriented. We notice though, consumers can find product related comments in non-product oriented platforms using some technical functions. For example, hashtags in Twitter help consolidate comments relating to a product. But they are designed to improve general information retrieval experience, instead of making Twitter a forum for consumer interaction. Non-product oriented platforms are typically used for maintaining relationship with friends or professionals, and broadcasting new information, rather than distributing product related information or evaluations (Trusov et al., 2009).

As discussed in Chapter 2, we believe the differences in contextual cues result in disparate subjective norms, inducing different user behaviours in interactions with social media platforms (Ajzen & Fishbein, 2005). For example, product oriented platforms prompt users to contribute content relevant to products, while non-product oriented platforms do not impose such rules but allow users to touch on any topics. This difference, we expect, affects the composition of posting population, as it somehow drives away

consumers who do not have strong motivation to engage in product related conversations from product oriented platforms. The next section will expand upon how this social media platform difference may influence composition of posting population and opinion evolution.

Hypothesis Development

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, the consumers who post comments online do not represent the general consumer base (Moe et al., 2011). 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 (Dellarocas & Narayan, 2006), because they have strong motivations to share their opinions, as discussed above (Anderson, 1998). 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. Providing that 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.

Opinion Evolution across Platforms

We predict that the sentiment reflected in online comments tend to converge over time, reflecting less disagreement amongst consumers who are posting comments, due to anchoring effects. First introduced by Tversky and Kahneman (1974), anchoring effect refers to the cognitive bias that people’s assessment reflects an influence from an implicit reference point, namely the anchor. People usually cannot make appropriate adjustment to counteract the effect of the anchor, and carry out assessments reflecting the influence of the anchor (Strack & Mussweiler, 1997).

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 (Strack & Mussweiler, 1997). In an experiment setting, participants are usually given only one piece of information (e.g. a number) as the anchor

by the researcher. While in the current 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. Moreover, research has found that it is very difficult to adjust people's assessment so as to eliminate the influence of an anchored reference point (Simmons, LeBoeuf, & Nelson, 2010; Strack & Mussweiler, 1997). Following this vein, every time consumers skim through recent comments, they unconsciously synthesize opinions expressed in them and set the anchor based on the average sentiment expressed in the posted product evaluations. In this way, their comments will somehow assimilate the posted ideas into their own comments because of anchoring effect. Gradually, the similarity of the comments within the site would increase.

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 stronger 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 (Fleming et al., 1990; Moe & Trusov, 2011b; Schlosser, 2005). 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 (Schlosser, 2005). 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 likely to be stronger 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 products (Blackshaw & Nazzaro, 2004; Brown et al., 2007; Huang et al., 2009). 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 (Kapoor & Piramuthu, 2009), 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 (Blackshaw & Nazzaro, 2004). 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 (Ellison, 2007; Java et al., 2007). Product related snippets are dispersed, and mingled 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 not well established due to the relatively poor availability and accessibility to the anchor (i.e. product related chatter).

In addition, there are comparatively fewer social consequences in non-product oriented social media platforms, and consumers are allowed more latitude to express their honest opinions. Non-product oriented outlets do not highlight contextual cues that heighten the awareness that postings will be read by other consumers who are in want of evaluative information. Therefore, people are less worried about questions like whether the comment reaches an acceptable quality level, or how others may judge their evaluative ability. 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.

Research Method

Data

The dataset used to test the hypotheses are the same as the one for Study1. Product oriented social media opinions are classified as pull based peer comments in Study 1, while non-product oriented social media opinions are classified as push based peer comments. Descriptive statistics for the volume and valence of social media comments are provided in Table 4-1.

Table 4-1. Summary statistics for social media comments

		Average	Std	Max	Min
Product oriented platforms	valence	0.729	0.234	1	0
	volume	14.084	72.510	2261	0
Non-product oriented platforms	valence	0.698	0.165	1	0.005
	volume	23.082	60.359	1968	0

Figure 4-1, 4-2, and 4-3 plot the evolvement of number of peer posts for three movies, which rank 25%, 50%, and 75% respectively in gross box office. As shown in these figures, movies with larger gross box office attract more peer comments. Spikes are mostly spotted during the early stage of a movie's release, and consumers much prefer non-product oriented platforms to talk about the movie when it does well at box office. Across three figures, we can see that posting behaviour changes over time and there are platform differences. The product oriented platform posts mostly concentrate within the early stage of a movie's release, while the non-product oriented platform users are still active in the later stages of a movie's release.

Figure 4-1. Comparison for movie ranking 25% in gross box office

Figure 4-2. Comparison for movie ranking 50% in gross box office

Figure 4-3. Comparison for movie ranking 75% in gross box office

Data Analysis and Results

We grouped the observations by the movie title 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 position of 90% are marked down as the cutoff value. Sentiment scores above the cutoff value for 90% 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 represents the daily proportion of extremely negative opinions in product and non-product oriented social media platforms respectively, and is used to test H1b. The calculation is similar to that of *Extr_positive*, except that *Extr_negative* is the proportion of comments whose sentiment score falls below the 10th percentile of all comments.

Control Variables. Our study controls for budget and the popularity of the leading artists (the first and second leading artist), which are usually indicators of the hype surrounding a movie. IMDb Pro data services (<http://pro.imdb.com/>) provides a STARMeter ranking for all actors and actresses, based on the inputs of millions of IMDb

users. The more popular the actor/actress, the smaller his or her rank (i.e. the most popular actor/actress is ranked number 1). We use the STARMeter rankings to measure the popularity of the leading artists. As per prior research, we also controlled for MPAA ratings (Ratings: R and PG) and genre (categories include: Drama and Thriller). We select the two most common genres from our sample and this choice is similar to those presented in prior studies (Basuroy et al., 2003; Boatwright et al., 2007; Dellarocas et al., 2007; Liu, 2006; Sawhney & Eliashberg, 1996) . We also control for the number of weeks since release. The detailed descriptions of the variables are shown in Table 4-2, and the correlations among the variables are given in Table 4-3.

Table 4-2. Description of Variables used in Empirical Model

Variable	Description
Dependent Variable	
Extr_positive	Proportion of extremely positive opinions, i.e. top 10%
Extr_negative	Proportion of extremely negative opinions, i.e. bottom 10%
SD_Valence	For H2a, H2b and H2c, daily standard deviation of comment valence within product or non-product oriented social media platforms
Key Independent Variables	
PO_Dummy	A dummy to differentiate comments from product oriented social media platforms (coded as 1) and those from non-product oriented social media platforms (coded as 0)
PO_Dummy*Weeks	The product of PO_Dummy and number of weeks since the movie is released
Controls	
PO_valence	The average valence of product oriented social media comments for previous week
NPO_valence	The average valence of non-product oriented social media comments for previous week
PO_volume	The number of product oriented social media comments for previous week
NPO_volume	The number of non-product oriented social media comments for previous week
Weeks	Number of weeks since the movie is released
Budget	The budget of the movie
Rank1	The popularity ranking of the leading artist. IMDb Pro data services (http://pro.imdb.com/) provide a STARMeter ranking for all actors and actresses, based on the inputs of millions of IMDb users. The more popular the actor/actress, the smaller his or her rank (i.e. the most popular actor/actress is ranked number 1). We use the STARMeter rankings to measure the popularity of the leading artists.
Rank2	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

Table 4-3 Correlation of Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 Ex_pos	1																	
2 Ex_neg	-0.09 ***	1																
3 SD_valence	0.31 ***	0.02 *	1															
4 PO_Dummy	0.12 ***	0.49 ***	0.22 ***	1														
5 PO_valence	-0.16 ***	0.12 ***	-0.06 ***	0	1													
6 NPO_valence	-0.36 ***	0.1 ***	-0.15 ***	0	0.15 ***	1												
7 PO_Dummy* Weeks	0.04 ***	0.23 ***	0 ***	0.64 ***	0.04 ***	0.03 ***	1											
8 NPO_volume	0	0.06 ***	0.32 ***	0	0.14 ***	-0.02 ***	-0.12 ***	1										
9 PO_volume	0.06 ***	0.24 ***	0.28 ***	0	-0.02 ***	-0.04 ***	-0.24 ***	0.39 ***	1									
10 Weeks	-0.04 ***	-0.15 ***	-0.16 ***	0	0.07 ***	0.05 ***	0.55 ***	0.22 ***	-0.45 ***	1								
11 Budget	-0.06 ***	-0.04 ***	0.12 ***	0	0	0.02 ***	0.05 ***	0.2 ***	0.05 ***	0.1 ***	1							
12 Rank1	0	0.04 ***	0.14 ***	0	-0.01 *	0.01 *	-0.08 ***	0.31 ***	0	-0.14 ***	-0.51 ***	1						
13 Rank2	0.01 +	0.05 ***	-0.15 ***	0	-0.03 ***	0.01	-0.07 ***	0.31 ***	-0.02 ***	-0.13 ***	-0.54 ***	0.65 ***	1					
14 MPAA-PG	-0.03 ***	0	-0.03 ***	0	-0.06 ***	0.03 ***	0.02 ***	-0.06 ***	-0.01 **	0.04 ***	0.26 ***	0.09 ***	-0.05 ***	1				

15 MPAA-R	- 0.01 ***	0.01	- 0.03 ***	0	0.13 ***	- 0.03 ***	- 0.02 ***	- 0.07 ***	- 0.03 ***	- 0.04 ***	- 0.32 ***	0.14 ***	0.13 ***	-0.3 ***	1			
16 Drama	- 0.04 ***	0.03 ***	- 0.08 ***	0	0.06 ***	0.13 ***	- 0.06 ***	- 0.03 ***	- 0.05 ***	-0.1 ***	-0.4 ***	0.09 ***	0.13 ***	- 0.28 ***	0.08 ***	1		
17 Thriller	0.04 ***	- 0.04 ***	0.13 ***	0	- 0.03 ***	-0.1 ***	0.01	0.15 ***	0.03 ***	0.01 **	0.14 ***	0.14 ***	-0.1 ***	- 0.21 ***	- 0.04 ***	- 0.12 ***	1	
18 Comedy	- 0.02 **	0	- 0.03 ***	0	- 0.07 ***	0	0.01 *	- 0.07 ***	0.01 +	0.02 ***	0.09 ***	0.13 ***	- 0.01	0.26 ***	0.06 ***	-0.3 ***	- 0.39 ***	1

Note: ***represents p-value<0.001; ** represents p-value<0.01; * represents p-value<0.05;+ represents p-value<0.1.

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.

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 4-4 and Table 4-5 tabulate the

estimates of our regression analysis using random effects and Figure 4-4 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 4-4 Random Effects Estimation (H1a and H1b)

	Extr_negative		Extr_positive	
	Coefficient	Std. Err.	Coefficient	Std. Err.
PO_Dummy (product oriented:1)	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	0.000	0.000	0.000	0.000
Budget	-0.007*	0.003	0.000	0.003
Rank1	-0.004	0.002	0.001	0.002
Rank2	-0.001	0.002	0.000	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.

Table 4-5 Random Effects Estimation (H2a, H2b, and H2c)s

	SD_valence	
	Coefficient	Std. Err.
Weeks	-0.001***	0.000
PO_Dummy (product oriented:1)	0.082***	0.002
PO_Dummy*Weeks	-0.006***	0.000
(N)PO_valence	-0.152***	0.008

(N)PO_volume	0.014***	0.000
Budget	0.004*	0.002
Rank1	-0.002	0.001
Rank2	-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	0.186***	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 4-4. Social media platform differences in SD_valence

As a robust test, we also report the results using fixed effects (Table 4-6) and Tobit model for H1a and H1b (Table 4-7) as follows, which arrive at the same conclusions as those analyzed using random effects.

Table 4-6. Fixed effects estimation

	Extr_positive		Extr_negative		SD_valence	
	Coefficient	Std. Err	Coefficient	Std. Err	Coefficient	Std. Err
PO_Dummy (product oriented:1)	0.165***	0.002	0.062***	0.003	0.083***	0.002
(N)PO_valence	0.243***	0.011	-0.384***	0.014	-0.150***	0.009
(N)PO_volume	0.002***	0.001	0.002	0.001	0.012***	0.001
Weeks	0.000	0.000	0.000	0.000	-0.001***	0.000

PO_dummy*Weeks					-0.006***	0.000
Intercept	-0.152***	0.008	0.349***	0.011	0.130***	0.003

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 4-7. Tobit model (H1a and H1b)

	Extr_positive		Extr_negative	
	coef	se	coef	se
PO_dummy	0.286***	0.005	0.141***	0.005
(N)PO_valence	0.786***	0.019	-0.985***	0.016
(N)PO_volume	0.028***	0.001	0.023***	0.001
Weeks	-0.002***	0.000	-0.001***	0.000
Budget	-0.002	0.002	-0.006**	0.002
Rank1	-0.006***	0.001	-0.008***	0.001
Rank2	-0.001	0.001	-0.004*	0.001
MPAA-PG	-0.004	0.007	-0.011	0.007
MPAA-R	-0.000	0.005	-0.013**	0.005
Drama	0.002	0.005	-0.007	0.005
Thriller	0.011*	0.005	0.017***	0.005
Comedy	0.002	0.005	0.001	0.005
Intercept	-0.754***	0.047	0.723***	0.043

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.

Findings

We first examine how the opinion composition varies across platforms. Table 4-4 shows that the proportion of positive comments is higher ($\beta = 0.164$, 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 ($\beta = 0.066$, p -value <0.001) in product oriented social media platforms.

Next, we examine how online opinions evolve over time and across platform. Table 4-5 shows that the standard deviation of comment valence is larger in product oriented social media platforms ($\beta = 0.082$, p -value <0.001), which is consistent with our findings in Table 4-4. Over time, however, Table 4-5 shows that 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.

Discussion and Conclusion

Several implications can be drawn from our analysis. Through a comprehensive data collection effort, we considered multiple sources of data. Moreover, by segregating the social media comments by platform, and by examining their evolvement across time, we are able to obtain detailed insights about the differences in opinion composition and evolution arising from social media platforms. This study is one among the first to compare social media platforms which makes it possible to produce unique insights into why social media platforms attract posters and readers of different demographics, and how posted opinions converge differently across platforms.

First, our results show that the posting population is different across outlets, with product oriented social media platforms prone to attracting more polarized comments. 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 satisfied and dissatisfied consumers intend to create an impact on other consumers, and they prefer product oriented social media platforms to non-product oriented social media platforms because the former is perceived to have an ambience 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 opinion 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.

Lastly, we reveal a paradoxical truth about product oriented platforms. We find that although product oriented platforms attract diverse opinions, they tend to “stifle” diversity of opinions. In the first set of hypotheses, product oriented platforms are predicted to host more diverse opinions than non-product oriented platforms. However, opinion diversity is expected to decrease faster for product oriented platforms due to a higher level of opinion convergence according to the second set of hypotheses. Therefore, we hypothesized that product oriented platforms both accommodate and discourage opinion diversity, which received empirical support in the analysis. In the subsequent sections, we discuss the significance of our findings to both research and practice.

Implications for Research

From a theoretical point of view, this research contributes to the list of emerging work on social media with a focus on understanding who tends to post in

different social media platforms, and how opinion evolution differs across platforms. Extant literature has shown that the posting population is not representative of the full consumer base, and posted opinions may not reflect the true attitude of the consumer. Prior research, however, is silent on whether and how differences across social media platforms may affect the composition of the posting population and how opinions evolve over time.

Our results point to the importance of differentiating between different social media platforms. Our understanding of the nature of online comments is still in its primary stage, and findings from prior literature are typically based on data collected from a single type of social media platforms. Our study furthers our understanding by showing that consumers' behavior varies across different social media platforms. To be exact, product oriented social media platforms are found to have a larger proportion of polarized opinions. Consumers at higher or lower levels of satisfaction tend to post in platforms such as discussion boards and forums, because they believe these outlets provide an efficient communication channel to reach a wider audience and to wield influence. By contrast, non-product oriented social media platforms like Twitter do not display a tendency 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 document evidence that

opinions tend to converge over time across both product and non-product oriented platforms, showing that consumers anchor their evaluations to what is already posted in the site, leading to gradual decrease in the diversity of comments. This anchoring effect is further intensified in product oriented social media platforms because users are always exposed to comments about products.

Implications for Practice

Our research informs marketers that social media platforms are not direct counterparts of each other. 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 what consumers actually think. They can monitor different social media platforms to get an overall idea about how consumers evaluate the product. In addition, our results show that the interactions on social media platforms is complex, and the 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 consumer opinions.

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 worthwhile issues that we leave for future research. For example, 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. As social media permeates daily life, it is meaningful to deepen and broaden our understanding of the nature and dynamics of social media.

APPENDIX A. DATA CLEANING PROCEDURE

In order to filter out data that contains the keywords but does not concern the movie, we carried out the following procedure.

Step 1: We sorted the keywords into those with generic or non-generic movie names. Movies whose keywords include generic names (e.g. Source Code) are more likely to have irrelevant data. To sort, we read through 30 random comments collected for each movie and if all comments are about the movie, the keywords are deemed to be non-generic. Else, it will be classified as generic where more interventions as described in the next step are required.

Step 2: For the list of movies with generic keywords as determined in step 1, we included only those online comments that satisfied any *one* of the following criteria: 1) had all major words of the keyword phrase capitalized e.g. “Fair Game”; 2) included any of the word(s), spoiler, premiere, trailer or movie; 3) included any of the name(s) of the director(s), writer(s), leading actor and actress.

Step 3: We read through 30 random comments for movies with generic keywords which satisfy the criteria specified in step2. If all 30 comments are relevant, then we stop filtering. If we spot irrelevant comments, we adopt a more stringent criterion. We further sample the comments obtained and try to identify *common phrases* that are frequently present in the irrelevant comments. For example, the movie “Black Swan” results in irrelevant comments captured on comics and album. For this instance, we apply additional filters to exclude these common, irrelevant terms, i.e. “comics” and “album”. After applying the filter, we randomly assess another 30

comments to ensure that all sampled comments are relevant ones. We repeat Step 3 iteratively until only relevant comments were selected for a random sample of 30.

APPENDIX B. DETAILS ON ALGORITHM FOR TEXT MINING

In this appendix, we describe the theoretical basis as well as the procedure we used to determine the sentiment scores for the social media comments. We adopted a machine learning method for sentiment classification as appeared in prior literature (Chang & Lin, 2011; Cortes & Vapnik, 1995; Schölkopf et al., 2001). The essence of this technique involves randomly selecting a sample of the messages which have prior sentiments attached to them by the authors of the messages. The sample of messages is then codified into a set of vectors for machine learning. Using these trained vectors, we predict the probabilities of which other messages are positive (or negative) by the similarity in the message structure. The assumption made here is that message with similar words are likely to have similar sentiment value. The theoretical basis of such a classification technique has been applied in similar IS research (Antweiler & Frank, 2004; Gu et al.) whereby the authors used a Naïve Bayes algorithm to train a subset of messages to recognize the significance of particular words that will impact the sentiment of the entire message.

Specifically in this study, we randomly select 10,000 online messages whereby sentiments of the messages were known. Examples of such messages can be movie reviews whereby a sentiment rating is provided by the author. This sample constitutes the training data set. We normalized and standardized the values of these sentiment ratings given that they can come from different sources. From the normalized values, we binary code the messages as i , where, i can be coded as either positive (1) or negative (-1). Each message is subsequently coded as a vector x^T , with T elements. T here represents the global set of unique words that are present in the training set. The

messages are transformed into vectors using the software Weka with the binary state of being a positive or negative message attached to it. With the training set, we used a quadratic minimizing algorithm (Chang & Lin, 2011; Wu, Lin, & Weng, 2004) to classify the vectors based on the similarity of the vector structures.

The trained data set allows us to predict the probability of which a new message represented by vector, y is rated as positive (or negative) given the similarities of the message structure between the said message and the trained messages, x^T . Specifically, here we are estimating:

$$p_i = P(y = i \mid x^T) \quad \forall x, y \in R: x, y \in [-1, 1]$$

Where p_i represents the probability of which a particular message, y is positive ($i = 1$) or negative ($i = -1$).

For our analysis, we compute the probabilities of which a message is positive ($i=1$), and the computed values of p_i ranges from 0 to 1 where a higher probability suggesting a greater likelihood of a positive message.

To ensure that our sentiment analysis is robust, as noted in the paper, we randomly sample our codification and compared that against a third party sentiment classification tool provided by a social media management firm which uses a different propriety sentiment analysis tool. We found relatively high inter-rater (computerized classification) reliability of 0.852, 0.822 and 0.926 for expert reviews, pull based peer comments and push based peer comments respectively.

REFERENCES

- Ajzen, I. & Fishbein, M. 2005. The Influence of Attitudes on Behavior. In D. Albarracin & B. T. Johnson & M. P. Zanna (Eds.), *The handbook of attitudes*: 173-221. Mahwah, NJ: Erlbaum: Lawrence Erlbaum Associates.
- Amabile, T. M. 1983. Brilliant but cruel: Perceptions of negative evaluators. *Journal of Experimental Social Psychology*, 19(2): 146-156.
- Anderson, E. W. 1998. Customer satisfaction and word of mouth. *Journal of Service Research*, 1(1): 5-17.
- Angelis, M. D., Bonezzi, A., Peluso, A. M., Rucker, D. D., & Costabile, M. 2011. On Braggarts and Gossips: A Self-Enhancement Account of Word-of-Mouth Generation and Transmission. *Journal of Marketing Research*, 49(4): 551-563.
- Antweiler, W. & Frank, M. Z. 2004. Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, 59(3): 1259-1294.
- Arndt, J. 1968. Selective Processes in Word of Mouth. *Journal of Advertising Research*, 8(3): 19-22.
- Asur, S. & Huberman, B. 2010a. Predicting the future with social media. *Arxiv preprint arXiv:1003.5699*.
- Asur, S. & Huberman, B. A. 2010b. *Predicting the future with social media*. Paper presented at the Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference
- Bansal, H. & Voyer, P. 2000. Word-of-mouth processes within a services purchase decision context. *Journal of Service Research*, 3(2): 166.
- Bass, F. M. 1969. A New Product Growth for Model Consumer Durables. *Management Science*, 15(5): 215-227.
- Basuroy, S., Chatterjee, S., & Ravid, S. A. 2003. How critical are critical reviews? The box office effects of film critics, star power, and budgets. *Journal of Marketing*, 67(4): 103-117.
- Bayus, B. L. 1985. Word of mouth: the indirect effects of marketing efforts. *Journal of advertising research*, 25(3): 31-39.
- Berinsky, A. J. 2002. Silent voices: Social welfare policy opinions and political equality in America. *American Journal of Political Science*, 46(2): 276-287.
- Berndt, A. & Koekemoer, M. 2012. Online Customer Complaints and Defamation. *Journal of Digital Marketing*, 3(1): 21-38.

-
- Blackshaw, P. & Nazzaro, M. 2004. Consumer-generated media (CGM) 101: Word-of-mouth in the age of the web-fortified consumer, *A Nielsen BuzzMetrics White Paper*, Vol. 25: 1-15.
- Boatwright, P., Basuroy, S., & Kamakura, W. 2007. Reviewing the reviewers: The impact of individual film critics on box office performance. *Quantitative Marketing and Economics*, 5(4): 401-425.
- Brock, T. C. 1965. Communicator-recipient similarity and decision change. *Journal of Personality and Social Psychology*, 36: 650.
- Brown, J., Broderick, A., & Lee, N. 2007. Word of mouth communication within online communities: Conceptualizing the online social network. *Journal of Interactive Marketing*, 21(3): 2-20.
- Burnkrant, R. E. & Cousineau, A. 1975. Informational and Normative Social Influence in Buyer Behavior. *The Journal of Consumer Research*, 2(3): 206-215.
- Cacioppo, J. & Petty, R. 1989. Effects of message repetition on argument processing, recall, and persuasion. *Basic and Applied Social Psychology*, 10(1): 3-12.
- Chaiken, S. & Maheswaran, D. 1994. Heuristic processing can bias systematic processing: Effects of source credibility, argument ambiguity, and task importance on attitude judgment. *Journal of Personality and Social Psychology*, 66: 460-460.
- Chandler, D. 1994. The transmission model of communication. *Retrieved May*, 6: 2011.
- Chang, C. C. & Lin, C. J. 2011. LIBSVM: a library for support vector machines. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 2(3): 1-27.
- Charlett, D., Garland, R., & Marr, N. 1995. How damaging is negative word of mouth? *Marketing Bulletin*, 6(1): 42-50.
- Chen, P.-Y., Dhanasobhon, S., & Smith, M. 2008. All reviews are not created equal: The disaggregate impact of reviews and reviewers at amazon. com: Available at SSRN: <http://ssrn.com/abstract=918083> or <http://dx.doi.org/918010.912139/ssrn.918083>.
- Chen, Y. & Xie, J. 2008. Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science*, 54(3): 477-491.
- Chevalier, J. A. & Mayzlin, D. 2006. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3): 345-354.
- Cialdini, R. B. & Goldstein, N. J. 2004. SOCIAL INFLUENCE: Compliance and Conformity. *Annual Review of Psychology*, 55(1): 591-621.

-
- Clemons, E. K., Gao, G. G., & Hitt, L. M. 2006. When online reviews meet hyperdifferentiation: A study of the craft beer industry. *Journal of Management Information Systems*, 23(2): 149-171.
- Cones, J. W. 1992. *Film finance & distribution: a dictionary of terms*: Silman-James Press.
- Cortes, C. & Vapnik, V. 1995. Support-vector networks. *Machine learning*, 20(3): 273-297.
- Crano, W. & Prislin, R. 2006. Attitudes and persuasion. *Annual Review of Psychology*, 57: 345-374.
- Dellarocas, C. & Narayan, R. 2006. A statistical measure of a population's propensity to engage in post-purchase online word-of-mouth. *Statistical Science*, 21(2): 277-285.
- Dellarocas, C., Zhang, X. M., & Awad, N. F. 2007. Exploring the value of online product reviews in forecasting sales: the case of motion pictures. *Journal of Interactive Marketing*, 21(4): 23-45.
- Dewan, S. & Ramaprasad, J. 2007. Impact of Blogging on Music Sales: The Long Tail Effect, *Workshop on Information Systems and Economics*.
- Dewan, S. & Ramprasad, J. 2009. Chicken and Egg? Interplay Between Music Blog Buzz and Album Sales. *PACIS 2009 Proceedings*: 87.
- Dewan, S. & Ramaprasad, J. 2012. Research Note—Music Blogging, Online Sampling, and the Long Tail. *Information Systems Research*, isre.1110.0405(published online before print): doi:10.1287/isre.1110.0405.
- Dhar , V. & Chang, E. 2007a. Does chatter matter? The impact of user-generated content on music sales. *Journal of Interactive Marketing*, 23(4): 300-307.
- Dhar , V. & Chang, E. 2007b. *Does chatter matter? The impact of user-generated content on music sales*. Paper presented at the IOMS: Information Systems Working papers.
- Dichter, E. 1966. How word-of-mouth advertising works. *Harvard Business Review*, 44(6): 147-160.
- Donnavieve, S., Satya, M., & Sivakumar, K. 2005. Online peer and editorial recommendations, trust, and choice in virtual markets. *Journal of Interactive Marketing*, 19(3): 15.
- Du, H. & Wagner, C. 2007. *The Role of Technology, Content, and Context for the Success of Social Media*. Paper presented at the SIGHCI 2007 Proceedings.

-
- Duan, W., Gu, B., & Whinston, A. 2008. Do online reviews matter?--An empirical investigation of panel data. *Decision Support Systems*, 45(4): 1007-1016.
- Elberse, A. & Eliashberg, J. 2003. Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures. *Marketing Science*: 329-354.
- Eliashberg, J. & Shugan, S. M. 1997. Film critics: Influencers or predictors? *The Journal of Marketing*: 68-78.
- Ellison, N. B. 2007. Social network sites: Definition, history, and scholarship. *Journal of Computer - Mediated Communication*, 13(1): 210-230.
- Feick, L. & Higie, R. A. 1992. The effects of preference heterogeneity and source characteristics on ad processing and judgements about endorsers. *Journal of Advertising*, 21: 9-24.
- File, K. M. & Prince, R. A. 1992. Positive word-of-mouth: customer satisfaction and buyer behaviour. *International Journal of Bank Marketing*, 10(1): 25-29.
- Fitzsimons, G. J. & Lehmann, D. R. 2004. Reactance to recommendations: When unsolicited advice yields contrary responses. *Marketing Science*, 23(1): 82-94.
- Fleming, J. H., Darley, J. M., Hilton, J. L., & Kojetin, B. A. 1990. Multiple audience problem: A strategic communication perspective on social perception. *Journal of Personality and Social Psychology*, 58(4): 593-609.
- Forman, C., Ghose, A., & Wiesenfeld, B. 2008. Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research*, 19(3): 291-313.
- Freedman, J. L. 1964. Involvement, discrepancy, and change. *The Journal of Abnormal and Social Psychology*, 69(3): 290.
- Gao, G. G., Greenwood, B. N., McCullough, J., & Agarwal, R. 2013. Vocal Minority and Silent Majority: How do Online Ratings Reflect Population Perceptions of Quality?: available at http://warrington.ufl.edu/departments/isom/docs/seminar/paper_2013Agarwal_OnlineRatings.pdf.
- Ghose, A., Ipeirotis, P., & Li, B. 2009. The Economic Impact of User-Generated Content on the Internet: Combining Text Mining with Demand Estimation in the Hotel Industry: available at http://people.stern.nyu.edu/bakos/wise/papers/wise2009-p2007_paper.pdf.
- Gilly, M. C., Graham, J. L., Wolfinbarger, M. F., & Yale, L. J. 1998. A dyadic study of interpersonal information search. *Journal of the Academy of Marketing Science*, 26(2): 83-100.

Godes, D. & Mayzlin, D. 2004. Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, 23(4): 545-560.

Godes, D. & Silva, J. C. 2012. Sequential and temporal dynamics of online opinion. *Marketing Science*, 31(3): 448-473.

Gruhl, D., Guha, R., Kumar, R., Novak, J., & Tomkins, A. 2005. *The predictive power of online chatter*.

Gu, B., Konana, P., Raghunathan, R., & Chen, M. Research Note—The Allure of Homophily: Evidence from Investor Responses on Virtual Communities. *Information Systems Research*: forthcoming.

Gu, B., Park, J., & Konana, P. 2012. Research Note—The Impact of External Word-of-Mouth Sources on Retailer Sales of High-Involvement Products. *Information Systems Research*, 23(1): 182-196.

Harmon, R. R. & Coney, K. A. 1982. The Persuasive Effects of Source Credibility in Buy and Lease Situations. *Journal of Marketing Research*, 19(2): 255-260.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. 2004. Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 18(1): 38-52.

Hermans, B. 1998. Desperately seeking: Helping hands and human touch. *First Monday*, 3(11): available at <http://firstmonday.org/ojs/index.php/fm/article/view/626/547>.

Holbrook, M. B. 1978. Beyond Attitude Structure: Toward the Informational Determinants of Attitude. *Journal of Marketing Research*, 15(4): 545-556.

Holbrook, M. B. & Hirschman, E. C. 1982. The experiential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research*, 9(2): 132-140.

Holbrook, Morris B. 1999. Popular Appeal Versus Expert Judgments of Motion Pictures. *Journal of Consumer Research*, 26(2): 144-155.

Holmes, J. H. & Lett, J. D. 1977. Product sampling and word of mouth. *Journal of Advertising Research*, 17(5): 35-40.

Huang, P., Lurie, N. H., & Mitra, S. 2009. Searching for experience on the web: an empirical examination of consumer behavior for search and experience goods. *Journal of Marketing*, 73(2): 55-69.

Java, A., Song, X., Finin, T., & Tseng, B. 2007. Why we twitter: understanding microblogging usage and communities, *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis*: 56-65. California: ACM.

-
- Kang, Y. S. & Herr, P. M. 2006. Beauty and the beholder: Toward an integrative model of communication source effects. *Journal of Consumer Research*, 33(1): 123-130.
- Kaplan, A. M. & Haenlein, M. 2011. The early bird catches the news: Nine things you should know about micro-blogging. *Business Horizons*, 54(2): 105-113.
- Kapoor, G. & Piramuthu, S. 2009. Sequential Bias in Online Product Reviews. *Journal of Organizational Computing and Electronic Commerce*, 19(2): 85-95.
- Kendall, J. E. & Kendall, K. E. 1999. Information delivery systems: an exploration of web pull and push technologies. *Communications of the AIS*, 1(14): 1.
- Klein, L. R. 1998. Evaluating the Potential of Interactive Media through a New Lens: Search versus Experience Goods. *Journal of Business Research*, 41(3): 195-203.
- Kotler, P. 2009. *Marketing-management*: Pearson Education India.
- Laurent, G. & Kapferer, J.-N. 1985. Measuring consumer involvement profiles. *Journal of Marketing Research*, 22(1): 41-53.
- Li, X. & Hitt, L. 2008. Self selection and information role of online product reviews. *Information Systems Research*, 19(4): 456-474.
- Liu, Y. 2006. Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*, 70(3): 74-89.
- Mabry, E. & Porter, L. 2010. Movies and MySpace: The Effectiveness of Official Web Sites versus Online Promotional Contests. *Journal of Interactive Advertising*, 10(2): 1-15.
- McAllister, I. & Studlar, D. T. 1991. Bandwagon, underdog, or projection? Opinion polls and electoral choice in Britain, 1979–1987. *The Journal of Politics*, 53(3): 720-741.
- McDonald, A. 2009. 2009 MPAA Theatrical Market Stats. *MPAA Reports*.
- McGuire, W. 1976. Some internal psychological factors influencing consumer choice. *Journal of Consumer Research*, 2(4): 302-319.
- McKnight, D. H., Choudhury, V., & Kacmar, C. 2002. Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3): 334-359.
- Mittal, B. & Lee, M.-S. 1989. A causal model of consumer involvement. *Journal of Economic Psychology*, 10(3): 363-389.
- Moe, W., Schweidel, D., & Trusov, M. 2011. What Influences Customers' Online Comments. *MIT Sloan Management Review*, 53(1): 14-16.
- Moe, W. W. & Trusov, M. 2011a. The Value of Social Dynamics in Online Product Ratings Forums. *Journal of Marketing Research (JMR)*, 48(3): 444-456.

-
- Moe, W. W. & Trusov, M. 2011b. The Value of Social Dynamics in Online Product Ratings Forums. *Journal of Marketing Research*, 48(3): 444-456.
- Moe, W. W. & Schweidel, D. A. 2012. Online Product Opinions: Incidence, Evaluation, and Evolution. *Marketing Science*, 31(3): 372-386.
- Mohr, I. 2007. Buzz marketing for movies. *Business Horizons*, 50(5): 395-403.
- Moore, G. A. 1991. Crossing the chasm: New York: Harper Business.
- Mudambi, S. M. & Schuff, D. 2010. What makes a helpful online review? A study of customer reviews on Amazon. com. *Management Information Systems Quarterly*, 34(1): 185-200.
- Nielsen. 2012. State of the media: the social media report 2012.
- Pornpitakpan, C. 2004. The persuasiveness of source credibility: A critical review of five decades' evidence. *Journal of Applied Social Psychology*, 34(2): 243-281.
- Reinstein, D. A. & Snyder, C. M. 2005. The influence of expert reviews on consumer demand for experience goods: a case study of movie critics. *The journal of industrial economics*, 53(1): 27-51.
- Rogers, E. M. 1995. *Diffusion of innovations*: Simon and Schuster.
- Sawhney, M. S. & Eliashberg, J. 1996. A parsimonious model for forecasting gross box-office revenues of motion pictures. *Marketing Science*, 15(2): 113-131.
- Schölkopf, B., Platt, J. C., Shawe-Taylor, J., Smola, A. J., & Williamson, R. C. 2001. Estimating the support of a high-dimensional distribution. *Neural computation*, 13(7): 1443-1471.
- Schlossberg, H. 1991. Customer satisfaction: not a fad, but a way of life. *Marketing News*, 25(20): 18-21.
- Schlosser, A. E. 2005. Posting versus lurking: Communicating in a multiple audience context. *Journal of Consumer Research*, 32(2): 260-265.
- Senecal, S. & Nantel, J. 2004. The influence of online product recommendations on consumers' online choices. *Journal of Retailing*, 80(2): 159-169.
- Shannon, C. E. & Weaver, W. 1949. *The mathematical theory of communication*. Champaign, IL US: University of Illinois Press.
- Simmons, J., LeBoeuf, R., & Nelson, L. 2010. The effect of accuracy motivation on anchoring and adjustment: Do people adjust from provided anchors? *Journal of Personality and Social Psychology*, 99(6): 917-932.

-
- Sobkowicz, P., Kaschesky, M., & Bouchard, G. 2012. Opinion Formation in the Social Web: Agent-Based Simulations of Opinion Convergence and Divergence, *Agents and Data Mining Interaction*, Vol. 7103: 288-303: Springer Berlin Heidelberg.
- Strack, F. & Mussweiler, T. 1997. Explaining the enigmatic anchoring effect: Mechanisms of selective accessibility. *Journal of Personality and Social Psychology*, 73(3): 437-446.
- Sundaram, D. S., Mitra, K., & Webster, C. 1998. Word-of-mouth communications: a motivational analysis. *Advances in consumer research*, 25(1): 527-531.
- Susarla, A., Oh, J.-H., & Tan, Y. 2012. Social Networks and the Diffusion of User-Generated Content: Evidence from YouTube. *Information Systems Research*, 23(1): 23-41.
- Swan, J. E. & Oliver, R. L. 1989. Postpurchase communications by consumers. *Journal of Retailing*, 65(4): 516-533.
- Tellis, G. 1988. Advertising exposure, loyalty, and brand purchase: a two-stage model of choice. *Journal of Marketing Research*, 25(2): 134-144.
- Toubia, O. & Stephen, A. T. 2012. Intrinsic versus Image-Related Utility in Social Media: Why do People Contribute Content to Twitter?: working paper, Columbia University.
- Trusov, M., Bucklin, R. E., & Pauwels, K. 2009. Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site. *Journal of Marketing*, 73(5): 90-102.
- Tversky, A. & Kahneman, D. 1974. Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157): 1124-1131.
- Van den Bulte, C. & Stremersch, S. 2004. Social contagion and income heterogeneity in new product diffusion: A meta-analytic test. *Marketing Science*, 23(4): 530-544.
- Van den Bulte, C. & Joshi, Y. V. 2007. New Product Diffusion with Influentials and Imitators. *Marketing Science*, 26(3): 400-421.
- Wang, A. 2008. Consensus and disagreement between online peer and expert recommendations. *International Journal of Internet Marketing and Advertising*, 4(4): 328-349.
- Wang, C., Zhang, X., & Hann, I.-H. 2010. *Social bias in online product ratings: a quasi-experimental analysis*. Paper presented at the Workshop on Information Systems and Economics (WISE), St. Louis, USA.
- Wangenheim, F. v. & Bayón, T. 2007. The chain from customer satisfaction via word-of-mouth referrals to new customer acquisition. *Journal of the Academy of Marketing Science*, 35(2): 233-249.

-
- Wertenbroch, K. & Dhar, R. 2000. Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, 37(1): 60-71.
- Westbrook, R. A. 1987. Product/consumption-based affective responses and postpurchase processes. *Journal of marketing research*, 24(3): 258-270.
- Wilson, E. & Sherrell, D. 1993. Source effects in communication and persuasion research: A meta-analysis of effect size. *Journal of the Academy of Marketing Science*, 21(2): 101-112.
- Wu, F. & Huberman, B. 2008. How Public Opinion Forms. In C. Papadimitriou & S. Zhang (Eds.), *Internet and Network Economics*, Vol. 5385: 334-341: Springer Berlin Heidelberg.
- Wu, F. & Huberman, B. A. 2010. Opinion formation under costly expression. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 1(1): 5.
- Wu, T.-F., Lin, C.-J., & Weng, R. C. 2004. Probability estimates for multi-class classification by pairwise coupling. *The Journal of Machine Learning Research*, 5: 975-1005.
- Zaichkowsky, J. L. 1985. Measuring the involvement construct. *Journal of Consumer Research*, 12(3): 341-352.
- Zeelenberg, M. & Pieters, R. 2004. Beyond valence in customer dissatisfaction: a review and new findings on behavioral responses to regret and disappointment in failed services. *Journal of Business Research*, 57(4): 445-455.
- Zhang, X. & Dellarocas, C. 2006. *The Lord Of The Ratings: Is A Movie's Fate is Influenced by Reviews?* Paper presented at the International Conference on Information Systems 2006 Proceedings.
- Zhang, X., Fuehres, H., & Gloor, P. 2010a. Predicting Stock Market Indicators Through Twitter "I hope it is not as bad as I fear", *COINs2010*.
- Zhang, Z., Ye, Q., Law, R., & Li, Y. 2010b. The impact of e-word-of-mouth on the online popularity of restaurants: A comparison of consumer reviews and editor reviews. *International Journal of Hospitality Management*, 29(4): 694-700.
- Zhu, F. & Zhang, X. 2010. Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing*, 74(2): 133-148.