Are Consumers More Likely to Contribute Online Reviews for Hit or Niche Products?

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ABSTRACT: User-generated content has been hailed by some as a democratizing force that enables consumers to discuss niche products that were previously ignored by mainstream media. Nevertheless, the extent to which consumers truly prefer to use these new outlets to discuss lesser-known products as opposed to spending most of their energies on discussing widely marketed or already successful products has so far

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remained an open question. We explore this question by investigating how a population's propensity to contribute postconsumption online reviews for different products of the same category (motion pictures) relates to various indicators of those products' popularity. We discover that, ceteris paribus, consumers prefer to post reviews for products that are less available and less successful in the market. At the same time, however, they are also more likely to contribute reviews for products that many other people have already commented on online. The presence of these two opposite forces leads to a U-shaped relationship between a population's average propensity to review a movie postconsumption and that movie's box office revenues: moviegoers appear to be more likely to contribute reviews for very obscure movies but also for very high-grossing movies. Our findings suggest that online forum designers who wish to increase the contribution of user reviews for lesser-known products should make information about the volume of previously posted reviews a less-prominent feature of their sites.

Key words and phrases: consumer behavior, econometrics, information intermediaries, online product reviews, online word of mouth, Web 2.0.

Online product review forums, blogs, discussion boards, and other forms of user-centered Internet media have emerged as an influential source of prepurchase information, with 26 percent of Internet users reporting that they have contributed to them and 61 percent reporting that they find them valuable and trustworthy.[1] These new media have been hailed by some as a democratizing force that enables consumers to discuss niche products that were previously ignored by mainstream media [2]. Nevertheless, the extent to which consumers truly prefer to use these new outlets to discuss lesser-known products as opposed to spending most of their energies on discussing widely marketed or already popular products has so far remained an open question.

Traditional theories of product-related interpersonal communication [4, 14, 20, 36] suggest that, ceteris paribus, consumers are more likely to engage in word of mouth (WOM) about less-known, unique products than about widely available, common products because discussing the former makes them look more intelligent and more helpful in the eyes of their interlocutors.[2] If such behavior carries over to the online domain, it might mean that consumers are indeed disproportionately more likely to contribute content for niche products. A series of recent studies, however, hint that this may not be the case. These studies argue that important aspects of the Internet, such as the popularity-based ranking of search engine results [24] and the prevalence of prominently displayed statistics about other consumers' choices [16, 37], might end up focusing consumer consumption decisions (e.g., Web site visits, downloads) on already popular products, a phenomenon somewhat analogous to Rosen's "superstar effect" [33].

Our study adds to this broad discourse. However, instead of looking at consumption decisions, it focuses on the drivers of *consumer content contribution.* Specifically, we investigate how a population's propensity to contribute online reviews for different products of the same category postconsumption relates to offline and online indicators of those products' popularity. We define *propensity to review* as the conditional probability that a "representative" consumer of a population will contribute a review for a product conditional on having purchased it.

Our analysis is based on a rich data set of user reviews posted for movies on a popular Web site together with detailed box office data for the same movies. The availability of both review and sales data allows us to relate the weekly volume of online reviews to the size of the purchasing population during the same period and, thus, to derive estimates of the population's average *postconsumption* propensity to review a movie.

We discover that, ceteris paribus, consumers prefer to post reviews for products that are less available and less successful in the market. At the same time, however, they are also more likely to contribute reviews for products that many other people have already commented on online. The simultaneous presence of these two opposite forces results in a U-shaped relationship between a purchasing population's average propensity to review a movie and that movie's box office revenues: moviegoers appear to be more likely to contribute reviews for very obscure movies but also for very high-grossing movies.

Our work extends prior theories of interpersonal (offline) product communication by considering how some of the unique properties of online product communications—most notably the persistence of previously posted content—affect people's propensity to contribute postconsumption content for a given product. Our results suggest that, consistent with traditional theories of product-related WOM, at the population level, consumers exhibit what appears to be a penchant for discussing obscure products online. However, this tendency appears to be moderated by the attraction of some consumers to joining popular online "conversations," a behavior that, in our opinion, is related to the persistence of previously posted online content and further reinforced by the prominent visibility of user review counts in current systems [37]. Our findings have interesting implications for marketing managers as well as for information intermediaries (infomediaries) interested in reducing the informational inequality between hit and niche products. We discuss these in detail in the final section of the paper.

The rest of the paper is organized as follows. Next, we discuss related work. The third section introduces our theoretical framework and develops our hypotheses. In the fourth section, we introduce our data set. The fifth section describes our model and presents our findings. Finally, we discuss managerial implications and outline opportunities for further research.

Related Work

Our study is most directly related to research on the motivations of online product review contribution. Most prior academic research on this topic has concentrated on assessing the relationship between consumer-generated content and product sales. Early, as well as recent, studies have focused on examining how consumer content influences peers and, in turn, sales [8, 9, 26, 35]. Other studies have examined the value of various metrics of online consumer content in influencing and predicting future sales [7, 10, 12, 15, 21, 28, 31].

Less attention has, so far, been given to the antecedents of online review contribution. Hennig-Thurau et al. [22] is, to our knowledge, the first study on the topic. The authors integrate a number of theories of interpersonal communication into a taxonomy of 11 possible motives for contributing online content. With the help of a survey instrument, they conclude that desire for social interaction, desire for economic incentives, concern for other consumers, and the potential for self-enhancement are the primary motivators of online review contribution. Dellarocas and Narayan [11] propose a metric of a population's propensity to engage in online WOM and demonstrate that results obtained through the use of this metric are consistent with traditional theories of WOM. Amblee and Bui [1] show that the volume of future online reviews has a positive correlation with a product's existing brand reputation as well as with the brand reputation of complementary goods.

None of the above studies overlaps with the main focus of our work, namely, an in-depth empirical analysis of the effect of a product's availability and popularity on a purchasing population's propensity to review that product online.

Our study also has indirect connections to the ongoing debate about whether Web 2.0 and social media increase or decrease cultural and consumption diversity. Some influential early studies observed that online retailers offer a much wider variety of products and sell more products that are less popular than do traditional retailers [6]. Since then, a number of researchers have looked more closely into how the Internet affects consumer demand for popular and niche products, often finding contradictory results. Oestreicher-Singer and Sundararajan [30] report that Amazon.com's co-purchase lists ("customers who bought X also bought Y") appear to induce a shifting of demand toward the "long tail" of less-popular books. On the other hand, Elberse and Oberholzer-Gee [18] study the evolution of home video sales in 2000–2005 and find evidence for the presence of both a "long-tail" and a "superstar" effect: although the number of titles that sell only a few copies every week increases almost twofold, among the best-performing titles an ever-smaller number of titles accounts for the bulk of sales. Using very different data sets and methods, Duan et al. [16], Hindman et al. [23], Salganik et al. [34], and Tucker and Zhang [37] independently study the effect of the availability of popularity information (e.g., download counts, "most visited" lists) on consumer actions and find that these reinforce consumer interest in the most popular vendors and products.

In contrast to the above studies that focus on *consumption* patterns, our study looks at how indicators of product popularity affect the corresponding patterns of *consumer-generated content contribution.* This has indirect relevance to consumption patterns because consumer-generated content has been hailed as a force that helps consumers locate products that were previously ignored by mainstream media and is, therefore, an important antecedent of consumption patterns [2].

Research Hypotheses

Our objective in this study is to understand how a population's average postconsumption propensity to discuss a product online relates to various indicators of that product's availability and popularity. To develop our research hypotheses, we draw on prior studies of the motives of interpersonal product communication. We then extend these studies by considering how key properties of the online domain, such as the persistence of previously posted content, are likely to affect people's propensity to contribute postconsumption online opinions.

Online product reviews bear many similarities to offline product-related WOM communication: both constitute a first-person account of a consumer's experience with a product and both are primarily addressed to other consumers. An initial understanding of how online review contribution relates to product popularity can thus benefit from extant knowledge in the literature on the motivations for (offline) WOM communication.

A seminal study of WOM communication motives is by Dichter [14]. Subsequent authors [4, 19, 36] have refined and provided empirical support for Dichter's framework but have not substantially altered it. Hennig-Thurau et al.'s [22] recent work on the motivations of electronic WOM is also largely based on Dichter's framework. Dichter identified four main motivational categories of WOM communication:

- *Self-involvement* or *self-enhancement:* Product-related conversation is motivated by the speaker's need to enhance himself or herself in front of his or her audience. In this context, WOM allows the speaker to gain attention, show connoisseurship, suggest status, give the impression of possessing inside information, and assert superiority.
- *Other involvement:* Consumers discuss products because of a genuine desire to help others make a better purchase decision.
- *Product involvement:* WOM conversations act as a tension-releasing mechanism when the consumer has had a particularly positive or negative experience with a product.
- *Message involvement:* This case refers to discussion that is stimulated by advertisements, commercials, or public relations.

Dichter's theory of self-involvement motivations suggests that consumers have a higher propensity to share their experiences with others when these make them look unique, intelligent, and savvy. This, in turn, implies that consumers would be more likely to discuss less well-known, "underdog" products for which they perceive that their interlocutors know less. Such behavior would also be consistent with the theory of other involvement: if consumers are primarily motivated by a desire to help others, discussing obscure products about which their listeners' knowledge may be limited would be more helpful (to listeners) than discussing widely available or already successful products for which listeners are more likely to have sufficient knowledge.[3]

We believe that it is useful to distinguish between market availability and market success as it is possible for a product to be widely available but not successful (e.g., a highly advertised movie that is widely released but fails to fill movie theaters), or vice versa (e.g., a Broadway play that only plays in one location but is sold out for the entire season, or a trendy restaurant that is fully booked for months). Our theoretical framework predicts that the propensity to review follows similar trends in both cases: perception of viewpoint uniqueness, whether because a product is less available or because fewer consumers have chosen to purchase it, increases a purchaser's propensity to discuss the product online.

The positive correlation between willingness to contribute online content and a contributor's perception of his or her viewpoints' uniqueness has been documented by Ling et al. [27]. Drawing on Karau and Williams's [25] collective-action model, Ling et al. show that people will contribute more to online communities when given personalized information showing that their contributions would be unique. In our setting, there is no personalized information but we hypothesize that prospective contributors use publicly available indicators of a product's availability and market performance to assess a product's popularity or obscurity, which in turn determines the perceived uniqueness of their online opinions.

The following two hypotheses emerge from the preceding discussion:

Hypothesis 1: Everything else being equal, the propensity to review a product online postconsumption is higher for products that are perceived to be less available in the market.

Hypothesis 2: Everything else being equal, the propensity to review a product online postconsumption is higher for products that are perceived to be less successful in the market.

Despite their similarities, offline WOM and online reviews have important differences whose consequences have not received enough attention in the literature. One critical distinction that sets apart these two modes of communication is that whereas the former "disappears into thin air," the latter remains in public repositories. The persistence of the online medium allows individuals to observe, engage with, and react to what the rest of the world is talking about a product online. Drawing on Dichter [14] and Hennig-Thurau et al. [22], we argue that this is likely to affect consumers' propensity to discuss products online in profound ways.

Consistent with the *message involvement* theory [14, 36], we postulate that persistent consumer-generated content about products constitutes a new form of "message" that can, by itself, stimulate further discussion and communication. Empirical evidence [39] suggests that the persistence of previous product opinions provides stimulation to subsequent reviewers, inducing a trend-following process that leads to the expression of increasingly extreme views.

The above argument is also consistent with Hennig-Thurau et al. [22], whose study shows that by participating in Web-based opinion platforms, consumers become part of a virtual community where they gain social benefit in terms of identification and social integration. Hennig-Thurau et al. also observe that comments written by others can also motivate consumers to write comments. We expect that a larger and more vibrant community (as measured by the volume of past contributions, which is easily visible even to first-time visitors) should induce more users to participate.

The following hypothesis follows from the preceding discussion:

Hypothesis 3: Everything else being equal, the propensity to post online reviews about a product postconsumption is positively related to the volume of previously posted reviews about the same product.

Previous work [15, 28] has shown that the volume of a product's online reviews correlates positively with its sales volume. Hypothesis 3, therefore, suggests that as reviews accumulate, the properties of the online medium steer the consumer population toward discussing popular products, a trend that is counter to what traditional WOM theory would predict (H1 and H2) and closer to theories that suggest that the Internet ends up reinforcing interest for already popular products.

Among the remaining elements of Dichter's framework, the theory of product involvement does not have direct implications for how a product's perceived market popularity affects the propensity to engage in postconsumption WOM. Nevertheless, it predicts the presence of a U-shaped relationship between perceived quality and propensity to engage in WOM: people are more likely to discuss products when they had extreme (good or bad) experiences, but less so when they had average experiences.[4] This pervasive property of WOM has been documented both in the offline [3] and online [11, 24] domains and needs to be controlled for in any empirical study of propensity to contribute product-related online content.

Data

Our analysis is based on a rich data set of user reviews posted for movies on a popular Web site together with detailed box office data for the same movies. A number of factors make the motion picture industry an ideal test bed for this type of study. First, it is an industry where consumer-to-consumer communication plays a very important role. Second, there is widespread availability of movie reviews on the Internet, and most reviews tend to be posted shortly after the time of consumption. Third, reliable sales data are publicly available for most movies, making it possible to relate the volume of online reviews posted during a given time period to the size of the purchasing population during the same time period and, thus, to derive estimates of the population's average postconsumption propensity to contribute online reviews.

Our data set consists of consumer reviews posted on Yahoo! Movies (http://movies.yahoo.com), together with detailed production and weekly box office data for the same movies. For the purpose of our analysis, we excluded titles that were not released in the United States, not released in theaters (e.g., DVD releases), or not released nationwide. For each of the remaining titles, we collected information about the movie's genre and Motion Picture Association of America (MPAA) rating (G, PG, PG13, or R). We also collected detailed user review information, including the date and time of each review, all available information from the contributor's Yahoo! user ID profile, the review's text, and the associated numerical or letter rating. Because the focus of our paper is on postconsumption WOM, we removed from our samples any reviews that were posted prerelease. Apart from Yahoo! Movies, we used Box Office Mojo (www.boxofficemojo.com) to obtain weekly box office data for every movie in our data set.

To provide stronger support for the robustness of our core findings, we analyze two similar data sets collected from the same Web site at different time periods. The first data set contains data about movies released in 2002 (data were collected in 2003) and the second for movies released in 2007 and 2008 (data were collected in 2009). Over the past five years, the Internet has evolved considerably, with the rise of Web 2.0 applications such as blogs and social networks. Yahoo! Movies has substantially revamped its Web site: in 2002, it only supported a single numerical rating (between 1 and 5) and had minimal social community features. In 2007–8, it supported several categories (story, acting, direction, visuals, overall) of letter ratings (ranging from F to A+) and had substantially more elaborate community features. For example, authors could create personal profiles, commenting on their movie tastes and posting lists of their favorite movies; users could click on an author's user ID and access his or her profile as well as all other movie reviews contributed by the same person. Users could also vote on the usefulness of a review. Such changes make it important to check whether our findings remain consistent in recent years, and verify that they are not an artifact of a specific period.[5]

The 2002 data set contains 104 movies and 63,889 reviews. The 2007–8 data set contains 143 movies and 95,443 reviews. Both data sets are remarkably similar in terms of their key summary statistics (Table 1).

Prior studies show that the volume of sales and the volume of reviews decline as people lose interest in a movie during later weeks [28]. For most movies in our data set, the weekly volume of reviews becomes very small (less than five reviews per week) after the fifth week of release. Furthermore, less-successful movies begin to drop out of theaters after five weeks, rendering later-week data unbalanced. We thus conduct our analysis using online reviews data from the first five weeks since a movie's opening. Because most movies open on a Friday, weeks are defined as Friday to Thursday. In our final data set, each record summarizes weekly performance and review data for each of the first five weeks of a movie's theatrical release. There are 520 observations (104×5) in 2002 and 715 (143×5) in 2007–8.

Model, Estimation, and Results

OUR STUDY USES SECONDARY DATA to identify factors that explain a *population's* average *postconsumption* propensity to review movie j during week t since its original release.

We define *propensity to review* as a consumer's probability of reviewing a movie *conditional on having watched it.*

The conceptual specification of our model is, thus, the following:

$$PROPENSITY_{jt} = \beta X_{jt} + \gamma Z_{jt} + \varepsilon_{jt}, \tag{1}$$

where *PROPENSITY* is the propensity to review; X are independent variables measuring market availability (H1), market popularity (H2), and volume of previous reviews (H3); and Z denotes our vector of control variables. In the next sections we detail the operationalization of each of the above measures.

Table 1. Summary Statistics of Our Data Set

2002 sample

Variable	Minimum	Mean	Median	Maximum
Weekly box office revenue (in millions)	0.01	11.8	6.3	151.6
Weekly volume of user ratings	1	125	43	3,802
Weekly average of user ratings (range 1–5)[1]	1	3.5	3.5	5
Screens in opening week	4	1,964	2,199	3,876
Total number of movies = 104				
Total number of user ratings = 63,889				

Movies by genre[2]	Number	Movies by MPAA rating	Number
Science fiction	11	G	5
Children	13	PG	12
Drama	40	PG13	47
Comedy	38	R	40
Romance	14	Other properties	
Action	36		
Thriller	30	Sequels	11

2007–2008 sample

Variable	Minimum	Mean	Median	Maximum
Weekly box office revenue (in millions)	0.03	8.82	5.3	102.9
Weekly volume of user ratings	1	133	71	1,956
Weekly average of user ratings (range 1–5)[1]	1.3	3.5	3.5	5
Screens in opening week	1	1,982	2,111	3,984
Total number of movies = 143				
Total number of user ratings = 95,443				

Movies by genre[2]	Number	Movies by MPAA rating	Number
Science fiction	20	G	5
Children	12	PG	21
Drama	51	PG13	65
Comedy	66	R	52
Romance	10	Other properties	
Action	32		
Thriller	39	Sequels	6

Notes: [1] Based on "overall" letter rating, converted to a number between 1 and 5 (F = 1, A+ = 5).
[2] Some movies belong to multiple genres.

Measuring a Population's Average Propensity to Review

To construct a measure of a moviegoing population's average postconsumption propensity to review a movie online from available data, we make the following mild assumptions:

A1: Only people who watch movies review them online.

A2: Most moviegoers watch a given movie at most once during the first five weeks of its release.

A3: Each moviegoer contributes at most one review per movie.

A4: Most online reviews are posted within a week of watching a movie.

Assumption 1 can be justified informally by looking at the text of online reviews. The overwhelming majority of reviews in our data set refer to specific details that imply that the reviewer has watched the movie. Assumption 2 is consistent with the commonly accepted behavior patterns of most moviegoers. We satisfy Assumption 3 by design because in our calculations of weekly review volumes, we only count one review per movie and Yahoo! ID.[6] To test Assumption 4, we calculate the correlation between the weekly volume of ratings and the lagged weekly box office revenues. Correlation was highest between volume and box office revenues of the same week and monotonically declined as the lag increased.

Under Assumptions 1–4, the moviegoing population's average propensity to rate movie j during week t is equal to

$$\begin{aligned} PROPENSITY_{jt} &= \frac{\text{Number of people who reviewed movie } j \text{ during week } t}{\text{Number of people who watched movie } j \text{ during week } t} \\ &= \frac{VOL_{jt}}{BOX_{jt} / (\text{Average ticket price})}. \end{aligned} \tag{2}$$

Because *average ticket price* is a constant in each of our two data sets (around \$6 in 2002 and \$8 in 2007–8), we can omit it from our model (it simply results in all the coefficients being multiplied by a constant amount). The dependent variable of our model (propensity to review) is the ratio VOL_{jt}/BOX_{jt}. Density plots (Figure 1) suggest that the distribution of VOL_{jt}/BOX_{jt} in our sample is highly skewed, whereas that of $\log(VOL_{jt}/BOX_{jt})$ is approximately normal. We, therefore, use $\log(VOL_{jt}/BOX_{jt})$ as our baseline measure of propensity.

Controlling for Heterogeneity of Populations Attracted by Different Movies

Our baseline measure of propensity $\log(VOL_{jt}/BOX_{jt})$ does not take into account the possibility that each movie might attract different types of moviegoers. This heterogeneity might interfere with our hypothesis testing. For example, it is possible that certain types of movies that tend to be less "commercial" (e.g., foreign, independent movies) also attract audiences that have a higher propensity to post online reviews

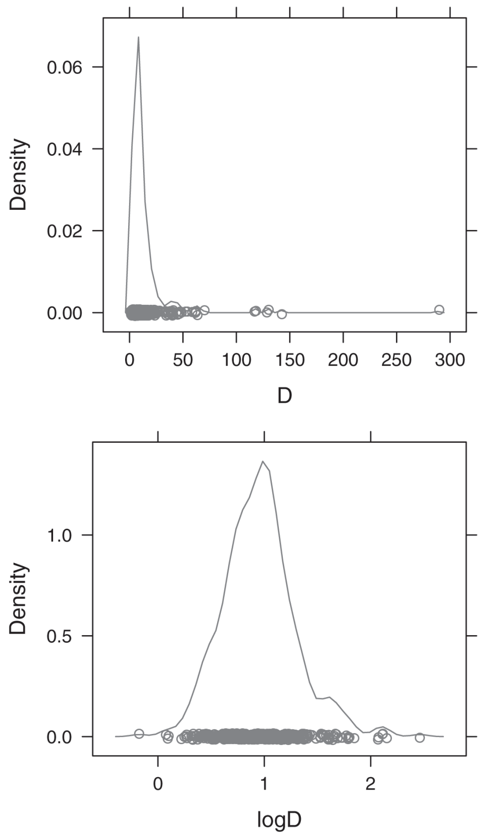

Figure 1. Density Plot of $D_{jt} = VOL_{jt}/Box_{jt}$ (review per millions in revenue) and Its Natural Logarithm

for *any* movie. In such a scenario, we would indeed observe a negative correlation between a movie's market availability and the population's average propensity to review it online. However, the true cause of this relationship would be the communication habits of the audience that such movies attract and not a reaction of moviegoers to a movie's perceived lower availability.

To address the above concern, we enhance our measure of propensity with a term that controls for differences in the online reviewing habits of each movie's population of viewers. The main idea is as follows: assume that viewers are divided into types, where a viewer's type is proportional to his or her intrinsic propensity to review *any* movie online. Assume, further, that the probability that a viewer of type θ will review movie j is given by $\theta a(j)$, where $a(j)$ captures the degree to which the attributes of movie j influence any viewer's propensity to review it. Assume, finally, that the incidence of different viewer types in movie j's population of viewers is characterized by a probability distribution $p(\theta | j)$. According to these assumptions, if $BOX(j)$ denotes the number of people who watched movie j during a given period, the expected volume of online reviews $VOL(j)$ posted for that movie during the same period is equal to

$$VOL(j) = BOX(j)\left(\sum_{\theta}\theta p(\theta|j)\right)a(j) = BOX(j)POP(j)a(j), \tag{3}$$

where $POP(j) = \Sigma_{\theta}\theta p(\theta | j)$. $POP(j)$ represents movie j's population of viewers' average intrinsic propensity to post online reviews.

Let us assume that a weekly estimate of $POP(j)$ can be constructed from our data (we discuss how below) and let us denote this estimate by POP_{jt}. We can now control for the fact that different movies attract populations with different intrinsic propensities to post online reviews by modifying our original model (1) as follows:

$$\log\left(\frac{VOL_{jt}}{BOX_{jt}POP_{jt}}\right) = \beta X_{jt} + \gamma Z_{jt} + \varepsilon_{jt}. \tag{4}$$

Comparing Equations (3) and (4), it is easy to see that the term $\log(VOL_{jt}/BOX_{jt}POP_{jt})$ in Equation (4) is proportional to $\log a(j)$—that is, it describes the degree to which the attributes of movie j influence *any* viewer's propensity to review it at week t.

The Appendix shows that a weekly estimate of POP_{jt} can be based on the following proposition:

> *Proposition 1: The average intrinsic propensity to review of the population of viewers attracted by movie* j *during a given time period can be approximated by the harmonic mean of the total annual number of movie reviews posted by people who reviewed movie* j *during the same time period.*

In the empirical analysis that follows, we test the robustness of our findings by fitting our model using both the simple $\log(VOL_{jt}/BOX_{jt})$ and enhanced $\log(VOL_{jt}/BOX_{jt}POP_{jt})$ propensity measure as our dependent variable.

Independent and Control Variables

Independent Variables

We use three independent variables to operationalize each of our three hypotheses (Table 2).

For Hypothesis 1, we use the number of theaters at which a movie is being exhibited on a given week ($THEATERS_{jt}$) as a measure of that movie's market availability.

For Hypothesis 2, we use a movie's weekly revenue per theater,

$$RPT_{jt} = \frac{BOX_{jt}}{THEATERS_{jt}},$$

as our measure of that movie's market success (success relative to expectations, the latter being embodied by the number of theaters at which the movie was released). Revenue per theater (also known as revenue per screen) is a widely used performance metric in motion pictures research and has been shown to provide one of the best predictors of a movie's long-term box office success [13, 17]. In this study, the use

Table 2. Summary of Variables

Components of the dependent variable	
VOL_{jt}	Volume of user reviews posted for movie *j* during week *t* of its theatrical release
BOX_{jt}	Box office revenues of movie *j* during week *t* of its theatrical release (in millions)
Independent variables	
$THEATERS_{jt}$	Count of theaters where movie *j* is exhibited during week *t* (in thousands)
RPT_{jt}	Revenue per theaters ($BOX_{jt}/THEATERS_{jt}$) of movie *j* during week *t*
$TSOFAR_{jt}$	Total volume of user reviews posted for movie *j* during weeks 1, ..., $t-1$ (in thousands)
Control variables	
AVG_{jt}	Arithmetic mean of numerical ratings (scale 1–5) associated with user reviews posted for movie *j* during week *t*
G, *PG*, *PG13*, *R*	Indicate movie's MPAA rating
SCIFI, *THRILLER*, *COMEDY*, *ROMANCE*, *DRAMA*, *ACTION*, *KIDS*	Indicate movie's genre
SEQUEL	Indicates whether movie *j* is a sequel
$COMPETITION_{jt}$	Count of movies (other than movie *j*) whose review volume during week *t* of movie *j*'s release was above the ninetieth percentile of weekly review volumes in our sample
$WK2_{jt}$, $WK3_{jt}$, $WK4_{jt}$, $WK5_{jt}$	Dummy variables that indicate weeks elapsed since movie *j*'s initial release. For example, $WK2_{jt}$ is 1 if $t = 2$ and 0 otherwise.
$HOLIDAY_{jt}$	Indicates whether week *t* of movie *j*'s release falls during summer or the Christmas holiday season

of this measure is particularly appropriate because, by controlling for the number of theaters, it allows us to disentangle a movie's market success from its availability and, thus, to separately test the effects of these two forces on a population's propensity to review.[7]

To evaluate how the volume of previously posted reviews affects subsequent moviegoers' propensity to review a movie (H3), we use the cumulative volume of all reviews ($TSOFAR_{jt}$) posted for a particular movie *j prior* to week *t* (i.e., during weeks 1, ..., $t - 1$).

Because our study aims to relate consumer perceptions of a movie's availability and popularity to propensity to review it online, we chose variables that can be easily perceived by moviegoers. The number of theaters at which a movie is exhibited is perceived indirectly through the proximity of the nearest movie theater playing a given movie to one's home. Revenue per theater has a high correlation with how full or how empty the movie theater was where the movie was watched. Finally, the total volume of previously posted reviews is prominently displayed by Yahoo! Movies next to each movie's average rating, which in turn is prominently displayed next to each movie's title.

Control Variables

We control for a number of factors that might influence the propensity to review but do not directly relate to the focal question of this work (Table 2).

Movie-Specific Effects. Past studies [11, 24] have documented a U-shaped (or J-shaped) relationship between propensity to review and perceived quality. The sources of this relationship were briefly discussed in the third section but are outside the scope of the current work. We control for the presence of such an effect by using the first- and second-order terms of the arithmetic mean (AVG_{jt}) of all numerical user ratings posted for movie *j* during week *t*, using mean-centered values to alleviate potential multicollinearity problems. In the case of the 2007–8 data, *AVG* was based on the "overall" letter rating, converted into a numerical score from 1 to 5 (F = 1, A+ = 5).

We further control for several secondary factors that might conceivably affect moviegoers' propensity to post online reviews. Specifically, dummy variables are used to control for movie genre (*ROMANCE*, *SCIFI*, *DRAMA*, *THRILLER*, *COMEDY*, *ACTION*, *KIDS*), MPAA rating (*G*, *PG*, *PG13*, *R*), and sequels (*SEQUEL*).

Peer Movie Effects. To estimate how the population's average propensity to review a movie might be affected by the presence of other widely talked-about movies playing that week, we define a variable ($COMPETITION_{jt}$) that captures the number of movies (other than movie *j*) whose weekly volume of reviews during week *t* of movie *j*'s release was above the ninetieth percentile of all weekly review volumes in our sample.

Time and Seasonality Effects. We control for time-dependent effects in people's propensity to post reviews about movie *j* in later weeks (e.g., because they lose interest as the movie gets "older") using dummy variables (*WK2*, *WK3*, *WK4*, *WK5*). We also control for possible seasonal changes in people's online communication habits during holidays (e.g., because of travel, family activities, etc.) by using a dummy variable ($HOLIDAY_{jt}$) that indicates whether an observation corresponds to a week that falls during the summer months (June–August) or during the Christmas holiday season (first and last week of the year) .

Model Specification

Putting all the variables described above into Equation (1), we get the following empirical model:

$$\begin{gathered}PROPENSITY_{jt} = \beta_0 + \beta_1 THEATERS_{jt} + \beta_2 RPT_{jt} + \beta_3 TSOFAR_{jt} \\ + \gamma_1 AVG_{jt} + \gamma_2 \left(AVG_{jt}\right)^2 + \gamma_3 G_j + \gamma_4 PG_j + \gamma_5 PG13_j + \gamma_6 SCIFI_j \\ + \gamma_7 DRAMA_j + \gamma_8 COMEDY_j + \gamma_9 ROMANCE_j + \gamma_{10} ACTION_j \\ + \gamma_{11} THRILLER_j + \gamma_{12} SEQUEL_j + \gamma_{13} COMPETITION_{jt} \\ + \gamma_{14} WK2_{jt} + \gamma_{15} WK3_{jt} + \gamma_{16} WK4_{jt} + \gamma_{17} WK5_{jt} + \gamma_{18} HOLIDAY_{jt} + \varepsilon_{jt}.\end{gathered} \tag{5}$$

R_j and $KIDS_j$ were the omitted variables for MPAA ratings and movie genres, respectively.

In the next section, we report the results of fitting the above model to each of our two movie samples (2002, 2007–8) using both the simple log(VOL_{jt}/BOX_{jt}) and enhanced log($VOL_{jt}/BOX_{jt}POP_{jt}$) propensity measure as our dependent variable. Each of these models is estimated using both ordinary least squares (OLS) as well as a random effects specification. This gives rise to $2 \times 2 \times 2 = 8$ model variants, summarized in Table 3.

The reason for using a random effects specification is the following: our baseline specification controls for several movie-specific attributes such as MPAA rating and genre. Nevertheless, it is quite plausible that there are additional (unobservable) movie-specific variables that might affect people's propensity to review a movie online. For example, Amblee and Bui [1] show that the propensity to review is positively correlated with a product's brand reputation, as well as with the brand reputation of complementary products. If so, then one might argue that a positive association between *PROPENSITY* and *TSOFAR* simply reflects the presence of some hidden variable that makes reviewers more eager to review a particular movie throughout its release history. Therefore, it is desirable to further control for unobserved movie characteristics. Using fixed effects does not work well for this data because we have only five data points per movie plus some of our key variables (such as *THEATERS*) do not have much variation across the first five weeks.[8] Instead, we estimate each model again using a random effects model, where the random effect term aims to capture the effect of unobserved movie-specific characteristics on people's propensity to review that movie.

Because box office revenue, theater counts, and online review volumes vary significantly across movies, the error variances may be unequal across observations in the sample. The Breusch–Pagan test rejects the homoskedastic error terms hypothesis at the $p < 0.001$ level; this suggests that heteroskedasticity in the error term is a concern. Further, since our sample contains five observations from the same movie over different periods, this implies that the error terms might be correlated with each other. To address the above concerns, we use the Huber–White clustered robust standard errors, which allows for both heteroskedasticity and autocorrelation in unobserved errors [38].

Results

Table 4 reports the results of estimating Equation (5) using the simple propensity measure, log(VOL_{jt}/BOX_{jt}), as our dependent variable. Column 1 contains the OLS

Table 3. Summary of Models

Model number	Dependent variable	Data set	Estimation method	Results reported on
1	$\log(VOL_{jt}/BOX_{jt})$	2002	OLS	Table 4, column 1
2			Random effects	Table 4, column 2
3		2007–2008	OLS	Table 4, column 3
4			Random effects	Table 4, column 4
5	$\log(VOL_{jt}/BOX_{jt}POP_{jt})$	2002	OLS	Table 5, column 1
6			Random effects	Table 5, column 2
7		2007–2008	OLS	Table 5, column 3
8			Random effects	Table 5, column 4

Table 4. Regression Results: Dependent Variable: $\log(VOL_{jt}/BOX_{jt})$

	(1)	(2)	(3)	(4)
	2002		2007–2008	
Variables	OLS	Random effects	OLS	Random effects
THEATERS	–0.166***	–0.153***	–0.248***	–0.172***
	(0.0231)	(0.0226)	(0.0201)	(0.0187)
RPT	1.227	1.016	–9.425**	–7.191**
	(1.506)	(1.336)	(3.926)	(2.830)
TSOFAR	0.145***	0.0662**	0.291***	0.165***
	(0.0392)	(0.0291)	(0.0452)	(0.0457)
AVG	0.125**	0.0925	–0.0381	–0.0626*
	(0.0597)	(0.0611)	(0.0304)	(0.0380)
$(AVG)^2$	0.159***	0.140***	0.0293	0.0489
	(0.0515)	(0.0435)	(0.0336)	(0.0418)
G	–0.260***	–0.292***	–0.116	–0.177**
	(0.0807)	(0.0863)	(0.0826)	(0.0709)
PG	–0.245***	–0.267***	–0.0403	–0.0892
	(0.0618)	(0.0686)	(0.0542)	(0.0627)
PG13	–0.0195	–0.0242	–0.0423	–0.0563
	(0.0444)	(0.0500)	(0.0338)	(0.0374)
SCIFI	0.210**	0.263***	0.0467	0.0406
	(0.0827)	(0.0865)	(0.0394)	(0.0472)
DRAMA	0.00425	0.00617	–0.0167	0.00767
	(0.0434)	(0.0472)	(0.0344)	(0.0377)
COMEDY	0.0366	0.0341	–0.0773**	–0.115***
	(0.0549)	(0.0598)	(0.0361)	(0.0403)
ROMANCE	0.0236	0.0400	–0.00922	–0.0131
	(0.0499)	(0.0653)	(0.0575)	(0.0611)
ACTION	0.0176	0.0162	–0.0582**	–0.0907***
	(0.0488)	(0.0487)	(0.0269)	(0.0337)
THRILLER	0.122**	0.116**	–0.0707**	–0.108***
	(0.0515)	(0.0536)	(0.0332)	(0.0379)
SEQUEL	0.0354	0.0798	0.0135	0.00579
	(0.0562)	(0.0659)	(0.0572)	(0.0643)
COMPETITION	–0.0160	–0.0211*	0.0278***	0.0119
	(0.0157)	(0.0122)	(0.0103)	(0.00865)
WK2	–0.262***	–0.235***	–0.129***	–0.118***
	(0.0228)	(0.0218)	(0.0278)	(0.0233)
WK3	–0.307***	–0.263***	–0.264***	–0.206***
	(0.0360)	(0.0302)	(0.0353)	(0.0310)
WK4	–0.374***	–0.321***	–0.361***	–0.253***
	(0.0450)	(0.0365)	(0.0441)	(0.0396)
WK5	–0.430***	–0.364***	–0.439***	–0.281***
	(0.0532)	(0.0414)	(0.0500)	(0.0461)
HOLIDAY	–0.0138	–0.0444	–0.00414	0.0650**
	(0.0307)	(0.0270)	(0.0311)	(0.0320)

(continues)

Table 4. Continued

	(1)	(2)	(3)	(4)
	2002		2007–2008	
Variables	OLS	Random effects	OLS	Random effects
Constant	1.441***	1.425***	1.876***	1.745***
	(0.0909)	(0.0823)	(0.0636)	(0.0598)
Observations	520	520	715	715
R^2	0.568	0.620	0.546	0.654

Notes: Clustered robust standard errors are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

estimates associated with the 2002 movie sample. We find that the coefficient of *THEATERS* is negative and significant (–0.166, $p < 0.01$). This suggests that the population exhibits a higher propensity to review movies that are less available, supporting Hypothesis 1. The coefficient of *TSOFAR* is positive and significant (0.145, $p < 0.01$), indicating that the presence of a large number of previously posted reviews has a positive correlation with the propensity of subsequent moviegoers to post reviews for the same movie. Thus, Hypothesis 3 is supported as well. It is also interesting to note that the estimated coefficient of *TSOFAR* is bigger in recent years, perhaps suggesting that users in recent years have higher degrees of involvement with previously posted reviews.

In column 2, we report estimates from the random effects model. We find that the coefficient of *THEATERS* remains negative and significant and that of *TSOFAR* is positive and significant. This increases our confidence that, even after controlling for idiosyncratic movie characteristics, availability is negatively associated with a moviegoer's propensity to post reviews, whereas the presence of previous reviews reinforces the propensity of subsequent moviegoers to post reviews for the same movie.

We further examine whether the above findings are robust in recent years. Columns 3 and 4 of Table 4 report findings based on the 2007–8 sample. The sign and significance of the coefficients of *THEATERS* and *TSOFAR* do not change, further strengthening support for Hypotheses 1 and 3.

The coefficient of *RPT* is generally negative and statistically significant only in the 2007–8 sample. Overall, our data provide only weak support for Hypothesis 2.

With respect to control variables, it is interesting to note that, consistent with previous studies [11], we find that the coefficients of both the first- and second-order terms of *mean-centered* AVG_{jt} are significant and positive, suggesting a J-shaped relationship between ratings and propensity to review. These coefficients become less significant in the 2007–8 data. As expected, the propensity to review a movie monotonically decays with the number of weeks since release. Accordingly, the coefficients of *WK2*, *WK3*, *WK4*, and *WK5* are all significant and increasingly negative in all models.

In general, estimation based on the 2002 and 2007–8 samples produces consistent findings. Table 5 reports the results of repeating the above estimations using

Table 5. Regression Results: Dependent Variable: $\log(VOL_{jt}/BOX_{jt}POP_{jt})$

	(5)	(6)	(7)	(8)
	2002		2007–2008	
Variables	OLS	Random effects	OLS	Random effects
THEATERS	–0.140***	–0.127***	–0.260***	–0.172***
	(0.0282)	(0.0274)	(0.0229)	(0.0217)
RPT	0.481	–0.261	–9.441**	–6.959**
	(1.795)	(1.606)	(4.187)	(3.007)
TSOFAR	0.167***	0.0868**	0.338***	0.205***
	(0.0471)	(0.0357)	(0.0515)	(0.0522)
AVG	0.200***	0.190**	–0.0271	–0.0495
	(0.0680)	(0.0737)	(0.0352)	(0.0418)
$(AVG)^2$	0.203***	0.195***	0.0340	0.0575
	(0.0565)	(0.0536)	(0.0387)	(0.0479)
G	–0.268**	–0.305**	–0.0857	–0.156*
	(0.124)	(0.125)	(0.0866)	(0.0802)
PG	–0.228***	–0.251***	–0.0239	–0.0830
	(0.0799)	(0.0855)	(0.0646)	(0.0733)
PG13	0.00727	0.00399	–0.0402	–0.0583
	(0.0502)	(0.0548)	(0.0387)	(0.0432)
SCIFI	0.242**	0.295***	0.0427	0.0364
	(0.0922)	(0.0956)	(0.0462)	(0.0551)
DRAMA	0.00353	0.00327	–0.0297	–0.00235
	(0.0500)	(0.0531)	(0.0396)	(0.0435)
COMEDY	0.0175	0.0103	–0.102**	–0.145***
	(0.0617)	(0.0664)	(0.0409)	(0.0462)
ROMANCE	0.0202	0.0348	–0.00559	–0.0108
	(0.0573)	(0.0711)	(0.0641)	(0.0699)
ACTION	–0.0293	–0.0338	–0.0843***	–0.122***
	(0.0583)	(0.0588)	(0.0322)	(0.0387)
THRILLER	0.115*	0.105	–0.112***	–0.153***
	(0.0640)	(0.0664)	(0.0393)	(0.0447)
SEQUEL	0.0188	0.0626	–0.00561	–0.0161
	(0.0695)	(0.0772)	(0.0655)	(0.0734)
COMPETITION	–0.0208	–0.0273	0.0313**	0.0110
	(0.0199)	(0.0168)	(0.0122)	(0.0108)
WK2	–0.270***	–0.245***	–0.148***	–0.135***
	(0.0315)	(0.0299)	(0.0299)	(0.0252)
WK3	–0.325***	–0.285***	–0.298***	–0.233***
	(0.0429)	(0.0370)	(0.0386)	(0.0337)
WK4	–0.393***	–0.345***	–0.425***	–0.304***
	(0.0527)	(0.0441)	(0.0495)	(0.0443)
WK5	–0.447***	–0.387***	–0.525***	–0.348***
	(0.0645)	(0.0551)	(0.0571)	(0.0536)
HOLIDAY	–0.0418	–0.0648*	–0.00805	0.0744**
	(0.0356)	(0.0331)	(0.0364)	(0.0364)

(continues)

Table 5. Continued

	(5)	(6)	(7)	(8)
	2002		2007–2008	
Variables	OLS	Random effects	OLS	Random effects
Constant	1.120***	1.118***	1.801***	1.650***
	(0.101)	(0.0912)	(0.0716)	(0.0673)
Observations	520	520	715	715
R^2	0.448	0.540	0.496	0.639

Notes: Clustered robust standard errors are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

$\log(VOL_{jt}/BOX_{jt}POP_{jt})$ as our dependent variable. Recall that this enhanced measure of propensity attempts to control for between-movie population heterogeneity. We observe no substantial changes in the signs and significance of our important coefficients. Our extended analysis supports our beliefs that our results indicate general tendencies of all moviegoers toward a movie's perceived market availability and popularity and are not due to between-movie population heterogeneity.

Effect of Multicollinearity

To detect sources of potential multicollinearity in our data, we calculate the correlation matrix of independent variables. We find that no pairwise coefficient exceeds 0.50 except that between *AVG* and $(AVG)^2$ in the 2002 data set. Estimation of the variable inflation factors (VIF) provides further evidence that multicollinearity is not a serious concern: only *AVG*'s VIF values exceed 4. We reestimated all the models by dropping *AVG* (Table 6). We find that all important coefficient estimates retain their original sign; moreover, their significance levels do not change substantially. The above exercise allows us to conclude with a fair degree of confidence that the coefficient signs and significance levels we report in this study are robust attributes of our data and not artifacts of correlation among our independent variables.

Effect of Autocorrelation

Past work [15] has shown that time series of online review volumes exhibit autocorrelation. To minimize the effect of autocorrelation in our results, we use Huber–White clustered robust standard errors consistently across all of our regressions, which are consistent and unbiased even with the presence of autocorrelation.

As an added test, we fitted our model separately for each week. Because *TSOFAR* does not have much variation during the first week (it is 0 for most movies, except in a few cases where prerelease reviews were allowed), the regression is conducted for weeks 2, 3, 4, and 5 only. The results are reported in Table 7. As evident, all of

Table 6. Additional Analyses to Address Multicollinearity Concerns: Dependent Variable: $\log(VOL_{jt}/BOX_{jt}POP_{jt})$

	(1)	(2)	(3)	(4)
	2002		2007–2008	
Variables	Random effects	Random effects with *AVG* dropped	Random effects	Random effects with *AVG* dropped
THEATERS	–0.127***	–0.132***	–0.172***	–0.177***
	(0.0274)	(0.0270)	(0.0217)	(0.0216)
RPT	–0.261	1.509	–6.959**	–7.622**
	(1.606)	(1.309)	(3.007)	(3.025)
TSOFAR	0.0868**	0.101***	0.205***	0.206***
	(0.0357)	(0.0367)	(0.0522)	(0.0508)
AVG	0.190**		–0.0495	
	(0.0737)		(0.0418)	
$(AVG)^2$	0.195***	0.0962***	0.0575	0.0773*
	(0.0536)	(0.0306)	(0.0479)	(0.0410)
G	–0.305**	–0.266*	–0.156*	–0.165**
	(0.125)	(0.144)	(0.0802)	(0.0826)
PG	–0.251***	–0.237***	–0.0830	–0.103
	(0.0855)	(0.0906)	(0.0733)	(0.0656)
PG13	0.00399	0.00630	–0.0583	–0.0632
	(0.0548)	(0.0575)	(0.0432)	(0.0430)
SCIFI	0.295***	0.283***	0.0364	0.0476
	(0.0956)	(0.0973)	(0.0551)	(0.0528)
DRAMA	0.00327	0.00962	–0.00235	–0.0191
	(0.0531)	(0.0532)	(0.0435)	(0.0441)
COMEDY	0.0103	0.0150	–0.145***	–0.139***
	(0.0664)	(0.0668)	(0.0462)	(0.0458)
ROMANCE	0.0348	0.0394	–0.0108	–0.0225
	(0.0711)	(0.0713)	(0.0699)	(0.0659)
ACTION	–0.0338	–0.0123	–0.122***	–0.116***
	(0.0588)	(0.0551)	(0.0387)	(0.0378)
THRILLER	0.105	0.0993	–0.153***	–0.146***
	(0.0664)	(0.0669)	(0.0447)	(0.0442)
SEQUEL	0.0626	0.0634	–0.0161	–0.00949
	(0.0772)	(0.0795)	(0.0734)	(0.0719)
COMPETITION	–0.0273	–0.0285*	0.0110	0.0119
	(0.0168)	(0.0170)	(0.0108)	(0.0109)
WK2	–0.245***	–0.247***	–0.135***	–0.135***
	(0.0299)	(0.0307)	(0.0252)	(0.0257)
WK3	–0.285***	–0.288***	–0.233***	–0.233***
	(0.0370)	(0.0370)	(0.0337)	(0.0339)
WK4	–0.345***	–0.351***	–0.304***	–0.307***
	(0.0441)	(0.0441)	(0.0443)	(0.0442)
WK5	–0.387***	–0.395***	–0.348***	–0.353***
	(0.0551)	(0.0544)	(0.0536)	(0.0532)

(continues)

Table 6. Continued

	(1)	(2)	(3)	(4)
	2002		2007–2008	
Variables	Random effects	Random effects with *AVG* dropped	Random effects	Random effects with *AVG* dropped
HOLIDAY	–0.0648*	–0.0731**	0.0744**	0.0698*
	(0.0331)	(0.0339)	(0.0364)	(0.0366)
Constant	1.118***	1.076***	1.650***	1.662***
	(0.0912)	(0.0913)	(0.0673)	(0.0672)
Observations	520	520	715	715
R^2	0.540	0.515	0.639	0.624

Notes: Robust standard errors are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

our major conclusions remain valid in the separate weekly regressions. This provides further confidence of the robustness of our findings.

Relationship Between Box Office Sales and Propensity to Review

The preceding analysis provides valuable insights into how various measures of product popularity affect online review contribution. Specifically, it suggests that at the population level, the propensity to post online opinions about products is influenced by the simultaneous presence of two forces: a tendency to review products that are less available and less popular in the market, coupled with a simultaneous tendency to review products for which there are high *cumulative* volumes of previously posted online comments. Past studies [15, 28] have established that *current* weekly volumes of online reviews exhibit a high correlation with weekly box office revenues. We therefore expect that the effect captured by Hypothesis 3 would usually favor products that have already been successful on the market, putting it in competition with the effect that is captured by Hypotheses 1 and 2.

To gain insight into the combined effect of these two, seemingly opposite, forces, we plot the logarithm of our measure of the population's average propensity to review a movie as a function of the logarithm of a movie's corresponding weekly box office revenue.[9] The resulting plot reveals an interesting U-shaped relationship (Figure 2). This is consistent with our model's results: as suggested by Hypotheses 1 and 2, the propensity to review is highest for less available movies and declines as a movie's weekly revenues increase. As revenues increase, so does the expected cumulative volume of previously posted reviews. As suggested by Hypothesis 3, this creates an opposite force that causes the propensity to review to increase again for very high-grossing movies.

Table 7. Regression by Week: Dependent Variable: $\log(VOL_{jt}/BOX_{jt}POP_{jt})$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2002				2007–2008			
Variables	*WK2*	*WK3*	*WK4*	*WK5*	*WK2*	*WK3*	*WK4*	*WK5*
THEATERS	–0.131***	–0.183***	–0.148***	–0.125**	–0.278***	–0.279***	–0.272***	–0.255***
	(0.0470)	(0.0340)	(0.0404)	(0.0555)	(0.0296)	(0.0283)	(0.0359)	(0.0428)
RPT	–2.872	1.174	–4.079	–3.703	–15.96**	–40.29**	–44.95	–173.4***
	(4.734)	(4.728)	(11.11)	(19.07)	(8.048)	(17.41)	(36.82)	(51.18)
TSOFAR	0.304***	0.191***	0.183***	0.142**	0.363***	0.354***	0.299***	0.334***
	(0.0892)	(0.0544)	(0.0581)	(0.0679)	(0.0646)	(0.0575)	(0.0651)	(0.0630)
AVG	0.0678	0.246**	0.341***	0.336**	–0.0818**	–0.0227	0.0401	0.174***
	(0.116)	(0.0952)	(0.116)	(0.148)	(0.0363)	(0.0409)	(0.0533)	(0.0565)
$(AVG)^2$	0.141**	0.203***	0.306***	0.287***	0.0236	0.0469	–0.00860	0.0332
	(0.0695)	(0.0591)	(0.0698)	(0.0889)	(0.0388)	(0.0434)	(0.0563)	(0.0595)
G	–0.252	–0.240*	–0.269	–0.330*	–0.104	–0.0455	0.116	–0.111
	(0.179)	(0.140)	(0.164)	(0.198)	(0.114)	(0.118)	(0.151)	(0.160)
PG	–0.229*	–0.158	–0.204*	–0.355**	–0.0845	0.00244	0.162*	–0.0920
	(0.128)	(0.104)	(0.119)	(0.150)	(0.0683)	(0.0722)	(0.0953)	(0.101)
PG13	–0.0657	–0.00490	0.0833	0.00805	–0.0266	–0.0754	0.0302	–0.0774
	(0.0785)	(0.0631)	(0.0715)	(0.0912)	(0.0445)	(0.0478)	(0.0626)	(0.0660)
SCIFI	0.208	0.0939	0.269**	0.155	0.134**	0.0111	–0.0365	–0.0811
	(0.128)	(0.105)	(0.123)	(0.160)	(0.0599)	(0.0628)	(0.0794)	(0.0832)

(continues)

Table 7. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2002				2007–2008			
Variables	*WK2*	*WK3*	*WK4*	*WK5*	*WK2*	*WK3*	*WK4*	*WK5*
DRAMA	0.0945	–0.0223	0.0185	–0.0798	–0.0720	–0.0184	–0.140**	0.00430
	(0.0786)	(0.0630)	(0.0736)	(0.0958)	(0.0461)	(0.0486)	(0.0620)	(0.0653)
COMEDY	0.0335	–0.0649	0.109	0.0639	–0.125**	–0.0489	–0.158**	–0.140**
	(0.0923)	(0.0744)	(0.0871)	(0.113)	(0.0519)	(0.0548)	(0.0670)	(0.0708)
ROMANCE	0.132	–0.0402	–0.0559	–0.0266	–0.0535	0.00685	0.0461	0.106
	(0.105)	(0.0853)	(0.0988)	(0.122)	(0.0760)	(0.0805)	(0.105)	(0.114)
ACTION	–0.0261	0.0528	–0.0823	–0.00742	–0.0602	–0.0551	–0.191***	–0.0883
	(0.0872)	(0.0705)	(0.0793)	(0.0992)	(0.0476)	(0.0513)	(0.0640)	(0.0667)
THRILLER	0.0663	0.0989	0.168*	0.113	–0.112**	–0.0784	–0.148**	–0.152**
	(0.0919)	(0.0741)	(0.0861)	(0.108)	(0.0521)	(0.0552)	(0.0699)	(0.0727)
SEQUEL	0.0242	0.0109	–0.0652	–0.0226	–0.0110	–0.0281	–0.212	0.0118
	(0.129)	(0.103)	(0.117)	(0.143)	(0.0999)	(0.106)	(0.136)	(0.143)
COMPETITION	–0.0819*	–0.00375	0.0217	–0.0312	0.0908***	0.0348	0.0266	0.0503*
	(0.0458)	(0.0322)	(0.0389)	(0.0457)	(0.0246)	(0.0227)	(0.0290)	(0.0279)
HOLIDAY	0.00820	–0.0453	0.0760	–0.0509	0.00707	0.0248	0.00837	–0.0414
	(0.0760)	(0.0615)	(0.0688)	(0.0878)	(0.0496)	(0.0579)	(0.0687)	(0.0735)
Constant	0.817***	0.907***	0.606***	0.755***	1.683***	1.579***	1.560***	1.592***
	(0.145)	(0.109)	(0.134)	(0.166)	(0.0895)	(0.0858)	(0.104)	(0.105)
Observations	104	104	104	104	143	143	143	143
R^2	0.395	0.549	0.549	0.396	0.619	0.623	0.504	0.538

Notes: Clustered robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

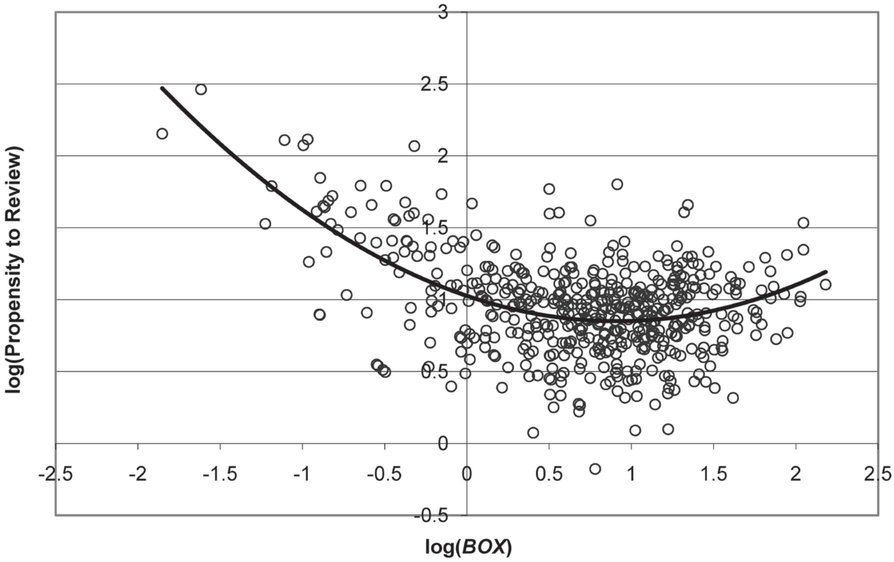

Figure 2. Logarithm of the Population's Average Propensity to Review a Movie $\log(VOL_{jt}/Box_{jt})$ as a Function of the Logarithm of That Movie's Weekly Box Office Revenues

Limitations

Our study uses secondary data to identify factors that affect a population's average postconsumption propensity to engage in product-related conversation. The advantage of using secondary data is that it allows inferences to be drawn from observations of actual behavior and, thus, avoids the self-reporting and nonresponse bias concerns that often plague survey methods [3]. However, inferences based on secondary data are indirect and, for that reason, somewhat tentative. A limitation of our data set is that we do not have information related to the set of movies that individual reviewers watched but decided not to review. This was not a handicap in estimating the factors that affect the population's average propensity to review movies, but would pose challenges if we wanted to study, say, the presence of population segments whose behavior is qualitatively distinct. As a result, our data set only allows population-level inferences; specifically, it does not allow us to tell whether the patterns we discovered characterize the majority of consumers or if they represent the aggregate behavior of heterogeneous population segments whose individual-level behaviors are qualitatively distinct.

In terms of its external validity, although our study only looks at reviews posted at one Web site, our source was, at the time of data collection, the most popular movie site on the Internet, attracting more than 10 percent of U.S. Web users.[10] Furthermore, although we look at a single product category (movies), the theoretical framework underlying our results relates to category-independent attributes such as market popularity and perceived availability. It is, therefore, plausible that our results extend to other categories of goods, although follow-up studies are, of course, needed to prove or disprove this conjecture.

Managerial Implications and Research Opportunities

Consumer-generated content has been hailed as a democratizing force that enables consumers to discuss products that were previously ignored by mainstream media [2]. One important motivation of this study is to explore whether consumers are using their newfound power to even out the informational playing field between popular and obscure products or whether they end up exacerbating the biases of mainstream media by focusing most of their attention on discussing widely marketed or already popular products.

Our empirical analysis shows that a population's average propensity to contribute online reviews for movies they have watched exhibits a U-shaped relationship with those movies' weekly box office revenues: moviegoers appear to be more likely to contribute reviews for very obscure movies but also for very high-grossing movies (Figure 2).

Our theoretical framework and empirical model provide insights that can help explain the underlying patterns of consumer behavior. Consistent with predictions of traditional theories of WOM communication, we find that the population's average propensity to contribute online reviews exhibits a strong negative relationship with important indicators of a movie's *market* availability (H1) and a negative (though statistically weaker) relationship with a movie's per theater revenue (H2). At the same time, however, the population exhibits an attraction to discussing movies for which large cumulative volumes of reviews have already been posted online (H3). As reviews accumulate, the last effect increasingly favors commercially successful wide-release movies.

We attribute the simultaneous presence of these two opposite effects to the diversity of reasons that motivate people to discuss products online. Consistent with psychological theories that relate a person's willingness to engage in product-related interpersonal communication to the likelihood that the person's contributions will be perceived as unique by others, consumers have a penchant for discussing more obscure movies. At the same time, the persistence of previous online content implies that consumers derive social utility from engaging with, and sometimes responding to, previously posted reviews. The limitations of this study do not allow us to conclude whether the same consumers simultaneously exhibit both of these tendencies or whether our results are driven by the presence of different population segments with different behavior. Additional research is needed to further elaborate the precise individual-level mechanisms that result in the observed population-level behavior.

Our main result has interesting implications for marketing managers and information intermediaries. From a marketing perspective, our findings suggest that introducing new products through an initial limited release phase (which will produce a lot of eager early reviewers) followed by a general release (whose late adopters will find the early conversation an added inducement to add their own viewpoints) can be beneficial in terms of maximizing the amount of attention that these products are likely to get in online product review forums.

From an information intermediary perspective, our study raises interesting questions related to the use of consumer content as a mechanism for reducing the informational inequality between hit and niche products. Reducing the informational inequality among different products need not be every infomediary's objective; there are, however, settings where it might generate concrete value. For example, Netflix (which charges users a flat monthly subscription fee, independent of usage) profits directly from shifting consumer demand to lesser-known movies because such movies are less costly to procure [21]. A number of past studies (e.g., [15, 28]) have established that the volume of user reviews has a positive effect on sales. A site such as Netflix would thus be interested in having a sufficient number of reviews for lesser-known movies. More broadly, from a social welfare perspective, the effort spent writing an additional review for an already well-reviewed product can generally be better spent reviewing another product about which there is less information.

Our results suggest that even though consumer populations exhibit a penchant for discussing niche products, certain properties of current online review sites also increase the propensity (of at least some of those consumers) to discuss already widely talked-about products. Infomediaries interested in influencing the mix of products that receive coverage on their sites should be aware of this tension and might wish to shift it in different directions by experimenting with alternative interface designs. For example, we postulate that making review counts and lists of "most discussed products" less-prominent features of online forums will help decrease the inequality of content volumes posted for different products. Recent work [34, 37] hints that this is indeed the case when one looks at consumption decisions, but we are not familiar with work that looks at this question in the context of content contribution. We believe that experimental evaluation of this and other related ideas represents another promising path for future research that stems out of this work.

Notes

1. From Rainie and Hitlin [32] and Nielsen [29], respectively. In the Nielsen study "consumer opinions posted online" were voted as the third-most-trusted form of prepurchase information, behind word of mouth from friends and newspapers, but ahead of all forms of paid advertising.

2. The third section provides a fuller exposition of these theories.

3. We note here that Dichter's theory of other involvement bears many similarities to theories of pure altruism that are often used to explain the contribution of public goods (see, e.g., [5]). Such theories represent yet another foundation on which we can base our arguments but do not add substantial new elements that do not already stem from Dichter's original framework.

4. See Hennig-Thurau et al. [22] for an extensive discussion of the psychological basis of such behavior and its relationship to theories of cognitive dissonance and homeostase utility.

5. We thank the review team for suggesting this point.

6. We do not rule out the possibility that a user might post multiple reviews for the same movie using multiple online identities. However, we are unable to detect this from our data and simply assume that such behavior does not take place on a large scale.

7. We thank an anonymous referee for suggesting this point.

8. The standard contract in the motion picture industry commits a theater to exhibiting a movie for at least four weeks.

9. We plot logarithms because of the highly skewed distribution of both quantities. The figure is based on the 2002 sample. The 2007–8 data show a similar pattern.

10. Source: Nielsen/MediaMetrix 2003 Ratings and Rankings.

11. It is possible that some registered users were not active on Yahoo! Movies during the entire year for which we collected data. For example, a user might choose to stop using Yahoo! in the middle of our data sample and switch to another movie site. However, as long as such changes in activity are not systematically associated with the types of movies users watch, *POP* still provides a consistent measure of average propensity to review a movie.

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Appendix

Proof of Proposition 1

This Appendix describes how we can derive an estimate of $POP(j)$—that is, a population's average propensity to review any movie—from our data. We make the assumption that over a sufficiently long period of time, most viewers watch a variety of different types of movies. Under this assumption, a viewer's intrinsic propensity to post online reviews is proportional to the total number of reviews that have been posted by that viewer over a sufficiently long time period (e.g., one year). We can, in fact, conveniently *define* a viewer's type to be equal to the total number of reviews he or she has posted during the entire period for which we have data (calendar years 2002 and 2007–8). Because all reviewers have an associated Yahoo! ID, we can calculate the types (θ) of all individuals who have been registered on Yahoo! since the beginning of our data collection period and who have posted at least one review on Yahoo! Movies during the time period covered by each of our samples.[11] We can then calculate the type distribution $q(\theta|j)$ of each movie's reviewers. To calculate $POP(j)$, what we need, however, is the type distribution $p(\theta|j)$ of movie j's *viewers*, including those who have chosen to not post a review. Although the latter distribution cannot be estimated directly from our data, we will show that the average intrinsic propensity to review of the population of viewers attracted by movie j during a given time period can be approximated by the *harmonic mean of the total annual number of movie reviews posted by people who reviewed movie* j *during the same time period*.

To simplify notation, the following proof omits the explicit dependence of the relevant quantities on week t.

From Equation (3),

$$VOL(j) = BOX(j)\left(\sum_{\theta}\theta p(\theta|j,t)\right)a(j) \Rightarrow POP(j) = \sum_{\theta}\theta p(\theta|j) = \frac{VOL(j)}{a(j)BOX(j)}.$$

Let $q(\theta|j)$ denote the probability that a reviewer of movie j belongs to type θ. As previously mentioned, we *define* a user's type θ to be equal to the total number of reviews posted by that user during the entire annual period for which we have data. In the rest of the proof we will, thus, use the same symbol (θ) to refer to a user's type as well as to that user's total annual number of posted reviews.

Based on the above, an estimate of $q(\theta|j)$ is then simply

$$q(\theta|j) = \frac{\text{volume of reviews of movie } j \text{ where reviewer's Yahoo! ID has type } \theta}{VOL(j)}.$$

From Bayes's rule and the assumption $\Pr[review|\theta,j] = a(j)\theta$ (i.e., the assumption that a user's intrinsic probability to post an online review is *proportional* to his or her type θ),

$$q(\theta|j) = \Pr\left[\theta|review, j\right] = \frac{\Pr\left[review|\theta, j\right]\times\Pr\left[\theta|j\right]}{\Pr\left[review|j\right]} = \frac{\left(a(j)\theta\right)\times p(\theta|j)}{VOL(j)/BOX(j)},$$

which gives

$$p(\theta|j) = \frac{VOL(j)q(\theta|j)}{BOX(j)a(j)\theta} = POP(j)\frac{q(\theta|j)}{\theta}.$$

Because $p(\theta|j)$ is a probability distribution, it must be

$$\sum_{\theta} p(\theta|j) = POP(j)\sum_{\theta}\frac{q(\theta|j)}{\theta} = 1.$$

Rearranging, we obtain

$$POP(j) = \left(\sum_{\theta}\frac{q(\theta|j)}{\theta}\right)^{-1}.$$

Observe that if θ_{ij} denotes the total annual number of reviews posted by reviewer i of movie j during the period covered by each of our data sets, then

$$\left(\sum_{\theta}\frac{q(\theta|j)}{\theta}\right)^{-1} = \left(\frac{1}{VOL(j)}\sum_{i}\frac{1}{\theta_{ij}}\right)^{-1} = H(\theta_{ij}),$$

where $H(\theta_{ij})$ denotes the harmonic mean of the total annual number of movie reviews posted by people (more specifically, by unique Yahoo! IDs) who contributed reviews for movie j during the period of interest. Q.E.D.