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Dynamic Effects among Movie Ratings, Movie Revenues, and Viewer Satisfaction

Sangkil Moon, Paul K. Bergey, and Dawn Iacobucci

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Sangkil Moon is Assistant Professor of Marketing and Paul K. Bergey is Associate Professor of Information System at North Carolina State University. Dawn Iacobucci is E. Bronson Ingram Professor of Marketing at Vanderbilt University. Correspondence author Moon's contact information is: email: smoon2@ncsu.edu, phone: (919)515-1802, fax: (919)515-6943. Bergey's contact information is: email: paul_bergey@ncsu.edu, phone: (919)515-6949, fax: (919)515-6943. Their mailing address is: NC State University, College of Management, Department of Business Management, Raleigh, NC 27695-7229. Iacobucci's contact information is: email: dawn.iacobucci@owen.vanderbilt.edu, phone: (615)322-4075, fax: (615)343-7177. Her mailing address is: Vanderbilt University, Own Graduate School of Management, Department of Marketing, 401 21st Avenue South, Nashville, TN 37203. The authors appreciate enormous assistance from

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Abstract

This research investigates how movie ratings from professional critics, amateur communities, and viewers themselves influence key movie performance measures (i.e., movie revenues and new movie ratings). Using movie-level data, the authors find that high early movie revenues enhance subsequent movie ratings. They also find that high advertising spending on movies supported by high ratings maximizes the movie's revenues. Furthermore, they empirically show that sequel movies tend to reap more revenues but receive lower ratings than originals. Using individual viewer–level data, this research highlights how viewers' own viewing and rating histories and movie communities' collective opinions explain viewer satisfaction. The authors find that various aspects of these ratings explain viewers' new movie ratings as a measure of viewer satisfaction after controlling for movie characteristics. Furthermore, they find that viewers' movie experiences can cause them to become more critical in ratings over time. Last, they find a U-shaped relationship between viewers' genre preferences and genre-specific movie ratings for heavy viewers.

Keywords: movie ratings, professional critics, amateur communities, movie revenues, consumer satisfaction

There are numerous industries in which experts offer opinions about the quality of products and brands. For example, movie critics make suggestions about a soon-to-be released movie's artistic and entertainment value; *Business Week* hosts Robert Parker's column recommending wines; *Consumer Reports* has long compared brands over numerous product categories, and so forth. Increasingly, consumers post online evaluations of products and brands, as when they review books on Amazon.com, movies on Netflix.com, video games on Gamespot.com, or restaurants on CitySearch.com.

Consumers find judgments from both professional critics and amateur communities helpful, in part because the sheer number of new products and the frequency of their launches (e.g., weekly releases for movies) contribute to overwhelming consumers in the choice process. In addition, many such products appear wholly unique, so a comparison of the movies,"Terminator Salvation" to "X-Men Origins: Wolverine" or among wines, the "Argentinian Malbec" to the "Italian Prosecco" is difficult, thus both critics' and other ordinary consumers' evaluations assist in decision making.

Under such environments, professional critics commonly provide reviews and ratings to help consumers make good choices as information that signals unobservable product quality (Kirmani and Rao 2000). Although amateur consumers can obtain useful information from critics, they are sometimes at odds with critics because of some fundamental differences between the two groups in terms of experiences and preferences (Chakravarty, Liu, and Mazumdar 2008; Holbrook 1999; Wanderer 1970). Therefore, consumers often seek like-minded amateurs' opinions in various ways.

The recent development and proliferation of online consumer review forums, where consumers share opinions on products, is having an enormous impact on the dynamics of word of mouth (WOM) by effectively connecting consumers (Chen and Xie 2008; Eliashberg, Elberse, and Leenders 2006; Godes and Mayzlin 2004; Godes et al. 2005; Mayzlin 2006; Trusov, Bucklin, and Pauwels 2009). These online forums lower the product information search costs, which motivates consumers to seek such review information (Stigler 1961). After all, consumer communities' collective opinions can have as much influence on other consumers' choices as professional critics' opinions. In addition to these two influence groups, consumers also make choices in accordance with their own judgments based on past experiences in the given product category, which can be contrary to opinions from either professional critics or amateur communities. In this sense, consumers are active information processors rather than passive information receivers (Bettman 1970).

To provide a comprehensive evaluation of how product reviews and ratings influence consumers' choices and satisfaction arising from their experiential consumption, we consider the opinions from these multiple sources. Such external and internal information sources are particularly important in movie choice because viewers constantly face the problem of choosing satisfying movies among many new and existing ones. Indeed, the development of the Internet has engendered movie rental service Web sites (e.g., Netflix, Blockbuster), on which members access a wealth of movie review information with only a minimal effort. Members can also post their own opinions with ease. In such an environment, the influence of online member communities' general opinions on movie choice is maximized (Chevalier and Mayzlin 2006; Liu 2006). While the contributions of this research are intended to broadly encompass many industries mentioned above, we focus on the movie industry, in part due to its enormous economy size ($10 billion in 2008 U.S. box office ticket revenues according to www.the-numbers.com/market).

This research attempts to highlight the relationships between such product ratings and product financial performance - namely various sources of movie ratings and movie performances (i.e., movie revenues and viewer satisfaction), while considering various movie quality characteristics (e.g., movie costs, original versus sequel). To accomplish this objective, we conduct an empirical analysis at two levels: the (aggregate) movie level and the (individual) viewer level. First, we focus on the movie-level analysis to examine the two-way dynamic influences between movie ratings and movie revenues.

In this analysis, we view movie revenues as the collective results of individual viewers' choices. In doing so, we focus on collective critics' and amateur communities' ratings for each movie but not on individual viewers' ratings. Second, to supplement this aggregate view, we examine how individual viewers' movie consumption influences their postconsumption evaluations. To do so, we conduct a viewer-level analysis, in which we test the influence of both the focal viewer's viewing and rating history and the movie community's collective opinions on the focal viewer's new movie rating while controlling for movie quality (i.e., movie characteristics).

This two-level analysis approach enables us to examine the relationships between movie ratings and movie performances from complementary angles, providing important managerial insights. Importantly, the (macro) movie-level analysis captures moviegoers' collective choices in the movie industry, whereas the (micro) viewer-level analysis taps into individual consumers' postconsumption experiences. We develop and test five hypotheses based on this two-way classification.

From a managerial perspective, on the basis of some key empirical findings, this research suggests that movie marketers should persistently promote movies that garner high ratings to sustain movie revenues and should cautiously consider sequels in spite of their originals' commercial success. For movie rental firms, this study provides insights into ways to recommend satisfactory movies on the basis of the focal member's rating history, the member community's overall movie rating patterns, and the movie's characteristics. Netflix maintains that approximately 60% of its members select movies according to movie recommendations tailored to their tastes. In addition, our results should be applicable to other consumption situations in which consumers continually face new products (e.g., new books, new music albums) and determine the expected value of the new products according to their own experiences, like-minded amateur communities' general opinions, and critics' professional reviews.

In the following section, we discuss the theoretical background and develop hypotheses pertaining to the relationships between movie ratings and performances. Our empirical analyses test the hypotheses using both the movie-level data and the viewer-level data. Finally, we discuss the managerial implications of our findings.

HYPOTHESES DEVELOPMENT

Movie-Level Effects: Movie Ratings and Revenues (H_1 ~ H_3)

Prior research has developed movie revenue evaluation models in various contexts, focusing particularly on theater revenues (Ainslie, Drèze, and Zufryden 2005; Eliashberg et al. 2000; Jedidi, Krider, and Weinberg 1998) rather than on video revenues (Prosser 2002). Some research has also examined the impact of critics' ratings and reviews on theater revenues. Specifically, Eliashberg and Shugan (1997) empirically find that critical reviews correlate with late and cumulative box office receipts but not with early box office receipts; thus, they conclude that critics are predictors rather than influencers. In contrast, some studies show that critics play a dual role as both predictors and influencers (Basuroy, Chatterjee, and Ravid 2003; Boatwright, Basuroy, and Kamakura 2007). According to Reinstein and Snyder (2005), when movies receive high ratings from either critics or ordinary viewers, revenues increase. Early high ratings can generate positive WOM that can spread to ordinary viewers.

Less obvious, however, is the hypothesis we wish to test regarding whether strong revenues can subsequently generate more positive reviews during the course of the movie. If we can confirm this reciprocating dynamic interaction between reviews and revenues, we would establish that high ratings effectively sustain high movie revenues and vice versa over the not-so-long life of the movie. Our reasoning is similar to that of Duan, Gu, and Whinston (2008), who indicate that a unique aspect of the WOM effect is the presence of a positive feedback mechanism between WOM and sales. Similarly, Godes and Mayzlin (2004) theorize that commercially successful TV shows can engender more buzz among ordinary viewers. The enhanced buzz is usually positive for commercially successful movies because of the generally positive correlation between movie ratings and movie revenues. In other words, movie viewers talk more about successful movies, which affects revenues and ratings, than unsuccessful movies. Behavioral learning theory characterizes this dynamic process as vicarious learning, as consumers learn from the market and the process positively reinforces their satisfaction (Nord and Peter 1980; Rothschild and Gaidis 1981). The favorable enhanced buzz from high-revenue movies contributes to enhanced movie ratings in following weeks because there are more viewers who had positive experiences with the movie. This relationship is strengthened by the mutual confirmation of the online community environment composed of ordinary viewers.

Movie marketers are known to enhance advertising spending for movies that was commercially successful in preceding weeks, which in turn draws more positive reviews of the movie viewers.[1] In other words, advertising can also play a role in confirming viewer satisfaction, which is translated into higher movie ratings in subsequent weeks (Spreng, MacKenzie, and Olshavsky 1996). Thus we will test the following hypothesis:

H_1: High movie revenues enhance subsequent movie ratings.

This hypothesis implies that early successful revenues from early adopters of new products serve as an information cue for late adopters' purchases and satisfaction. WOM is known to be a powerful and effective force, assisting the diffusion of consumer packaged goods, durables, and services in the market. Early commercial success is similarly a proxy of assurance of high quality from early adopters, a segment often acknowledged as experts in the relevant product category, thus the early sales figures anoint credibility to the product launch, enhancing its success.

The movie literature takes somewhat of a signaling theory's perspective, e.g., in that a consumer

[1] Our empirical analysis confirms this strategy as common practice by movie marketers. The correlation between weekly theater revenues (during the previous week) and weekly ad spending (during the current week) is positive and significant and increases over subsequent weeks. This evidence indicates that movie marketers allocate their advertising money according to movies' commercial successes as they adjust distribution intensity (i.e., the number of screens) in response to the weekly theater revenues (Krider et al. 2005).

witnesses early commercial success of a movie can infer that the movie has qualities that make it popular, and might also infer that the movie has artistic or creative merit. The literature maintains that the same quality signal from two different sources – one from marketers (advertising) and the other from consumer communities (ratings) – can effectively influence consumers' choices in the marketers' favor by greatly reducing uncertainties regarding new products' unobservable quality (Kirmani 1997; Nelson 1974).

Some recent research suggests that, in the movie industry, certain signals may become less useful in the presence of others; for example, Basuroy, Desai and Talukdar (2006) find the attenuating role of third-party information sources (e.g., critics' review consensus and cumulative WOM) on the strength of the adverting signal. Other research argues that advertising and ratings indeed function synergistically, enhancing revenues when well-known movies (through large budgets and heavy advertising) receive positive WOM (through high movie ratings) (Basuroy, Chatterjee, and Ravid 2003; Liu 2006). To contribute to this line of inquiry, we will also test an interactive hypothesis from analogous sources. We predict an interactive effect that advertising spending upgrades revenues further when ratings are more positive. Our theorizing suggests that if movie ratings are positive, then potential consumers are more likely to respond to the advertising, thus enhancing the effect of advertising on revenues.

Note that both factors must be in play—neither is sufficient on its own.[2] That is, positive ratings alone cannot effectively increase revenues because not enough potential viewers know about the movie. In addition, highly advertised movies cannot generate enough revenues without obtaining favorable ratings from ordinary moviegoers because negative WOM spreads more quickly for these types of movies than others. Yet, we anticipate that neither piece of information is sufficient because

[2] In general, high-cost movies generate high revenues and profits, but not always, and ratings, or consumers' acceptance of products does matter. Consider the movie *Hotel Rwanda*. Its costs and revenues were low ($31million and $32 million, respectively), but its average ratings were high (9.5/10). In contrast, consider *Charlie's Angels: Full Throttle*. Its costs ($147mm) were more than its revenues ($102mm) with poor ratings (5.7/10).

the effect is interactive and synergistic. Our theorizing may be consistent with signaling theory, if both sets of signals are calibrated to be equally effective. Realistically, we acknowledge that one set of signals may seem to be more diagnostic as a cue than another set of signaling information (Lynch 2006). Thus, we predict an interactive effect, but without specifying that one contributing signal attenuates another:

H_2: Positive ratings enhance the effectiveness of advertising spending to raise movie revenues.

Movie sequels build on the original movies' commercial success (Basuroy and Chatterjee 2008). That is, viewers tend to see the high quality of their originals as a signal to the quality of sequels as consumers associate various products of the same brands in product quality (Erdem 1998). With generous production budgets and heavy advertising based on the originals' brand power, sequels usually achieve box office success, even if they do not tend to meet the box office levels attained by their parent movies (Basuroy and Chatterjee 2008; Ravid 1999).

Yet, while sequels can make money, they are often rated less favorably than original movies. That is, the original movie's success leads to high expectations for the sequel, which will be difficult to meet, thereby leading to less satisfaction (Anderson 1973; Oliver 2009). Viewers may be less satisfied and less impressed because of satiation on experiential attributes arising from sequels' lack of novelties and surprises, which results in lower ratings by moviegoers. Figuratively speaking, once the punch line is known, the humor is less effective. Distancing a movie somewhat from the expectations of the original pays off; Sood and Drèze (2006) find that dissimilar sequels were rated higher than similar ones and that sequels with descriptive titles (e.g., *Pirates of the Caribbean: Dead Man's Chest*) were rated higher than those with numbered titles (e.g., *Spider-Man 2*). Low ratings on a sequel tend to spread in the movie population, thus limiting its revenues in following weeks, which does not bode well for a sequel's long run. Such low ratings of sequels may partially explain why subsequent sequels are rarely made.

Therefore, we hypothesize that the effects of both higher revenues and lower ratings of sequels are likely realized predominately in the early weeks after release because sequels tend to stimulate their loyal consumer base quickly. That is, viewers who already liked an original movie will tend to see its sequel early compared with an unknown, new original movie. Accordingly, these sequel movie effects are also likely to dissipate quickly and, therefore, would not be as strongly pronounced a few weeks after release. Thus, we predict:

> H_3: Sequels reap higher revenues but lower ratings than originals, predominately in the early weeks after release.[3]

General Viewer-Level Effects: Own Past Ratings and Community Opinions

Movie revenues are one indicator of results of collective consumers' choices. Individual viewers' ratings are another significant measure, effectively summarizing consumer satisfaction in the movie industry. Higher ratings may lead viewers to choose other movies that share preferred characteristics (e.g., sequel, same actor), and the reasons for satisfaction can be spread to online consumer communities through text reviews. Viewer preferences can develop into a stable and established preference for viewers, such as favorite genres or favorite stars. This is particularly important for online movie rental firms (e.g., Netflix), because members have unlimited access to other members' ratings and reviews. For these firms, members' increased satisfaction enhances their loyalty to the company.

Those movie rental firms invest tremendous time and effort into developing an effective movie recommendation system based on (a) the individual member's rating history, (b) the member community's overall rating patterns of the movie of interest, and (c) the movie's characteristics. The firms can then use the system for customer relationship management by using these information sources. Beyond such a recommendation system, it is equally important to understand how such information

[3] This hypothesis developed for movies can be potentially extended to other entertainment products such as books (e.g., Harry Potter series by J. K. Rowling), video games, and music albums. Whether the same logic applies should be empirically tested. The hypothesis can be further extended to incremental product developments in consumer packaged goods (e.g., Coke Zero, Pepsi ONE). One quality about movies that make them different from consumer packaged goods and, even books, is their extremely short life cycle.

sources are associated with members' ratings on new movies for insights into how the new ratings are determined.

To understand the individual member's ratings, we examine six factors: (1) number of movies rated, (2) average rating, (3) rating standard deviation, (4) percentage of same genre, (5) genre-specific average rating, and (6) most recent rating (refer to Table 4). The anticipated effect of each factor is described next.

First, the member's number of movies rated indicates the frequency of movie viewing to identify segments traditionally referred to as light and heavy segments. Overall movie viewing frequency indicates general liking toward movies, with heavy viewers liking movies more. Therefore, we expect a positive association between number of movies rated and new movie rating. Second, the member's average rating shows how strict or lenient he or she is when rating movies on average. Lenient raters tend to rate new movies higher than strict raters, and, accordingly, we expect a positive association between average rating and new movie rating. Third, the member's rating standard deviation represents the variability of the member's ratings across different movies and reflects his or her risk tolerance in choosing movies. In other words, a wide rating variability may indicate that a member's choices have been experimental and risky; in such a case, the member can end up with more disappointing movies than members with a narrow rating variability. Thus, we expect a negative association between rating standard deviation and new movie rating.

Fourth, the member's percentage of each movie genre in the member's rating history measures how often the member sees movies of the same genre. For example, thriller junkies view most movies in the genre because they like the genre the most of all the movie genres. This internal disposition tends to lead them to rate thriller movies high. Thus, we expect a positive association between percentage of same genre and new movie rating. Fifth, the member's historical average movie rating for the same genre also measures his or her general preference toward movies of the same genre.

Logically, we expect that a rating for a new movie of the same genre is positively associated with members' general preference toward the same genre. Sixth, we theorize that a recent satisfactory movie experience raises the aspiration level, whereas a recent disappointing experience lowers the aspiration level (Anderson 1973). According to Prospect Theory (Kahneman and Tversky 1979), the aspiration level set by the recent movie experience should function as a reference point, yielding a negative association with most recent rating and next rating.

Next, we turn to an understanding of the second factor group of the movie recommendation system, the member community's overall rating patterns, and to do so, we examine five factors: (1) number of ratings, (2) average rating, (3) rating standard deviation, (4) percentage of highest rating, and (5) percentage of lowest rating (refer to Table 4 again). These factors echo community opinions and are comparable to online WOM effects. First, the community's accumulated number of ratings of a movie indicates how many members have already seen the movie. Because more interested members view the movie before less interested members, we expect that the accumulated number of ratings to be negatively correlated with the new rating. Second, we expect that the community's historical average rating of the movie of interest to be positively correlated with the new rating because members tend to rate the same movie similarly; i.e., most viewers rate good movies high and bad movies low. Third, the community's historical rating standard deviation of the movie of interest measures the degree of evaluation disagreement toward the same movie. More diversely discussed movies (i.e., those with high rating standard deviations) can attract more viewers by raising their curiosity than less discussed movies, especially in the ubiquitous and freely accessible online movie community environment. However, negative reviews of a movie tend to disappoint viewers who are attracted by increased discussion because these viewers are likely to have high expectations by positive comments about the movie. Thus, we expect a negative association between rating standard deviation and a new movie rating. Lastly, the community's percentage of the highest and lowest ratings of the movie of interest indicate two opposite extreme ratings (e.g., five and one on a five-point scale, respectively) and is a strong indicator of new ratings beyond the community's simple average rating. Thus, the highest rating is positively correlated with a new movie rating, and the lowest rating is negatively correlated with a new movie rating.

These two data perspectives together along in association with movie characteristics will converge to lend a better understanding of how both the consumers' own past consumption experiences and the community opinions influence consumers' postconsumption evaluations in the movie category. Recently, marketing scholars have emphasized "connected" consumers in the Internet era, in which people can easily exchange consumption information (Chen and Xie 2008; Chevalier and Mayzlin 2006). However, consumers still value and use their own experiences (i.e., internal information) in decision making, in addition to community opinions (i.e., external information). In general, consumers are likely to seek various types of information sources in order to reduce uncertainty as the perceived risk associated with a purchase increases (Murray 1991; West and Broniarczyk 1998). In the movie industry, the uniqueness of each movie makes movie choice challenging, along with the financial and transaction costs (e.g., ticket price, travel to the theater).

In-Depth Viewer-Level Effects: Rating Pattern Developments with Experiences (H_4 ~ H_5)

In the previous subsection, we have focused on illuminating two groups of factors that influence amateur viewers' new ratings – viewers' own past ratings and movie communities' opinions. What can be further considered based on this discussion is how amateur viewers' ratings develop as they acquire more movie consumption experiences (Alba and Hutchinson 1987). Therefore, in this subsection, we present two in-depth hypotheses on individual viewers' rating pattern developments: one hypothesis on viewers' rating changes over time (H_4) and the other hypothesis on how viewers' movie consumption experiences are associated with their genre preferences (H_5).

First, we intend to examine how amateur viewers' ratings can change over time. We will test and verify that members with more ratings experiences rate movies lower, similar to critics' ratings, which are generally lower than amateurs' ratings because of the critical nature of their reviews.[4] By watching more movies, members develop a reliable, large reference base and, accordingly, should be able to analyze movies similar to professional critics. Alba and Hutchinson (1987) indicate that increased familiarity (i.e., the number of product-related experiences) results in increased consumer expertise (i.e., the ability to perform product-related tasks successfully). Furthermore, we expect members to choose preferred movies first and then a set of movies that do not include their best choices.

At the same time, members' ratings become less variable with experiences because their consumption experiences become stabilized over time. Specifically, on the one hand, it becomes more difficult to satisfy them, and thus they give high ratings less often than before. On the other hand, their own improved expertise and accumulated experience enable them to avoid movies that are unsuitable to their tastes, and thus they give low ratings less often than before. Therefore, amateurs' movie ratings become stabilized in the form of less variability with consumption experiences.

H_4: Amateur viewers' movie viewing experiences generate less favorable ratings with less variability.

In the long run, amateur viewers' ratings should stabilize at a certain level because there will not be any more substantial learning experience in critiquing movies. Therefore, this hypothesis is primarily focused on amateur viewers who are acquiring relative new movie consumption experiences as opposed to seasoned and experienced amateur viewers.

Next, given the association between movie preferences and ratings with genre (Liu 2006), such as children being huge fans of animation movies, we expect that viewers give their favorite genres (more precisely, members' frequently viewed genres) high ratings because they are internally

[4] This argument is empirically confirmed by our data used for this research.

predisposed to like that category of movies (upward "preferred genre effect"). In contrast, as we predict in H_4, as viewers choose more movies beyond their best choices in their non-favorite genres, they may rate those movies lower without having the "preferred genre effect" as in their favorite genres (downward "viewed set effect"). That is, as viewers choose more movies, they settle for less attractive movies because they have exhausted their top choices in certain genres. Thus, the relationship between genre proportion (i.e., the percentage of movies seen in the genre compared to all movies seen for that individual viewer) and average genre rating may be non-monotonic because of these two conflicting effects and warrants further investigation.

Specifically, we expect "genre loyalists" with high range of genre proportions to generate high ratings approximately proportional to their genre proportion because of their strong internal inclination toward their favorite genres. In most cases, their strong inclination toward their frequently viewed genres prevents them from choosing from other less favored genres. That is, genre loyalists are strongly predisposed to specific aspects of their favorite genres. For example, thriller movie loyalists enjoy how the story unfolds and entertains their own anticipated scenarios. Thus, such strong preferences for their favorite genres lead the loyalists to rate most movies in their preferred genres favorably (upward effect by preferred genres). By contrast, this effect should be weak or non-existent for viewers who balance multiple genres, and, accordingly, they will exhibit a downward effect by viewed set. Lastly, a low range of genre proportions is expected to show a medium range of ratings due to viewers' choosing only the most recognizable movies in the genre only a little known to them under certain special occasions (e.g., through intensive advertising exposure, friends' strong recommendation). However, their lack of strong inclination toward the movie's genre leads them to have only a moderate level of satisfaction despite the movie's strengths.

Importantly, we hypothesize that this U-shaped relationship is pronounced only for heavy viewers, who gain enough consumption experiences through enhanced analysis and elaboration abilities to process product information (Alba and Hutchinson 1987). We do not expect the relationship to be strong for light viewers (i.e., novices) because their experiences do not develop fully either the upward effect ("preferred genre effect") or the downward effect ("viewed set effect").

> H_5: Among experienced viewers, the relationship between their genre proportion (i.e., genre preference) and genre rating is U-shaped.

EMPIRICAL ANALYSIS

We divide our empirical analyses into two parts according to the different nature of the available data. First, we provide the empirical results of H_1–H_3, using movie-level data from various sources including Rotten Tomatoes for professional critics' ratings and Yahoo! Movies for amateurs' ratings. These data do not include information on individual critics or individual amateur viewers. Therefore, with individual members' data mainly from Netflix, we run a regression analyzing individual viewers' movie ratings and test H_4 and H_5.

Movie-Level Data

The data contain specific information regarding 246 movies that cover six major genre categories: thriller, romance, action, drama, comedy, and animation. The movies were released during the May 2003–October 2005 period in theaters and on video. Table 1 provides a summary on these data, such as movie characteristics, costs, and revenues.

We gathered the ratings information on the 246 movies from two popular movie Web sites: Rotten Tomatoes and Yahoo! Movies. Both sites allow members to post movie ratings but differ in terms of membership conditions. The Rotten Tomatoes site comprises accredited movie critics exclusively. Accordingly, these members are active in either select movie critic societies/associations or print publications. They are regarded as professional movie critics. In contrast, the Yahoo! Movies site is open to the public and, for the most part, comprises amateur movie lovers (see Table 1).

TABLE 1 ABOUT HERE

Movie-Level Analysis: Movie Ratings and Revenues (H_1 ~ H_3)

In the weekly regression summarized in Table 2, high weekly theater revenues induced more favorable amateurs' ratings in the following week in six of the seven weeks tested, thus supporting H_1. Week 1 was the only exception (with theater revenues in Week (=opening week) and movie ratings in Week 1), which suggests that viewers in the opening week (Week 0) tended to have mixed evaluations about the movie, perhaps because they saw the movie for different reasons. For example, heavy advertising from movie marketers, or insufficient and inconsistent information from like-minded moviegoers can make satisfactory choices difficult. During the opening week, however, enough people view the movie and spread their reviews and ratings in both online and offline domains. In general, then, late viewers make better informed choices, which is empirically supported by more positive ratings in the following weeks. In the process, commercially successful movies can generate more satisfactory viewers who then rate the movies higher. That is, these viewers choose the movies because of previous ratings and reviews.

TABLE 2 ABOUT HERE

We tested H_2 regarding the interaction effects of movie ratings (from either critics or amateurs) with ad spending on box office revenues using weekly data. Table 3 provides the significant variables at the .05 level; for the initial independent variables used in each regression, see the Appendix. In the weekly analysis, we used the previous week's ad spending measures (i.e., weekly ad spending, weekly theater ad proportion, and weekly movie ad proportion) and the accumulated movie ratings (i.e., critics' and amateurs' ratings) up to the previous week to measure their effects on the following week's theater revenues. We used the accumulated ratings because moviegoers can review all the past ratings to determine which movie to see.

TABLE 3 ABOUT HERE

In this weekly analysis, we confirmed that the interaction effects of ratings and spending (critics' ratings × ad spending and amateurs' ratings × ad spending) were significant in Week 2 through Week 7, whereas the main effects of ratings were not. This implies that movie revenues cannot be maximized without the combination of ratings and ad spending in these weeks; thus, H_2 is empirically supported for the later weeks. The nonsignificant main effects of both ratings (critics' and amateurs' ratings) indicate that ratings alone cannot increase movie revenues without enhanced buzz created through advertising spending. In contrast, we observe a mixture of positive and negative main effects of the movie cost variables (i.e., weekly ad spending, weekly theater ad proportion, and weekly movie ad proportion). Although we expect that movie costs are positively correlated with movie revenues, significantly negative movie cost effects imply that some advertising money was excessively wasted beyond its proper use, based on its effective combination with favorable ratings (measured by both interaction terms). In other words, negative movie cost effects occurred after the regression is accounted for by both significantly positive interaction term effects. Notably, our empirical analysis shows that movie marketers tend to allocate more advertising dollars to movies that collect high revenues in preceding weeks. It demonstrates that, in many cases, marketers used advertising money inefficiently because they did not consider both revenues and ratings in allocating their advertising resources.

In contrast, in the opening week (Week 0), we found that only one main effect (critics' ratings) and one interaction effect (amateurs' ratings × ad spending) were significant. The result of Week 0 implies that critics' ratings have a significant main effect on theater revenues because critics' reviews and ratings are intensively published in various outlets shortly before opening week (Week 0). In the same week, amateurs' ratings showed no significant main effect probably because there are only a limited number of amateur reviews before a movie's release. Accordingly, high amateur ratings can only enhance revenues with the help of substantial ad spending in the week. In the following week

(Week 1), we observe one significant main effect (amateurs' ratings) and one significant interaction effect (critics' ratings × ad spending). In this particular week, amateurs' ratings create enough information and buzz from early moviegoers and thus do not need the support of heavy advertising due to strong buzz and attention on new and fresh movies among ordinary moviegoers. In contrast, the combination of critics' ratings and ad spending enhances movie revenues effectively beginning this week. After the first two weeks, because of reduced voluntary attention and buzz among ordinary viewers, only a combination of good ratings and heavy ad spending made a substantial influence on theater revenues.

Next, we tested H_3, which compares sequels and their contemporaneous originals. Table 3 shows that the positive impact of sequels on theater revenues occurred only in the first two weeks after the movie's release and that the impact was much stronger in the opening week (Week 0) than in the following week (Week 1). Afterward, the impact weakened, probably because the buzz and attention for the sequel dissipated quickly. Our weekly analysis in Table 2 shows a negative impact of a sequel on movie ratings in Weeks 1 and 2 as well. In brief, the empirical results show that sequels can have a positive impact on theater revenues based on its originals' success but they leave viewers relatively unimpressed and unsatisfied than they were with original movies. Yet, these sequel effects are pronounced only in the early weeks and become subsequently neutralized because the fan base stemming from the original tends to view the sequel early.

Viewer-Level Data

We used individual members' movie rental and rating histories data from the Netflix Prize site for the individual viewer–level analysis. The public data contain more than 100 million ratings of 17,770 movie titles from 480,000 randomly chosen, anonymous Netflix members. We collected the data between October 1998 and December 2005, and they reflect the distribution of all ratings received during the period. The title and release year of each movie are also provided.

From the Netflix Prize public data, we selected 13,734,151 ratings of the 246 movies used for our previous movie-level analysis and matched this viewer-level data with the movie-level data. The data included 456,476 Netflix members. The ratings selected cover the June 2001–December 2005 period. The rating average of the 246 movies was 3.38 on a five-point scale, with an average of 55,830 ratings for a movie.

General Viewer-Level Analysis: Own Past Ratings and Community Opinions

We developed a regression model comprised of three groups of factors that we anticipated should influence new movie ratings (dependent variable): (a) individual member–based variables (X), (b) community-based variables (Y), and (c) movie characteristics variables (Z) (see Table 4). We analyzed the impacts of the three groups of factors on new movie ratings to comprehensively provide empirical findings regarding consumer satisfaction with movies. Thus, we used the following linear regression, where the dependent variable R represents member h's rating for movie m at time t (West and Broniarczyk 1998). Our regression reflects continuously updated temporal information at the given time point to evaluate the new rating R.

(1) $R_{hmt} = \alpha + \beta X_{hmt} + \gamma Y_{mt} + \delta Z_m + \varepsilon_{hmt}$.

The X_{hmt} variables represent the rating member's individual viewing experiences and preferences. X, which is varied for three dimensions of member (h), movie (m), and time (t), is composed of the six specific individual member–based variables based on the focal member's viewing and rating history. Next, the five Y_{mt} variables measure community opinions, which are comparable to online WOM effects. Unlike X, Y varies in the dimensions of movie (m) and time (t), but not vary across members (h) as collective group opinions. Finally, Z_m includes 11 movie characteristics variables. We use these variables as control variables to measure more accurately how both the X and Y variables influence the dependent variable; Z does not vary across members (h) or time (t) as fixed movie (m) characteristics.

TABLE 4 ABOUT HERE

To fit this model, we removed members with fewer than 10 ratings over the 246 movies. Then, we randomly selected 1 of every 300 members to make the regression more manageable. The selected sampling resulted in 43,204 ratings from 1014 members. The average rating across the members was 3.59. The average number of ratings of the members was 42.6 of the 246 movies.

Table 4 shows the estimation results of the regression model. All the individual member-based variables (X) and community-based variables (Y) showed the expected signs, and 9 of the 11 X and Y variables (X and Y) were significant at the .05 level. Between the two insignificant variables (X_3 and X_6), most recent rating (X_6) was close to the cutoff level. Despite its expected sign, rating standard deviation (X_3) was insignificant, perhaps because wide rating variability elicits high ratings as well as low ratings across members. Notably, all the five community-based variables were significant. In particular, the results of percentage of highest rating (Y_4) and percentage of lowest rating (Y_5) imply that the two extreme ratings are strong indicators of additional ratings from new viewers of the same movies beyond average rating (Y_2). Basuroy, Chatterjee, and Ravid (2003) find that negative reviews hurt performance more than positive reviews help performance (negativity bias). Our research confirms this theory because the absolute estimate value of the percentage of the lowest rating (.02176) is much larger than that of the percentage of the highest rating (.01376).

Finally, most movie characteristics variables (Z) were also significant. All five genre dummy variables were significant, which indicates their differential impact on ratings. The sequel dummy variable has a negative impact on the new rating, which is consistent with our previous empirical results, in support of H_3. The Motion Picture Association of America (MPAA) rating dummy variable has a positive sign, which indicates that R-rated movies are rated higher than non-R-rated movies. Similarly, a longer movie tends to be rated higher. After we account for all the movie-related factors in the regression, production budget has a negative impact on ratings. This result implies that big-budget movie producers tend to spend excessively beyond financially justifiable quality improvements. In association with video release factors, videos released on holidays and those released shortly after their theater release tend to be rated higher. Last, both video bonus materials and high video ad spending show a positive impact on ratings. In brief, the results of the Z variables add face validity to our overall regression results.

In-Depth Viewer-Level Analysis: Rating Pattern Developments with Experiences (H_4 ~ H_5)

Table 5 shows our temporal trend analysis of individual members' rating changes over time as they view more movies. For this analysis, we sorted the Netflix data used for the regression in Table 4 in the ascending order of the rating time for each member. We applied the generalized least squares (GLS) estimation to correct for the heteroskedasticity (i.e., unequal variances) problem in the data (Goldberger 1991; Griffiths, Hill, and Judge 1993). Panel A in Table 5 shows the relationship between members' viewing experiences (member rating order) and the rating mean across all members at the overall level and each of all the six genres, which is consistently negative. The negative ratings at the overall level imply that members tend to rate recently viewed movies more strictly as they acquire more consumption experiences. The same pattern was confirmed in five of the six genres at the .10 significance level. Similarly, Panel B in Table 5 shows that members' ratings tend to become less variable with consumption experiences at the overall level. Again, the same pattern is confirmed in five of the six genres at the .10 significance level. In addition, we found that the correlation between the movie rating average and the rating frequency was positive across movies (.557, $p \leq .01$) but negative across members (–.064, $p \leq .01$). The positive correlation across movies implies that popular movies are rated higher; however, the negative correlation across members indicates that more experiences can make viewers tougher raters, in support of H_4 along with Table 5.

TABLE 5 ABOUT HERE

We tested the hypothesized U-shaped relationship between the member's genre proportion and genre-specific rating average (H_5) and confirmed the curvilinear relationship (Figure 1). We theorized that genre loyalists, who see a majority of movies in one or two genres, rate movies higher because of their strong preference for the favorite genres. Furthermore, perhaps, they do a better job at selecting good movies in their favorite genres because of their genre-specific expertise. In contrast, genre switchers, who tend to watch various movies across genres, tend to rate movies lower because they settle for less satisfactory movies after they exhaust their top choices in chosen genres. This genre-related rating pattern becomes more pronounced for heavy viewers (i.e., experts) than light viewers (i.e., novices).

Panel B of Figure 1 illustrates our empirical results of the relationship among viewers overall, heavy viewers, and light viewers according to the regression results in Panel A. In the heavy viewers segment, which shows the most pronounced relationship among the three groups, the genre-specific movie rating moves lower until the genre-specific proportion reaches 23% (for genre switchers). As mentioned previously, we expected that these viewers sample less satisfactory movies in their non-favorite genres after exhausting their favorite movies in the same genres. After they passed the lowest threshold, the genre rating began to increase quickly and reached the highest possible rating (i.e., five) when the member's genre proportion hit 77%.

FIGURE 1 ABOUT HERE

DISCUSSION

Movie-Level Effects: Empirical Findings and Managerial Implications

From a managerial perspective, this study shows that ratings are associated with movie performance as measured by both movie revenues and viewer satisfaction. Our movie-level data analysis implies that marketers should allocate more ad dollars to movies that garner early high ratings by professional critics. These ratings tend to lead to high ratings by amateurs, which in turn can contribute to enhanced revenues. Enhanced revenues can also raise movie ratings in the subsequent weeks (H_1). Moreover, the revenues of highly rated movies are enhanced when the movies are heavily advertised (H_2).

Our weekly data analysis (Table 3) reveals that ad dollars can be used efficiently over the course of new movies, which usually last only a couple of months in theaters. Specifically, we found that prerelease critics' ratings contribute significantly to the theater revenues in the opening week (Week 0), when amateurs' ratings do not virtually exist. In contrast, amateurs' ratings begin to influence theater revenues in the following week (Week 1). In later weeks, only high ratings supported by heavy ad spending can sustain theater revenues because high ratings alone are not sufficient to maintain moviegoers' attention without heavy advertising in later weeks. In contrast, movie ratings and reviews can capture moviegoers' attention more easily in the early weeks because they are published in many newspapers and magazines and spread through Internet movie communities in time for new releases. In summary, in the early weeks, critics' early ratings can be an important quality signal of movies for marketers to allocate advertising money among available movies in theaters (Nelson 1970; Nelson 1974). To obtain more sustained revenues in the later weeks, marketers should sustain their ad spending on movies supported by high ratings. This pattern suggests that marketers should allocate their ad dollars on movies that garner high ratings not only in early weeks but also in later weeks.

Many movie producers assume that making sequels of commercially successful original movies is a safe investment because they can effectively take advantage of the established fan base of the originals (H_3). Our empirical finding (Table 3) that sequels have a positive impact on theater revenues only in the first two weeks implies that the fan base reacts swiftly to sequels' releases and becomes exhausted quickly. Despite such commercial success at the box office, sequels tend to leave their viewers less satisfied in the early weeks (Table 2), perhaps because sequels are usually a strengthened and intensified version (e.g., more violent action, stronger special effects) of the originals' frameworks and story lines (Sood and Drèze 2006). Furthermore, high expectations formed by successful originals are likely to make viewers less satisfied (Anderson 1973). Therefore, a front-loaded advertising strategy should be considered when promoting sequels.

Finally, a diminishing fan base may explain why subsequent sequels can be a risky investment and suggests that studios should be cautious about extending sequel movies into a long series (Basuroy and Chatterjee 2008).[5] Thus, sequels can be a relatively safe investment based on the original movies' commercial success, but satisfying the fan base is a critical factor in turning sequels into successful long-term series, such as the James Bond movies. These results on movie sequels should inform brand extensions and brand alliances (Rao, Qu, and Ruekert 1999) of other experiential hedonic goods because brand extensions are common and often effective in such product categories (e.g., Harry Potter book series).

Viewer-Level Effects: Empirical Findings and Managerial Implications

First, for movie rental companies (e.g., Netflix, Blockbuster), we may assume that movie ratings are an effective measure of a member's satisfaction, and satisfied members stay with the company longer. This study highlights members' satisfaction mechanism based on their viewing and rating histories and movie communities' opinions as internal and external information sources, respectively (Murray 1991). Indeed, Netflix's emphasis on the importance of providing better recommendations to members is clearly indicated by Netflix Prize, a contest in which the firm will give potential $1 million to a team with the best ideas on how to improve the company's movie recommendation system.

Second, insights from our research findings regarding the roles of members' own experiences

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[5] For example, three No.3 blockbuster movies in 2007 fell short of expectations at the box office compared with their first sequels. Specifically, *Spider-Man 3* (2007) reaped $337 million compared with $374 million by *Spider-Man 2* (2004), *Shrek the Third* (2007) made $323 million compared with $441 million by *Shrek 2* (2004), and *Pirates of the Caribbean: At World's End* (2007) reached only $309 million compared with $423 million by *Pirates of the Caribbean: Dead Man's Chest* (2006).

and community opinions suggest that these consumer voices can strengthen companies' market orientation (Jaworski and Kohli 1993; Kohli and Jaworski 1990). Notably, marketers are especially interested in how to use online consumer forums in their favor (Dellarocas 2006; Mayzlin 2006). Godes and colleagues (2005) indicate that at least some of the social interaction effects in such forums are partially within the firm's control. For example, in our movie data, we saw that the number of accumulated ratings on the focal movie by the member community has a negative impact on the new rating (Y_1 in Table 4) because of the correlation between the member's interest level and viewing timing. That is, most interested viewers see the new movie first and less interested ones see it later. Cinematch, Netflix's movie recommendation system, does not fully consider such factors indicated in Table 4, which can potentially improve the system's accuracy.

In addition, when community opinions have a significant influence on members' choices, marketers can emphasize community opinions to persuade members. By emphasizing positive aspects of less viewed movie DVDs, they can increase of the uses of less frequently viewed stocks of movie DVDs more efficiently. We point out that the intention of this particular research is in providing insight into a viewer rating mechanism rather than developing a full-fledged rating forecasting model.

Finally, such recommendation systems are essential to the survival and success of new and existing products as an effective customer relationship management tool (Ansari, Essegaier, and Kohli 2000; Bodapati 2008; Iacobucci, Arabie, and Bodapati 2000; Krasnikov, Jayachandran, and Kumar 2009; Moon and Russell 2008). Ubiquitous online community forums can be a significant information source to improve the performance of such recommendation systems to firms that develop new products (e.g., books, music, video games).

Limitations and Future Research

We indicate some limitations of this research and shed light on potential future research avenues arising from the limitations. First, this research was primarily based on our analysis of the demand side of the movie industry and limited in integrating the supply side (e.g., production and distribution processes and costs) into our analysis with the same level of intensity and focus. Because supply-side factors influence movie profits as much as demand-side factors, further research could take a more balanced and integrated approach of demand and supply of the industry. Second, we used summary ratings but we did not analyze the content of the textual reviews (Chevalier and Mayzlin 2006; Wyatt and Badger 1990). Third, we tapped into individual viewers' postconsumption evaluations but not their choices per se. We dealt with the choice issue only at the aggregate movie level. Research on individual choice in movies could be conducted with proper data acquisition. Note that such research would require a sophisticated choice model development because the set of available movies is huge and does change across both viewers and time.

From a substantive perspective, research on sequels' impact on movie performances both in the theater and on video in association with viewers' ratings would provide useful information to movie production studios. For example, star power is well known in the movie industry (Albert 1998; Ravid 1999) and has been proved in the success of sequels. As we noted previously, some sequels do not use the same stars as the originals but still can be successful. It would be worthwhile to investigate the magnitude of star power in sequels by comparing sequels with and without the same stars as the originals.

This research could be applied to similar hedonic consumption situations in which consumers continually face new products and thus need to determine the value of the new products according to their own experiences and the community's general opinions (e.g., entertainment goods such as books and music). In these categories, the Internet enables ordinary consumers to share their ratings and reviews based on their own experiences with other like-minded consumers.

Other product categories are not immune from the impact of expert and consumer ratings. Automobiles are rated on design and functionality by experts, and on consumption experience attributes by ordinary drivers. Services from restaurants to dry cleaners are endorsed by experts and by consumers who have tried the services and wish to have a voice in encouraging or warning others. Thus, expert ratings have long and broadly existed in many product categories. With easy online posting, consumer ratings are exploding in popularity, indeed motivating experts to provide ratings of products heretofore unrated (e.g., dietary content in fast food meals). Hence, while this research focused on movies, its applicability should be much broader. In many purchase categories, it is important to begin to tease apart the individual and synergistic effects of WOM induced by ratings and advertising dollars, the dynamic effects of subsequent product launches, and the moderating effects of customers' relative experiences.

Appendix: Variable Descriptions

This appendix provides a detailed description of the variables used in our analysis.

Details on Table 1

- 8 major studios: Buena Vista, Fox, MGM-UA, Miramax, Paramount, Sony, Universal, Warner.
- 7 major holidays: New Year's Day, Presidents Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas.
- Video release lagging days: the number of days between theater release and video release dates.
- Total costs = production budget + ad costs. All movie costs and revenues are based on the first eight weeks after either theater release or video release except for production budget.
- The number of theater screens is the accumulated number of weekly screens.
- Total revenues = box office revenues + video rental revenues + video sales revenues.

Details on Table 2

- The initial set of independent variables is made up of the following for both regressions: genre (six categories; reference category = animation), sequel, running time, MPAA rating (R vs. non-R ratings; reference category = non-R ratings), theater distribution by the eight major studio distribution, and theater revenues (previous week).
- Week indicates the week of amateurs' movie ratings (dependent variable).

Details on Table 3

- The initial set of independent variables are genre (six categories; reference category = animation), sequel, holiday week, number of theater screens, running time, MPAA rating (R vs. non-R; reference category = non-R), theater distribution by eight major studio distribution, theater ad proportion (= theater ad spending for the focal movie/ad spending in all theater movies in the corresponding weeks (%) [previous week]), movie ad proportion (= theater ad spending for the focal movie/(ad spending in all theater movies in the corresponding weeks + ad spending in all video movies for the corresponding weeks) (%) [previous week]), ad spending [previous week], critics' ratings, amateurs' ratings, critics' ratings × ad spending [previous week] (interaction term), and amateurs' ratings × ad spending [previous week] (interaction term).

Details on Table 5

- Member rating order indicates the rating's serial number in order for each member.
- Rating mean indicates the average of all the ratings that belong to each rating order across all the members.
- Rating standard deviation indicates the standard deviation of all the ratings that belong to each rating order across all the members.
- The overall case is based on all the rating cases across all the six genres included.
- The overall case covers up to #129 in member rating order to select only cases with at least 21 members for each rating order. Rating mean becomes very unstable after #129.
- In each of the six genre cases, we included only observations with more than five members for each genre rating order.

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TABLE 1
Summary of the 246 Movie Data Sample

Category	Variable	Summary Statistics			
Movie characteristics	6 genres	thriller (35, 14%); romance (25, 10%); action (51, 21%); drama (50, 20%), comedy (74, 30%); animation (11, 4%)			
	sequel	36 movies (15%)			
	8 major studio distribution	theater distribution (181, 74%); video distribution (186, 76%)			
	MPAA rating	R (78, 32%); non-R (PG-13, PG & G) (168, 68%)			
	7 major holiday release	theater release (34, 14%); video release (36, 15%)			
	Variable	**M**	**SD**	**Minimum**	**Maximum**
	running time (minutes)	108	19	68 *Pooh's Heffalump Movie*	201 *Lord of the Rings: The Return of the King*
	video release lagging days	143	39	67 *From Justin to Kelly*	431 *Luther*
Movie costs	production budget ($1,000)	47,798	39,098	150 *Pieces of April*	210,000 *Spider-Man 2*
	ad costs ($1,000)	14,132	8,441	271 *Eulogy*	45,981 *Shrek 2*
	total costs ($1,000)	61,930	44,622	2,193 *Pieces of April*	242,077 *Spider-Man 2*
	theater screens	11,325	6,403	44 *Eulogy*	27,354 *Shrek 2*
Movie revenues	box office revenues ($1,000)	42,418	44,897	54 *Eulogy*	301,861 *Shrek 2*
	video rental revenues ($1,000)	24,381	13,121	803 *She Hate Me*	62,068 *The Day After Tomorrow*
	video sales revenues ($1,000)	15,359	24,088	82 *Northfolk*	233,090 *Finding Nemo*
	total revenues ($1,000)	82,158	74,164	1,246 *She Hate Me*	473,118 *Finding Nemo*
Rotten Tomatoes movie ratings (critics' ratings)	number of ratings	150	43	33 *I am David*	257 *The Passion of the Christ*
	average rating: 10-point scale	5.50	1.46	1.80 *Alone in the Dark*	8.69 *Lord of the Rings: The Return of the King*
Yahoo! Movie ratings (amateurs' ratings)	number of ratings	1,509	2,585	29 *Eulogy*	34,672 *The Passion of the Christ*
	average rating: 10-point scale	6.89	1.40	2.16 *House of the Dead*	9.50 *Hotel Rwanda*

Notes: MPAA = Motion Picture Association of America.

TABLE 2
Determinants of Amateurs' Movie Ratings: Stepwise Linear Regression

Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Intercept	1.66354	1.02730	1.30307	.69374	1.75857	2.19604	1.69142
Genre (Thriller)	-.85705	NS	NS	NS	NS	NS	NS
Sequel	-.28891	-.32098	NS	NS	NS	NS	NS
Running time	NS	NS	NS	.00766	NS	NS	.01127
MPAA rating	NS	NS	NS	NS	NS	NS	NS
Theater revenues: $ millions (previous week)	NS	0.007	0.018	0.017	0.098	0.090	0.047
Amateurs' ratings (previous week)	.81645	.84198	.80520	.77912	.70521	.65247	.58119
R^2	.7609	.8017	.6627	.6496	.5620	.3894	.3785
N	246	243	239	236	229	223	210

Notes: Dependent variable = weekly amateurs' movie ratings (current week). Each regression included only significant independent variables at the .05 level. Each movie showed its first eight weeks (Week 0 [=opening week] ~ Week 7) after its release in the data used. NS = not significant.

TABLE 3
Determinants of Box Office Revenues: Stepwise Linear Regression

Week	**0**	**1**	**2**	**3**
Intercept	-32,138,681	-4,037,404	-440,143	-321,435
Sequel	9,398,002	1,450,018	NS	NS
Holiday week	5,445,809	4,383,865	976,660	1,919,559
Major studio release	NS	-1,725,768	NS	NS
Weekly number of screens	12,205	NS	615	NS
Running time	91,297	NS	NS	NS
Weekly ad spending	-2,592	NS	-827	-914
Weekly theater ad proportion	NS	NS	NS	NS
Weekly movie ad proportion	NS	NS	NS	NS
Critics’ ratings	4,117,721	NS	NS	NS
Amateurs’ ratings	NS	578,971	NS	NS
Critics’ ratings × ad spending	NS	65	117	40
Amateurs’ ratings × ad spending	217	NS	67	93
Box office revenues (previous week)	N/A	.49371	.44448	.65020
R^2	.6182	.8480	.8972	.9132
Adjusted R^2	.6086	.8442	.8942	.9113
N	246	246	243	239
Week	**4**	**5**	**6**	**7**
Intercept	-451,267	-295,158	-334,726	-207,801
Sequel	NS	NS	NS	NS
Holiday week	670,210	463,581	NS	406,835
Major studio release	NS	NS	NS	NS
Weekly number of screens	943	540	1,617	1,206
Running time	NS	NS	NS	NS
Weekly ad spending	-2,402	-2,715	-3,351	-5,210
Weekly theater ad proportion	-1,885,493	-941,568	-2,207,783	NS
Weekly movie ad proportion	2,576,562	2,196,000	2,420,714	1,329,766
Critics’ ratings	NS	NS	NS	NS
Amateurs’ ratings	NS	NS	NS	NS
Critics’ ratings × ad spending	204	40	66	359
Amateurs’ ratings × ad spending	161	176	488	143
Box office revenues (previous week)	.28627	.48853	.11823	.26666
R^2	.8969	.9292	.8540	.8827
Adjusted R^2	.8932	.9266	.8492	.8787
N	236	229	223	210

Notes: Dependent variable = weekly theater revenues (current week). Each regression included only significant independent variables at the .05 level. Each movie showed its first eight weeks (Week 0 ~ Week 7) after its release in the data used. NS = not significant.

TABLE 4
Regression Estimates of the Viewer-Level Rating Regression Model (Netflix Data)

Variable Group	Variable	Estimate	SE	*p*-Value
	Intercept	-1.01621	.09838	<.001
Individual member–based variables (X) (by the member)	(1) number of movies rated (+)	.00055	.00011	<.001
	(2) average rating (+)	.04041	.01444	.003
	(3) rating standard deviation (-)	-.00132	.01903	.472
	(4) percentage of same genre (+)	.20626	.04627	<.001
	(5) genre-specific average rating (+)	.93723	.01141	<.001
	(6) most recent rating (-)	-.00580	.00369	.058
Community-based variables (Y) (based on the focal movie)	(1) number of ratings (-)	-.00022	.00004	<.001
	(2) average rating (+)	.08662	.02050	<.001
	(3) rating standard deviation (-)	-.09462	.03030	<.001
	(4) percentage of highest rating (+)	.01374	.00054	<.001
	(5) percentage of lowest rating (-)	-.02176	.00099	<.001
Movie characteristics variables (Z)	genre - thriller	.54469	.02980	<.001
	genre - romance	.41895	.02915	<.001
	genre - action	.29751	.02845	<.001
	genre - drama	.22314	.02955	<.001
	genre - comedy	.46865	.02911	<.001
	sequel	-.05267	.01300	<.001
	MPAA rating (R = 1, non-R = 0)	.02891	.00993	.002
	running time	.00259	.00030	<.001
	production budget ($ millions)	-.00095	.00015	<.001
	theater revenues ($ millions)	.00021	.00015	.074
	holiday video release	.03485	.01233	.002
	video release (days after theater release)	-.00026	.00012	.015
	video release by the 8 major studios	-.00489	.01054	.322
	video bonus materials	.02858	.01391	.020
	video ad spending ($ millions)	.01240	.00261	<.001

Notes: N = 43,204. The sign next to each variable indicates the sign expected by our theory.

TABLE 5
Trend Analysis of Individual Viewers' Rating Changes Over Time (Netflix Data)

Panel A
Dependent Variable = Rating Mean

Genre	Intercept	Member Rating Order	R^2	N
Overall	*3.67597 (<.001)*	*-.00295 (<.001)*	*.57*	*129*
Thriller	3.49238 (<.001)	-.02320 (<.001)	.80	24
Romance	3.59049 (<.001)	-.01508 (.081)	.16	20
Action	3.66009 (<.001)	-.00323 (.034)	.11	42
Drama	3.90672 (<.001)	-.01695 (<.001)	.58	35
Comedy	3.41070 (<.001)	-.00216 (.155)	.05	45
Animation	4.14090 (<.001)	-.04585 (.009)	.65	9

Panel B
Dependent Variable = Rating Standard Deviation

Genre	Intercept	Member Rating Order	R^2	N
Overall	*1.11418 (<.001)*	*-.00144 (<.001)*	*.21*	*129*
Thriller	1.13149 (<.001)	-.01257 (.009)	.27	24
Romance	1.06233 (<.001)	-.00725 (.006)	.35	20
Action	1.12570 (<.001)	-.00589 (<.001)	.44	42
Drama	1.04798 (<.001)	-.00280 (.097)	.08	35
Comedy	1.10261 (<.001)	-.00301 (.020)	.12	45
Animation	.95692 (<.001)	-.00569 (.486)	.07	9

Notes: The number in parentheses indicates the *p*-value for the corresponding estimate.

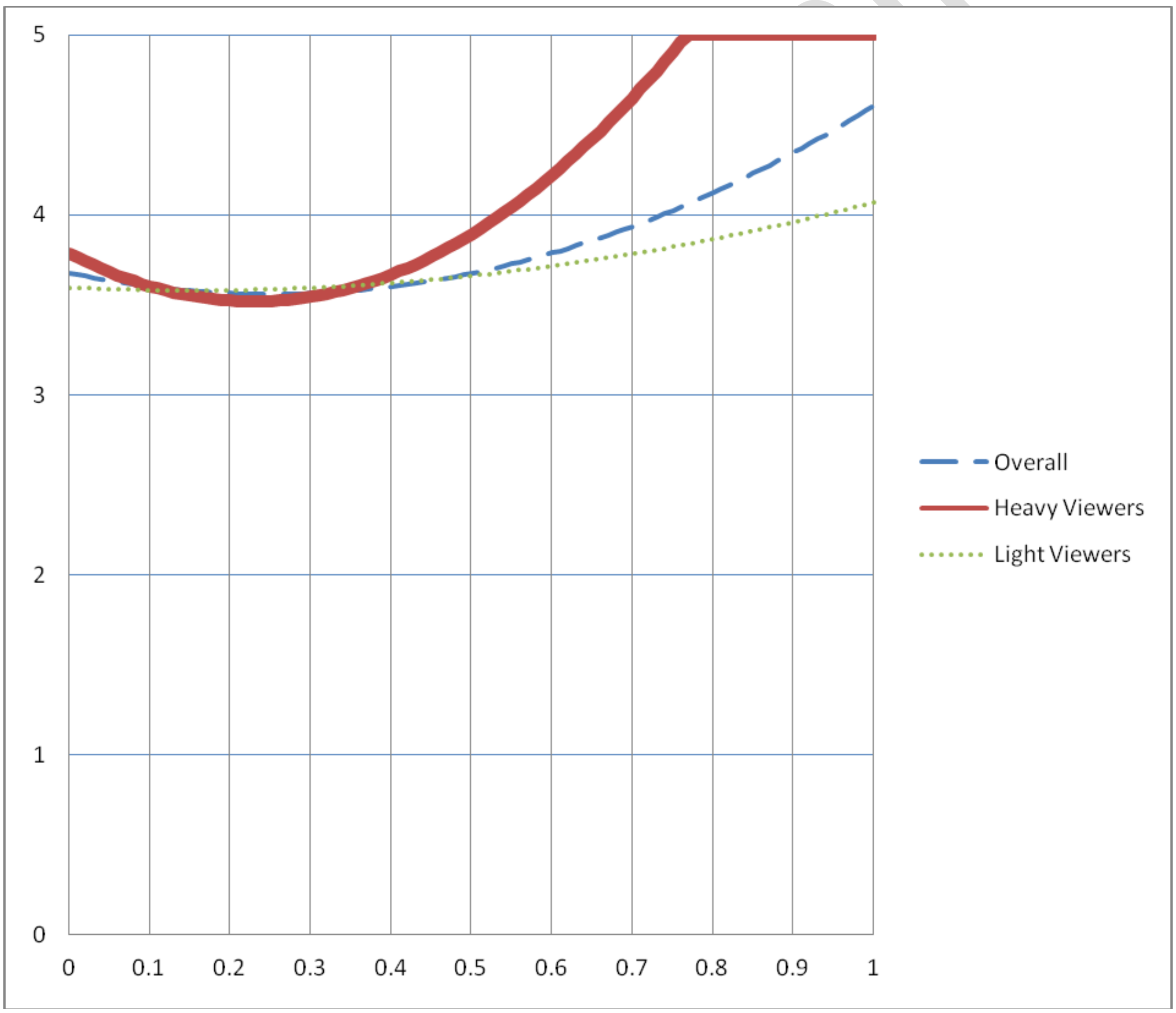
FIGURE 1
U-Shaped Relationship Between Member's Genre Proportion and Genre Ratings

Panel A

Variable	Overall	Heavy Viewers	Light Viewers
Intercept	3.67588 (<.001)	3.78521 (<.001)	3.59785 (<.001)
Member's Genre Proportion (Linear)	-.93434 (<.001)	-2.33033 (<.001)	-.21382 (.568)
Member's Genre Proportion (Quadratic)	1.86631 (<.001)	5.09324 (<.001)	.68759 (.295)

Notes: Dependent variable = movie rating. We divided all the members in the first regression (overall) into two groups of approximately same size: heavy viewers and light viewers. The number in parentheses indicates the *p*-value for the corresponding estimate.

Panel B



Notes: In the line graph, the x-axis is member's Genre Proportion and the y-aixs is Movie Rating on a five-point scale.