***How Relevant Are Experts In The Internet Age? Evidence from the Motion Pictures Industry*?**

Suman Basuroy*
Ruby K. Powell Professor and Associate Professor
Division of Marketing and Supply Chain Management
Price College of Business
The University of Oklahoma
307 West Brooks, Adams Hall 3
Norman, OK 73019-4001
Phone: (405) 325-4630
Fax: (405) 325-7668
Email: suman.basuroy-1@ou.edu

S. Abraham (Avri) Ravid
Syms Professor of Finance
Syms School of Business
Yeshiva University
Belfer Hall
500 W. 185 St. NY NY 10033
212 960 0125
Email: ravid@yu.edu; saravid@yahoo.com

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Pros vs. buzz- How Relevant Are Experts In The Internet Age? Evidence from the Motion Pictures Industry.

Abstract

Our paper integrates and extends the current research on expert opinions and user generated content in the context of the motion pictures industry. We find that contrary to widespread speculation in the popular press, expert opinions still matter a great deal even in the presence of internet generated word-of-mouth. We corroborate work by Chintagunta, Gopinath and Venkatraman (2010) which shows that "buzz" (user reviews volume) is endogenous and once endogeneity is properly addressed, its seeming effect on revenues disappears. However, the valence of user reviews matters. We also show that WOM and expert reviews may diminish the effect of one another on revenues. Also, expert reviews enhance marketing activities, whereas user reviews and marketing activities may be substitutes. Finally, contrary to popular belief and industry views, we show that for platform release movies, only expert opinions matter rather than WOM. All in all, this paper seems to demonstrate the decisive effect of professional critical reviews even in the presence of ubiquitous user generated content.

"*Rumors of Critic's Demise Are Greatly Exaggerated*"

- Joe Morgenstern (Wall Street Journal, April 29, 2006)

INTRODUCTION

Professional experts and critics play an important role in consumers' decisions in many industries (Basuroy, Chatterjee and Ravid 2003, Caves 2000, Elberse and Eliashberg 2003, Eliashberg and Shugan 1997, Goh and Ederington 1993, Greco 1997, Hennig-Thurau, Houston and Sridhar 2006, Holbrook 1999, Vogel 2004). However, the growth of online word-of-mouth and user generated contents seems to challenge the importance of professional critics as established in the literature. In particular, recent marketing and economics studies document the significant impact of online word-of-mouth and user generated comments (Chevalier and Mayzlin 2006 Chintagunta, Gopinath and Venkataraman 2010 (henceforth, CGV (2010)), Liu 2006, Luan and Neslin 2009, Moon, Bergey and Iacobucci 2010, Zhu and Zhang 2010). This exponential growth in readily available online reviews which presumably better reflect popular tastes, has led to speculation regarding the demise of professional reviews. For example, Dellarocas, Awad and Zhang (2004) write that online forums "*…are emerging as a valid alternative source of information to mainstream media, replacing our societies' traditional reliance on the 'wisdom of the specialist;' by the 'knowledge of the many'*." In this context, this paper addresses a number of key questions: (1) Given the significant growth of user generated comments and word-of-mouth online, do opinions of professional experts still matter? (2) How do expert opinions and word-of-mouth interact in affecting sales? (3) How do product characteristics moderate the impact of expert opinion and word-of-mouth opinion on revenues?

Our paper integrates and extends the current research on expert opinions and user generated content in marketing and makes a number of key contributions within the context of the motion picture industry. *First*, we examine the relative effects of two major sources of information in any marketplace during a new product release – expert opinion and user generated comments. We find that, contrary to widespread speculation in the popular press, expert opinions still matter a great deal even in the presence of word-of-mouth and internet postings. An important recent study by CGV (2010) contradicts some recent published studies and shows that the "buzz" or volume of WOM is not a determinant of movie revenues, but user valence matters. We corroborate these findings in a different setting and during a later time period, and suggest that expert reviews are important even in this context and in fact, seem to have more of an effect than user generated ratings.

Second, we study how expert opinion interacts with word-of-mouth and user generated content – an aspect missing in the extant literature.

Third, we explore how expert and word-of-mouth reviews are moderated by firm-generated promotional activities (advertising). Marketing activities of firms can render both word-of-mouth and expert reviews less relevant since advertising may provide information (Basuroy, Desai and Talukdar 2006). On the other hand, expert reviews may be helpful in advertising and enhance the value of marketing activities. We find that the latter is the case.

Fourth, we explore how expert and word-of-mouth reviews are moderated by distribution strategies of studios. Specifically, we examine how experts and word-of-mouth opinions affect movies that use a platform release strategy. Einav (2007) writes: “Conventional wisdom is that a platform release creates word-of-mouth that is necessary for success” (p. 30). We test this idea along several dimensions.

A key problem in the extant literature in dealing with word-of-mouth is endogeneity and autocorrelation in the data which may yield biased OLS estimates. In this paper, we control for potential endogeneity of word-of-mouth, screens, critical reviews and advertising using instruments and we correct for both heteroskedasticity and autocorrelation. We use generalized method of moments (GMM) estimates as they are more efficient in the presence of heteroskedasticity and endogeneity (Wooldridge 2003).

Our study of expert reviews and WOM is based on the motion pictures industry. We chose the motion picture industry for a number of reasons. First, the movie industry has served as a fertile ground for research in economics and marketing and in particular, for studies on the role of expert/critical reviews (e.g., Basuroy, Chatterjee and Ravid 2003, Eliashberg and Shugan 1997, Hennig-Thurau, Houston and Walsh 2006, Holbrook 1999 2005, Ravid, Wald and Basuroy 2006). Second, in the movie industry the price of the product is fixed, which simplifies matters relative to other industries where prices need to be considered (see Chevalier and Mayzlin’s (2006) study of the book industry or Zhu and Zhang’s (2010) analysis of the video game industry). Thus, we have a cleaner test of the relative effects of experts and user generated content (word-of-mouth) on revenues. Finally, and importantly, both expert opinions and weekly online word-of-mouth, weekly advertising data, and weekly box office data, can be collected or purchased to create a rich data set for empirical analysis of the motion pictures industry. In other industries, such data are not readily available and approximations are necessary (for example, Chevalier and Mayzlin (2006) use rank data of books to approximate sales data of books).

The rest of the paper is organized as follows. In the next section we discuss the theoretical background and formulate our hypotheses. Next, in the empirical analysis section, we describe the data and the methodology and present the results. Finally we conclude with a general discussion and the managerial implications of our research.

THEORY AND HYPOTHESES

Experts versus WOM

Experts and critics play an important role in consumers' decisions in many industries (Caves 2000, Goh and Ederington 1993, Greco 1997; Hennig-Thurau, Houston and Sridhar 2006, Holbrook 1999, Vogel 2001). The role of critics is very prominent in the film industry (Basuroy, Chatterjee and Ravid 2003, Eliashberg and Shugan 1997, Ravid, Wald and Basuroy 2006). More than a third of Americans actively seek the advice of critics (*Wall Street Journal*, March 25, 1994; B1), and more importantly for our purposes, about one out of every three filmgoers says she or he chooses films because of favorable reviews. The literature discusses two potential roles of movie critics - that of *influencers*, i.e. actively influencing the decisions of consumers in the early weeks of a release cycle, and that of *predictors*, i.e. merely predicting the public's decisions. Eliashberg and Shugan (1997) were the first to define and test these concepts. They find that critics predict box office performance but do not influence it. Basuroy, Chatterjee and Ravid (2003), on the other hand, find that critical reviews are correlated with weekly box office revenues over an eight-week period, thus showing that critics play a dual role - they both influence and predict outcomes. Recent research also supports the overall significant impact of the role of professional critics (Basuroy, Desai and Talukdar 2006, Hennig-Thurau, Houston and Walsh 2006, Hennig-Thurau, Houston and Sridhar 2006, Holbrook 1999, Holbrook and Addis 2007, Kamakura, Basuroy and Boatwright 2006, Ravid, Wald and Basuroy 2006). Thus, if the internet has not led to a fundamental shift in behavior, we can still expect critics to be instrumental in consumer movie-going decision.

However, both industry insiders and academics believe that user generated content and word-of-mouth increasingly influence people's choices in the selection and consumption of goods, perhaps to the exclusion of traditional reliance on expert opinion (Bughin, Doogan and Vetvik 2010, Chevalier and Mayzlin 2006, Holbrook and Addis 2007, Liu 2006, Zhu and Zhang 2010). Dellarocas, Awad and Zhang (2004) write that word-of-mouth and online forums such as http://movies.yahoo.com "*…are emerging as a valid alternative source of information to mainstream media, replacing our societies' traditional reliance on the 'wisdom of the specialist;' by the 'knowledge of the many'.* Liu (2006) argues that two potential characteristics of the movie industry may underlie the general belief that WOM is influential for consumers and hence, box office revenues. First, since movies are a product of popular culture, they generate wide public attention through popular television shows (e.g., Late Night with Jay Leno, etc.), newspaper reports or the internet (e.g., yahoo). According to the theory of information, accessibility and influences (Chaffee 1982) may prompt interpersonal communication about movies, and may have an effect on consumer choices. Second, movies are experiential products and hence it is difficult to judge the quality of a movie before seeing it. It is known that as the difficulty of a product evaluation prior to a purchase increases, “consumers often engage in WOM to gather more information” (Harrison-Walker 2001, Rogers 1983). Similarly, Babej and Pollak (2006) in an online Forbes .com article state that, “*In an age of ratings Web sites and consumer generated content, they [movie critics] are just one voice of many. Maybe a particularly authoritative voice, but no longer the popes they used to be*.” However, there are different views on this issue. Joe Morgenstern, the movie critic of the *Wall Street Journal* writes, “*Far from worrying that my supposed power will be diminished by the recent democratization of criticism, I find encouragement in the change, as any sensible person should*” (Morgenstern 2006, p. P6, April 29, 2006, *Wall Street Journal*). Hence, we test the following main hypotheses:

H1a: Expert reviews will have a significant impact on the financial success of movies even in the presence of user generated reviews.
H1b: WOM will significantly affect box office revenues.

We should note that H1a and H1b can be true simultaneously (as we indeed find). One way to think of this issue is to consider Holmstrom's (1979) classic study, which suggests that contracting should use any available information. In our context, consumers may sensibly consider all available information. However, it can be that only one of the hypotheses is correct. If the world has not changed, then H1a will be correct and H1b will not, if the world has dramatically changed as some argue, H1a will not hold any more and H1b will take its place.

Interactions of WOM and Expert Reviews

There is little research on the interactions of professional critical reviews with WOM in affecting revenues. If at least one of the elements - either WOM or professional critical reviews, is found to influence outcomes, it can be that an interaction matters. It may be that if one signal is very high the other one matters less. In other words, for movies that are extremely well reviewed, the impact of WOM will be lower, and similarly, for movies with terrific WOM, professional reviews are less important. However, it can also be that the effects are independent, in which case hypothesis 2 below will not be correct. There is not much work in marketing on these issues, but there is an economic literature on the value of multiple signals, starting with Holmstrom (1979) and others. The literature includes some theory papers as well as experimental economic studies, such as Duffy and Feltovich (2006). The views on the impact of a marginal additional signal are mixed, depending on the setting and the assumptions of the model. We formulate the hypothesis below conforming to the idea of decreasing marginal returns to information:
H2: The interaction of the valences of user ratings and expert opinions will exhibit a negative relationship in affecting box office revenues.

Experts versus WOM and Promotional Activity - Advertising

This section addresses the moderating effect of marketing activity on the impact of WOM and expert opinions on product sales. A movie is typically considered to be an "experience product," that is, it is usually judged in terms of its enjoyment value. Since the quality of such products is difficult to assess prior to consumption, information asymmetry and hence evaluation uncertainty becomes an issue (Basuroy, Desai and Talukdar 2006, Eliashberg and Sawhney 1994). In order to mitigate information asymmetry, studios engage in extensive advertising (Kirmani and Rao 2000).The economics literature (Albrecht 1981) proposes that independent information should reduce evaluation uncertainty (and, thus, information asymmetry). As discussed, the two key sources of independent information about a product are expert opinions and word-of-mouth. Thus Basuroy, Desai and Talukdar (2006) and Albrecht (1981) suggest that when advertising interacts with independent information sources, its impact should diminish[1]. Similarly, Bagwell (2007) suggests that advertising, in addition to its informative role, may have a persuasive role. This role may have a lower impact on consumers in the presence of additional independent information such as expert reviews or WOM. Hence we propose:

H3a: Both WOM and expert opinions will lessen the impact of marketing activities of firms on box office revenues.

Some work suggests that hypothesis H3a may not be strictly true and that there should be a differential effect of expert opinions and WOM on marketing activities. In particular, movie advertisements typically display positive professional reviews (quotes), and such reviews may be a most effective marketing tool (Basuroy, Ravid and Rao 2012). However, WOM cannot be used in such a fashion.

Thus, H3b suggests:

H3b: WOM and expert opinions may have a differential interaction with marketing activities, where expert opinions may enhance marketing activities whereas WOM will not.

Experts versus WOM and Distribution Strategy: The case of Platform Release

In this section we study how specific distribution strategies may be affected by word-of-mouth and expert opinions. We consider one specific form of movie distribution strategy, possibly the most important one next to a wide release, namely, platform release. Einav (2007) describes this strategy: "Platform release involves an initial release in a small number of theaters, often only in big cities…The movie then expands to additional screens and to more rural areas" (p. 130). Platform release is used by distributors typically for movies that they believe do not have an obvious appeal to mainstream audiences, because perhaps the movies' actors are unknown or the subject matter is difficult. For example, *Slumdog*

[1] This issue is explored in a different (local) context in Chintagunta et al. (2010).

Millionaire had a completely unknown cast and was shot entirely in India often using subtitles. *Memento* had a difficult and complicated subject matter. Both were initially released on fewer than 50 screens.

Studios have used platform strategies for decades. *The Doctor* starring William Hurt as an arrogant surgeon who experiences the bitterness of the medical system when he develops cancer, opened July 26, 1991 in six theaters. “It's a movie that we knew critics and audiences would respond to,” commented (then) Touchstone President David Hoberman. It was also a tough sell. Although William Hurt had an impressive critical standing, he was not a major box-office star, and the subject matter was a downer. “There’s no small-arms fire, and not even a hint of sex. So Disney's strategy was to open it slowly, let positive reviews settle into place and hope for good word of mouth from audiences.”

Platform release offers studios another significant advantage. Studios can test the waters and then decide whether it is worth spending more money on promoting the film. Einav (2007) writes that “Conventional wisdom is that a platform release creates word-of-mouth that is necessary for success” (p. 30). In this context, WOM and critical reviews can play a decisive role in the life of a movie over time, whereas in the case of wide release the game is basically over after the opening week.

Since platform release movies often tend to be niche movies, Holbrook’s (1999) theories of popular appeal and expert judgments should also apply. He argues that in general, “ordinary consumers prefer entertainment that is more readily accessible, easier to assimilate, and less demanding in the difficulties it poses; whereas professional critics gravitate toward more challenging artworks of higher complexity, greater difficulty, and more intellectually taxing demands (p. 148).” Joe Morgenstern, the well-known film critic of the Wall Street Journal writes: “… movie critics still play a crucial role in supporting independent films. We may well be more useful than ever in that regard, because the independent film movement is struggling more desperately than ever … (April 29, 2006).” Thus, if the audience who is more likely to consider “art house” movies is more attuned to professional reviews, experts may play a bigger role in platform releases. On the other hand, studios argue that it is the “buzz” that elevates such movies as the Blair Witch Project to a blockbuster status and it may be that then critical reviews do not matter. Based on these arguments, we formulate our final set of hypotheses:

H4a: For platform release movies, expert opinions can exhibit a significant positive effect on box office performance.

H4b: For platform release movies, WOM can exhibit a significant positive effect on box office performance.

Clearly, as in previous cases, it may be that neither H4a nor H4b are supported or that both are consistent with our findings. In the next section, we describe the our data and methodology.

DATA AND METHODOLOGY

We identify a random sample of 200 films that had theatrical release in the US market between December 2006 and February 2008[2]. The data include 6 movies from 2006, 171 movies from 2007 and 23 movies released in January and February of 2008. Since in 2007 there were 189 movies released in theaters domestically by the members of MPAA[3] (Motion Pictures Association of America which includes the main studios) this is a rather sizeable sample. The sample includes a wide variety of movies. Our lowest grossing movie is *The Air I Breathe* that was released on January 25, 2008 and earned a mere $19,487 with a production budget of $10 million. The highest grossing movie in our sample is *Shrek the Third* released on May 18, 2007, earning about $320.71 million.The financial data was purchased from a standard industry source, www.baseline.hollywood.com. Baseline provides information regarding the studio, release date, MPAA rating, budget, as well as weekly domestic box office revenues (*Box*) and theater counts (*Screen*), and other revenues sources. The size of the data set is comparable to those used in recent works (Basuroy, Chatterjee and Ravid 2003, Elberse and Eliashberg 2003) and larger than some data sets in several user reviews studies. Liu (2006), for example, used a selected sample of 40 movies only from the summer months of 2002, whereas CGV (2010) used a sample of 148 movies.

There are various sources which aggregate professional critical opinions and internet user reviews. We looked for a site which includes both types of reviews, because moviegoers are more likely to view both types of reviews when they visit the site, and thus our tests can be cleaner. Thus we use a single website – www.rottentomatoes.com which displays professional critics' ratings as well as user ratings next to each other on the same webpage[4]. We collect the number of user reviews per week (*UserVolume*) which is the same variable as the volume of reviews used by CGV (2010). We also collect the valence of user ratings, which is the average user rating per week (*UserRating*). CGV (2010) and Chevalier and Mayzlin (2006) underscore the importance of the valence of user reviews metric. We also collect the valence of the critic rating which is the average critic rating (*CriticRating*) provided by rotten tomatoes website.

Our advertising data (*Advertising*) cover weekly television and print advertising expenditures for each film as collected by Kantar Media (www.kantarmedia.com). The data is weekly – a common unit of analysis for the motion picture industry (see, Ho, Dhar and Weinberg 2009). Following Elberse and Eliashberg (2003) and Liu (2006) we incorporate a time varying control variable in the analysis in order

[2]In our dataset, there are 200 movies, each followed for 10 weeks. Thus there are 2000 observations – movie-week data points as is shown in the OLS regressions. However, for the majority of the GMM estimations have 1970 observations, as 3 of the movies have several missing values. Hence we get 30 fewer observations (movie-weeks).

[3] Source- MPAA.org

[4]Following CGV (2010), our original intention was to use the Yahoo website for the user review data (although it did not aggregate professional reviews). However, the Yahoo website has changed recently and it no longer displays both the user ratings and critic ratings in a manner that enables the researcher to obtain the data.

to gauge potential competition. This variable is the number of newly released films in the top 20 movies (*Newfilm*) each week.

We also incorporate 5 genre variables – *action*, *comedy*, *drama*, *romance* and *thriller*. Each one is coded as a dummy variable. The default is all other genres. A broader content classification is a film MPAA rating. Prior research shows that ratings have an important effect on revenues (Ravid 1999, DeVany and Walls 2002, Palia et al. 2008). Hence we use 2 dummies for MPAA ratings - GPGPG13 for films belonging to either G, PG or PG13 ratings, and R. In much of the work R-rated films fared worse than G and PG rated films, but generally better than unrated films. The default in our analysis is films which are not rated.

The impact of star power on movie revenues has been debated in the literature, and in general, star participation, however defined, did not seem to affect revenues per se (See Ravid 1999, De Vany and Walls 1999, Elberse 2007). However, star power may have a competitive and "insurance" role (See Basuroy, Chatterjee and Ravid 2003, CGV 2010). Therefore, we use star power in competing movies as an instrumental variable in our IV regressions. There are various ways to compute star power. We follow CGV (2010) and Goetzmann et al. (2012) and use *starmeter*. *Starmeter* uses proprietary algorithms that take into account several measures of popularity for people and titles. The primary measure captures who or what is being viewed by the public imdb.com website. Other factors include box office receipts and user quality votes on a scale of 1-10. The rankings are updated on a weekly basis. We use weekly *starmeter* rankings in our study. We also use studio dummies (9 major studios) to capture possible studio level effects (See Elberse and Eliashberg, 2003).

As noted, part of our analysis concerns platform releases. Einav (2007) categorizes films opening on less than 600 screens as platform release movies. We follow that definition. PLATFORM is a dummy variable that takes a value of 1 if a movie is released on less than 600 screens, and 0 otherwise.

Table 1 contains all the key variables, their definitions, references, where these variables have been previously used as well as the sources for our data. Table 2 provides descriptive statistics. Table 3 is the correlation matrix.

Insert Tables 1, 2 and 3 Here

Because of varying lengths of theatrical runs of movies in our sample, we follow the work of Basuroy, Chatterjee, and Ravid (2003), Eliashberg and Shugan (1997) and Liu (2006) and restrict the empirical analyses to the first 10 weeks of the run. As is the case in previous studies, the first 10 weeks typically account for more than 90% of the box office revenues. In the next subsection, we describe the model and the instrumental variables we use to correct for possible endogeneity.

Model Specification

Following CGV (2010), we use the following key revenue equation (1):

$$\begin{aligned} &Log(Box_{it}) = Const + \beta_1 UserVolume_{it} + \beta_2 UserRating_{it} + \beta_3 CriticRating_i + \beta_4 Screen_{it} \\ (1) \quad &+ \beta_5 gpgpg13_i + \beta_6 r_i + \beta_7 action_i + \beta_8 comedy_i + \beta_9 drama_i + \beta_{10} romance_i + \beta_{11} thriller_i \\ &+ \beta_{12} Newfilm_{it} + \beta_{13} Age_{it} + \beta_{14} Adv_{it} + \sum_{k=1}^{9} \beta_{13k} S_k + \sum_{k=1}^{10} \beta_{14k} W_k + \mu_i + \varepsilon_{it} \end{aligned}$$

The main difference between CGV (2010) equation (1) and ours is the inclusion of expert ratings, which is the focus of our study. In addition, we have additional control variables such as the genres, studios, age of films and a measure of competition in the market place. Our main independent variables of interest are as follows (see table 1) UserVolume=Volume (number) of user reviews per week for movie *i* in www.rottentomatoes.com website; UserRating=Average user rating per week for movie *i* in www.rottentomatoes.com website (this is the valence of users comments); CriticRating=Average critic rating for movie *i* in www.rottentomatoes.com website (this is the valence of critics);

Our control variables include: Screen=number of screens per week for movie *i*; gpgpg13=dummy variable taking the value of "1" if the movie has either g, pg or pg13 rating and "0" otherwise; r=dummy variable taking the value of "1" if the movie has "R" rating, and "0" otherwise; action/comedy/drama/romance/thriller=dummy variables taking the value of "1" if the movie belongs to a specific genre, and "0" otherwise; newfilm=number of new films per week competing with the focal movie; Adv=advertising dollars spent by movie *i* in various media per week; S=studio dummies (9 of them); W=week dummies; μ_i=movie-specific effect. To test the interaction of critics and users valence hypotheses, we add the appropriate interaction terms in equation 1 above.

Instrumental Variables. We identify four potential endogenous variables in our analysis: UserVolume, UserRating, CriticRating and Screen. Omitted variable bias (unobserved movie quality) is one of the major factors for endogeneity. Thus, higher "quality" movies may receive better average ratings from both critics and users as well as induce a higher volume of internet reviews which consequently can generate higher box office revenues. CGV (2010) identify viable instruments for three of these variables, namely, UserVolume, UserRating, and Screen.

We follow their guidelines, and as instruments for *UserRating* and *UserVolume*, we use competitive controls such as average critic score for competing movies in the prior week (COMPREVIEWi), the average star power of competing movies in the previous week (COMPSTAR*i*), and the average proportion of movies of the same genre as the focal movie playing in the prior week (PROPGENRE*i*). As CGV (2010) argue, the key reason that these variables are appropriate instruments is because they are functions of competition variables, from prior weeks. Average user rating and the volume of users ratings for movie *i* in prior week are likely to be higher (lower) if the quality of the competing movies in the prior week (as represented by the competition variables) is lower (higher). Furthermore these competition variables are uncorrelated with the focal film quality. We also follow CGV (2010) for the instrument for screens (Neelamegham and Chintagunta 1999), namely, the average number of screens that show movies of the same genre as the focal movie (COMPSCREEN*i*).

Another potential endogenous variable is advertising. However, we follow CGV (2010) and note that (a) prerelease advertising accounts for the vast majority of advertising spending in the movie industry (e.g., Elberse and Anand 2007 find that 88% of television advertising spending was spent prior to initial release), (b) prerelease advertising budgets are typically a fixed proportion of production budget (see Ravid 1999, Vogel 2007). These factors alleviate concerns regarding the endogeneity of prerelease advertising.

We focus on the valence of professional critic reviews, or average critic rating. Arguably this may be an endogenous variable as well, since critical reviews correlate strongly with unobserved movie "quality." Therefore, for identification, we need appropriate instruments. We use multiple instruments for critics' ratings. The first instrument is the experience of critics (in years). Studios often invite professional critics on their sets, arrange for interviews with stars and directors, provide them with details regarding the movies, etc. Such sources of information and inside scoops are the bread and butter of the profession. A critic's career can be in serious jeopardy if studio connections were severed. It has been reported that Rod Lurie, formerly of Los Angeles magazine, was "banned for life" by Warner Bros. for describing Danny DeVito as "a testicle with arms" in his Other People's Money review (Lovell, 1997). Therefore, establishing a cozy relationship with studios is necessary for professional movie reviewers. On the one hand, one may conjecture that a young critic, who needs to build connections, cannot be too critical. Older critics can be in a different position vis a vis corporate headquarters. More established critics may be able to defy the studios and still enjoy access to the stars and be invited to movies, since they are too powerful to be ignored. On the other hand, there is an entire literature in finance and economics which suggests that people later in their career may require higher incentives to act in accordance with shareholders' values (Gibbons & Murphy 1992, Prendergast & Stole 1996, Scharfstein and Stein 1990, Zwiebel 1995). In line with this research, Ravid, Wald and Basuroy (2006) argue that professional movie critics with a better reputation exhibit stronger corporate biases than those with a worse reputation. Another possibility is that studios that decide to influence critics target well-known reviewers i.e. those with higher reputation[5]. As incentives change over a critic's career, we expect critics' age and experience

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[5] We should keep in mind that it is easier to cheat for movie critics than for say, stock analysts. Whereas an analyst who gives a buy recommendation to a failing company may be "found out" if the company goes bankrupt, the value of movies is more subjective. A critic may think a movie is terrible and yet give

to be correlated with the quality of reviews. However, age and experience of reviewers are completely uncorrelated to the unobserved "quality" of the movie. It is difficult to obtain data on critics' tenure and experience, but we are able to find critics' age, which we use as an instrument.

Our second instrument is the number of local newspapers that review the focal movie. A local newspaper is defined as any newspaper or magazine other than *New York Times*, *Wall Street Journal* and *USA Today*. This definition is consistent with the one used by our data provider, Kantar Media. There are a number of reasons to expect reviews in local papers to be systematically different than reviews in national media. First, local audiences are more likely to follow local media. A recent survey by the Readership Institute of Northwestern University finds that local papers have much higher local readership than other papers—in 2006, 71% of respondents read a local paper whereas 24% read a paper other than (or in addition to) a local paper" (Gurun and Butler 2012, page 565). Thus, reviews in local media may be potentially important sources of information for movie-goers. Rinallo and Basuroy (2009) demonstrate that Italian newspapers and magazines give more coverage of Italian fashion companies and their products in their editorials compared to newspapers and magazines in the UK, France, Germany and the USA. Thus it is likely that product reviews (movies) in local media may be more positively biased compared with national media. Since the number of national newspapers is limited, we expect that the larger the number of local newspapers and magazines that review a particular movie, the larger the average rating of the movie. However, the number of local newspapers is obviously uncorrelated with the unobserved movie quality[6].

Estimation

The availability of instruments enables us to address the correlation between user review measures, critical reviews measures and the error term. However, we still have the issue of correlation in

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it a good review, and there is no obvious reckoning. Films do not "go bankrupt." For example, the movie *Chicken Little* which opened on 11/4/05 was described as a "terrible movie" by the *New York Times*, panned by the *Wall Street Journal* and yet, *Time* magazine said: "It is one of the funniest and most exhilarating movies in years." Larry King, the influential TV host, was quoted in the ad for that movie as saying: "A pure delight! *Chicken Little* has something for everyone."

[6] We tried several other potential instruments. For example, David Card at Berkeley and other noted labor economists have used "distance" as an instrument for education. We identified the headquarters of each newspaper and organization (television stations, internet sites) that review a movie in our sample. Then we calculated their distance from Los Angeles. We were expecting the correlation of average critic rating and distance from LA to be negative, but it was not; it was virtually insignificant, .04. The apparent reason for this is that corporate headquarters may not be correlated with the actual location of the reporters or reviewers. We also tried a mid-week release dummy (for movies released not on weekends) which had other issues and we thought of joint corporate ownership of studios and media as an instrument, but except for Fox studios and News corp. we could find no other examples of corporations owning both studios and relevant media.

the error term for a movie across weeks. We use week fixed effects to control for such autocorrelation along with a Newey-West methodology. We use a generalized method of moments (GMM) procedure that accommodates such correlations while also allowing us to explicitly deal with the endogeneity of user ratings and critic ratings. In addition, GMM is also preferred in the presence of heteroskedasticity. For more information, see CGV (2010).

Insert Tables 4, 5 and 6 Here

In table 4 we report results for equation (1). The unit of observation is movie-week. Model 1 is a simple OLS estimation without any endogeneity correction and with no fixed effects (movie, week, or studio). In this model, we only have 4 variables. All four coefficients are positive and significant. Interestingly, even in this simple model, we note that the coefficient of CriticRating is statistically larger than that of UserRating (F-stat=165.39, $p < .00$). However, both are positive and significant.

In Model 2, we add several control variables to the OLS regression in Model 1. In addition, we add the three types of fixed effects – movie, week and studio. The results of Model 2 show that with the exception of UserRating, the other three variables are positive and significant. In addition, advertising is positive and significant, while the effect of competition (newfilms) is negative and significant (See, Elberse and Eliashberg 2003). Other control variables have signs and magnitudes which are consistent with prior literature - for example, GPGPG13 and R are positive, in other words, such films perform better than unrated films and the coefficient of the former variable is larger (See Ravid 1999, De Vany and Walls 2002). Importantly, the sign of user volume is positive and significant, consistent with prior literature, such as Liu (2006). In other words, based on OLS analysis we may reach the conclusion that user volume (buzz) drives revenues. Once again, we note that the coefficient of CriticRating is statistically larger than that of UserRating (F-stat=42.17, $p < .00$).

We now discuss the impact of instrumenting for the endogenous variables in equation (1) and the relative impacts of critic rating and user rating. Model 3 in table 4 does not include movie-fixed effects, but does include studio and week fixed effects. To estimate Model 3 we use GMM while controlling for autocorrelation, but not heteroskedasticity. Models 3, 4, and 5 use the instruments discussed above for user volume, user rating and screens. We also instrument for a fourth variable, critics rating. The instruments for this latter variable are critics' experience and the number of local newspapers that carry a review of the movie. The first thing we notice is that the sign of the coefficient of UserVolume is reversed and it becomes negative and very weakly significant - only at .10 level. However, UserRating and

CriticRating are still both positive and significant, in other words, even after controlling for endogeneity ratings matter - both user reviews and expert opinions.

The first stage regressions show that the instruments as well as the exogenous variables explain the variations in the endogenous variables. Especially, for the critic ratings, both instruments have strong positive coefficients indicating that enhanced experience and reviews in a larger number of local newspapers improve average critic rating. We use the Stock and Yogo's F-statistic to examine whether the proposed instruments jointly explain the endogenous variables. The results indicate that the F-statistics average value is over 10 and that the instruments cannot be excluded from the first –stage model; they are relevant. Furthermore, we also test for the over-identifying restrictions. For this Model 3, the Hansen's J-statistic is 0.72 with a p-value of 0.69. This suggests that indeed the instruments appear to be orthogonal to the error term in the box office equation. However, in this Model 3, the coefficient of CriticRating is not statistically larger than that of UserRating (F-stat=.98, $p < .32$). Most of the control variables again have predictable signs.

Model 4 is a GMM model with both autocorrelation and heteroskedasticity corrections. In this model we use all three types of fixed effects – movie fixed effects, week and studio fixed effects. Similar to Model 3, we find that the coefficient of UserVolume is negative, but it is not significant any more. The coefficients of UserRating and CriticRating are both positive and significant. Once again, we note that the coefficient of CriticRating is statistically larger than that of UserRating (F-stat=172.93, $p < .00$).

Model 4 is in fact, the most statistically "correct" test of hypotheses 1a and 1b and we find here that both professional critical reviews and user reviews drive movie revenues supporting both hypotheses as well as the conjecture, "*Rumors of Critics' Demise Are Greatly Exaggerated*".

The significance of user volume found in previous research (Liu, 2006) disappears, and the sign, similar to CGV (2010) is sometimes even negative. Thus it can be that the significance found in prior work is due to reverse causality- i.e. popular movies lead to much buzz on the internet.

It is also important that we are able to replicate and extend the findings of CGV (2010) on a much different sample from a different period and in the presence of professional critical reviews.

Model 5 is a GMM model with both heteroskedasticity and auto-correlation, but the dependent variable includes the opening week data only. Critics' reviews appear typically before the movie opens, and user reviews appear throughout the life of the movie. Neither UserVolume nor UserRating are significant here; however, the coefficient of CriticRating is positive and statistically significant. It is also statistically larger than that of UserRating. While we control for week and studio fixed effects in this model, due to data constraints we are unable to control for movie fixed effects. This regression illustrates in the most convincing way that critics affect movie going decisions - we see that in the first week only critical reviews matter. This supports the findings of earlier papers such as Eliashberg and Shugan (1997) and Basuroy, Chatterjee and Ravid (2003) even in the internet age, using a much more sophisticated and extended statistical methodology. Next we test hypotheses 2, 3 and 4.

In Table 5 we report the interaction results. Model 1 in Table 5 examines the interaction effect of the UserRating and CriticRating. Because the function of an endogenous variable (s) is also endogenous, the interaction term is endogenous requiring instruments. To create this additional instrument, we use an interaction of two existing instruments, COMPSTAR (instrument for userrating) and critics' age (instrument for CriticRating). In terms of results, we note that the coefficient of UserVolume is not significant in this Model 1. We find that both UserRating and CriticRating are significant and positive. Most importantly, we find that the coefficient of the interaction term is negative and significant, although somewhat weak - at .09 level. Thus we have some confirmation of H2. Another fact that we note in Model 1 of Table 5 is that the coefficient of CriticRating is statistically larger than that of UserRating at .05 level. The net effect of both critical reviews and user reviews on revenues is still positive, but at the margin we show that one variable diminishes the impact of the other as suggested in H2.

We next test for H3. The results are described in Model 2 of Table 5. The two key interactions are those of critic rating and user rating respectively with advertising. Here too, we use two additional instruments to account for these two interactions – by interacting the instrument of UserRating (COMPSTAR) and the instrument for CriticRating (critic's age) with the advertising expenses of other movies belonging to the same genre in a specific week. The results show that the coefficient of CriticRating*Adv is positive and significant, while that of UserRating*Adv is negative and significant. This supports hypothesis 3b. We find that critics' ratings enhance advertising, and in this sense, expert reviews and advertising seem to act in a complementary fashion. As noted, this is consistent with Basuroy, Ravid and Rao (2012) and can also be interpreted in the framework proposed by Bagewll (2007) where advertising may be complementary to other information. However, the interaction of user ratings and advertising is negative and significant. Thus we cannot support hypothesis 3a. It may be that the persuasive role of advertising (Bagwell, 2007) diminishes the impact of user ratings, whereas professional reviews, prominently featured in ads, increase it.

We next test H4 - interactions critics and user valence with platform release. The results are described in Model 3 in Table 5. As noted, we follow CGV (2010) and other scholars (Einav 2007, Ho, Dhar and Weinberg 2009) in defining a platform release as a release in 600 theaters or less (for these movies a PlatformRelease dummy takes the value of 1). Then we create interaction terms by interacting CriticRating and UserRating with PlatformRelease. We use two additional instruments to account for these two interactions – by interacting the instrument of UserRating (COMPSTAR) and the instrument for CriticRating (critic's age) with the number of screens showing a movie of the same genre as the focal movie in the specific week. The interesting finding from this analysis is that the coefficient of

CriticRating*PlatformRelease is positive and significant. Thus it appears that expert ratings significantly boost the revenues of platform release movies. This result validates one interpretation of Holbrook's (1999) idea and the wide-spread notion that expert reviews support "art-house" movies. These findings also support hypothesis 4a. The coefficient of UserRating*PlatformRelease is negative but not significant – corroborating the finding of CGV (2010) regarding the interaction of platform release movies and user ratings (see, CGV 2010, p. 950). This does not support the studios' views of using the internet to enhance movie awareness (hypothesis 4b). In addition, we find that the main effect of platform release movies is negative but it is not significant.

Robustness Checks

The model in equation 1 and the results reported in Table 4 allow only for a contemporaneous effect of WOM on revenues. It is quite possible that there is a lag in the effect of WOM on revenues - in other words, past internet chatter and reviews affect current box office results. In Table 6 we report the results GMM estimation using lagged endogenous variables. Each model in Table 6 replicates the corresponding model in Table 4 but with lags. All results reported in Table 6 are very similar to those in Table 4. In each model in Table 6, the coefficient of CriticRating is positive and significant and it is statistically larger than that of lagged UserRating. The only difference is that in some of the models lagged user ratings are still positive but lose significance, suggesting that current user ratings are more important. The last column replicates our first week column in table 4, but here we have of course week 2 only. Now user ratings matter as well as critics' ratings.

Oberholzer-Gee and Strumpf (2007) suggest that a weighted average of current and lagged variables may be a better measure. Following their idea, we use a weighted average of current and past endogenous variables UserVolume, UserRating and CriticRating. The dependent variable is current sales. We use a weight of .66 for current period and a weight of .34 for the lag. We also try a few other combinations of weights. The results are similar to the ones in tables 4 and 6 and not reported here. This is of course not very surprising[7].

Discussion, Managerial Implications and Conclusion

Marketing practitioners and scholars are paying significant attention to user generated content and word-of-mouth.WOM communication in the form of online product reviews and commentaries has become a major source of information for consumers. The phrase "word of mouth" returns 22 million hits on Google. Amazon lists many practitioner books on the subject with evocative titles such as *Word of Mouth Marketing: How Smart Companies get people Talking, Word of Mouth: A Guide to Commercial Voice-over Excellence,* and others. There is also a Word Of Mouth Marketing Association

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[7] We also tried to run regressions with the lagged dependent variable on the right hand side. The coefficients of interest had similar signs and significance to what we find in the rest of the paper so the results are not reported.

(www.womma.org) that claims to be “the leading trade association in the marketing and advertising industries that focuses on word of mouth …” The general understanding from practitioners’ perspective is that WOM’s effect on sales and revenues is positive and significant (as documented by some academic work, case studies or stories). In the movie business studios expend much effort in creating internet presence. The topic has garnered active interest amongst scholars, and indeed some work seems to support the popular view about WOM. CGV (2010) were the first to show that, at least as far as movies go, buzz is not significant in determining revenues. The valence of user ratings, however, matters. Our work on a very different data set and in a later time period confirms these findings. This is important in itself because it suggests that the findings in CGV (2010) are very general. However, we also suggest for the first time, that even in the presence of ubiquitous internet reviews, consumers pay more attention to experts than the popular press seems to believe.

The popular sense that WOM (or buzz) is statistically related to movie revenues is supported by OLS analysis. However, similar to CGV (2010) using IV regressions we show that the causality may run the other way, i.e. if many people see the movie, then there are many internet postings. The take-away from this result is that managers have to be cautious regarding their belief in the marketing prowess of WOM. The rosy picture painted by popular media regarding the ubiquitous positive impact of “buzz” has to be taken with a grain of salt. However, confirming the recent results of CGV (2010), we also find that the ratings users provide matter.

Our findings that professional critical reviews are still important seem rather intuitive - would you buy a computer based upon a review of a knowledgeable expert, or would you prefer an opinion posted on the internet by Joe Shmoe from Nowhereland USA? While the movie-going experience is different than a consumer product such as a laptop or computer, our findings suggest that even for movies, an element of expertise is important. This perhaps explains the cozy relationships studios still maintain with critics and the existence of blurbs from critics which are an integral part of most movie advertisements (See Ravid, Wald and Basuroy 2006 and Basuroy, Ravid and Rao 2012). Some new research (Basuroy, Ravid and Rao 2012) seems to support the notion that the most useful content a movie advertisement can display is favorable critical reviews. Our results on the interactions of advertising and the valence of critics and users support this view.

The importance of professional expert reviews is emphasized when we analyze the opening week results and platform releases. In both cases, it is only expert views that drive revenues rather than user ratings. While this is an intuitive result, it is not what much of the popular press believes - what we say is that you need solid positive professional evaluation, rather than internet chatter to drive your movie home. Finally, we also show that glowing positive reviews by either users or professionals may render the other source redundant, which suggests some substitution between the two types of reviews.

The bad news our analyses provide for the studios is that what matters most can be manipulated least. Buzz or traffic on the internet can be relatively cheaply generated. However, our work seems to indicate that it does not buy you much marketing value. User ratings matter and they may be, and apparently are, manipulated to some extent (See Mayzlin et al, 2012). After all, nobody checks the id of each internet reviewer and how related he may be to the film producer or writer. Professional reviews may be influenced, but are by far the hardest to manipulate. However, even in the age of the internet, experts have more of an effect on the movie going public. In a way, it all makes sense - a rational public places greater trust in sources which are less subject to manipulation and whose views reflect some expertise. The good news for studios, however, is that if you do receive good notices, using them in advertising and to promote platform releases can enhance public awareness of your product and move the film forward.

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TABLE 1: List of Variables Used in the Analysis, Their Definitions, References, and Sources

Variables	Variable Definition	Literature Support	Data Source
Box_{it}	Main dependent variable. Box office revenue of film *i*in week *t*	Basuroy, Chatterjee and Ravid (2003; Liu (2006)	Baseline
$UserVolume_{it}$	Endogenous variable. Number of user comments for film *i* in week *t*.	Liu (2006); CGV. (2010)	www.rottentomatoes.com
$UserRating_{it}$	Endogenous variable. Average user rating of film *i* in week *t*.	Liu (2006); CGV. (2010)	www.rottentomatoes.com
$CriticRating_{i}$	Endogenous variable. Average critic rating of film *i*.	Basuroy, Chatterjee and Ravid (2003); Liu (2006)	www.rottentomatoes.com
$Screen_{it}$	Endogenous variable. The number of screens for film *i* in week *t*	Basuroy, Chatterjee and Ravid (2003); CGV (2010)	www.boxofficemojo.com
$gpgpg13_{i}$	Dummy variable =1 if the film is rated either G, PG or PG13, 0 otherwise	Ravid (1999); De Vany and Walls (2002)	Baseline
r_{i}	r=1 if the film is R-rated, 0 otherwise	Ravid (1999);); De Vany and Walls (2002), Fee (2002);Liu (2006)	Baseline
Action, *Comedy*, *Drama*, *Romance*, *Thriller*	Each of these genres is a dummy variable		Baseline
Adv_{it}	Weekly advertising dollars in '000.	CGV (2010)	Kantar Media
$Newfilm_{it}$	Number of new films in the Top 20 per week; this serves as a measure of competition	Elberse and Eliashberg (2003); Liu (2006)	www.boxofficemojo.com
Age_{it}	Average age of films in weeks in the Top 20 per week	Elberse and Eliashberg (2003); Liu (2006)	www.boxofficemojo.com
Instrumental Variables			
$CompReview_{it}$	Average critic rating of competing movies in prior week.	Chintagunta et al. (2010)	www.rottentomatoes.com
$CompStar_{it}$	Average star power of competing movies in prior week	Chintagunta et al. (2010)	www.rottentomatoes.com
$PropGenre_{it}$	Average proportion of movies of the same genre as the focal movie in prior week	Chintagunta et al. (2010)	www.boxofficemojo.com
$CompScreen_{it}$	Number of screens that show movies of the same genre as the focal movie in the prior week	Chintagunta et al. (2010)	www.boxofficemojo.com
$LocalPapers_{i}$	Number of local newspapers carrying critical reviews of movie *i*		www.rottentomatoes.com
$CriticExperience_{i}$	Experience of critics measured by their age		www.rottentomatoes.com

TABLE 2: Descriptive Statistics

Variables	**N**	**Mean**	**SD**	**Min**	**Max**
Box_{it} *(millions, weekly)*	2400	3.27	10.34	0	160.10
$UserVolume_{it}$	2400	7.65	11.85	0	104
$UserRating_{it}$	2400	3.46	1.39	0	5.00
$CriticRating_{i}$	2400	5.78	1.46	2	8.9
$Screen_{it}$	2400	656	1044	0	4362
$gpgpg13_{i}$	2400	0.47	0.49	0	1
r_{i}	2400	0.47	0.50	0	1
Action	2400	0.09	0.28	0	1
Comedy	2400	0.21	0.40	0	1
Drama	2400	0.29	0.45	0	1
Romance	2400	0.05	0.22	0	1
Thriller	2400	0.10	0.29	0	1
Adv_{it}*(thousands, weekly)*	2376	76.90	9.22	28.98	82.18
$Newfilm_{it}$	2400	11.92	3.21	3	19
Age_{it}*(weeks)*	2400	4.41	1.83	2.2	17.5
Instrumental Variables					
$CompReview_{it}$	2399	5.62	8.32	4.24	6.35
$CompStar_{it}$	2400	120.40	302.05	15.10	2361.20
$PropGenre_{it}$	2399	0.26	0.28	0	0.79
$CompScreen_{it}$	2400	447.52	378.72	0	2471
$LocalPapers_{i}$	2376	19.39	4.85	4	29
CriticExperience	2376	50.89	3.81	38.67	59.33

TABLE 3: Correlation Table of continuous variables

		1	2	3	4	5	6	7	8
1	Box_{it}	1.00							
2	$UserVolume_{it}$	0.14	1.00						
3	$UserRating_{it}$	0.08	0.22	1.00					
4	$CriticRating_{i}$	0.01	-0.12	0.08	1.00				
5	$Screen_{it}$	0.68	0.18	0.14	-0.06	1.00			
6	Adv_{it}*(thousands, weekly)*	0.01	0.04	-0.01	0.07	-0.02	1.00		
7	$Newfilm_{it}$	-0.06	-0.03	-0.01	0.01	-0.03	-0.19	1.00	
8	Age_{it}*(weeks)*	-0.01	-0.01	-0.01	-0.04	0.01	-0.06	-0.09	1.00

Table 4. OLS and Instrumental Variables Regression Results Using GMM Estimations. The dependent variable is weekly movie revenues.

	Model 1 OLS	**Model 2 OLS**	**Model 3 GMM + Auto-Correlation**	**Model 4 GMM+ Auto-Correlation+ Heteroskedasticity**	**Model 5 GMM+ Auto-Correlation+ Heteroskedasticity OPENING WEEK**
Endogenous variables					
UserVolume	0.010***(.00)	0.007***(.00)	-0.030*(.02)	-0.002(.00)	-0.002(.01)
UserRating	0.001**(.00)	0.000(.00)	0.023**(.01)	0.004***(.00)	0.001(.02)
CriticRating	0.066***(.01)	0.080***(.01)	0.056***(.02)	0.048***(.003)	0.120***(.03)
Screen	0.001***(.00)	0.001***(.00)	0.001***(.00)	.001***(.00)	0.001***(.00)
Control variables					
gpgpg13		0.447***(.08)	0.163(.12)	.032*(.02)	0.038(.25)
r		0.421***(.03)	0.161*(.09)	.050**(.02)	0.086(.23)
Advs(Thousands, weekly)		0.002**(.00)	0.003***(.00)	0.002***(.00)	0.003(.00)
Newfilm		-0.008***(.00)	-0.009***(.00)	-0.008***(.00)	-0.016*(.01)
Age(Weeks)		-0.001(.00)	-0.002(.01)	-.002(.00)	0.013(.00)
Action		-0.126(.08)	0.126**(.07)	0.100***(.03)	0.235*(.13)
Comedy		-0.165(.14)	0.006(.06)	0.029**(.01)	0.164(.13)
Drama		-0.013(.06)	0.032(.08)	0.035***(.01)	0.207*(.12)
Romance		-0.174*(.10)	-0.008(.09)	0.025(.03)	0.287(.19)
Thriller		-0.041(.12)	-0.011(.05)	-.011(.02)	0.151(.11)
N	2000	1990	1970	1970	197
F-value	2369.22	135.81	197.64	896.40	149.00
R-Sq.	.909	0.952	.83	.905	.94
Adjusted R-Sq.					
Movie Fixed Effects	No	Yes	No	Yes	No
Week fixed effects	No	Yes	Yes	Yes	Yes
Studio fixed effects	No	Yes	Yes	Yes	Yes
F-test (p-value) for testing CriticRating>UserRating	165.39 (.00)	42.17 (.00)	0.98 (.32)	172.93(.00)	6.57(.01)
Tests for Endogeneity: Relevance and Exogeneity of Instruments					
1^{st} Stage F-Statistic (average)			45.44	24.54	6.02
Hansen J-Statistic (p-value)			0.721(.69)	180.05 (.75)	0.84(.66)

***significant at .01 level; ** significant at .05 level; * significant at .10 level. Standard errors are in brackets.

Table 5. Testing Interactions Using Instrumental Variables Regressions Using GMM Estimations. The dependent variable is weekly movie revenues.

	Model 1 Interaction of Critic and User valence	**Model 2 Advertising Interactions of Critic and User valence**	**Model 3 Platform Release Interactions of Critic and User valence**
Endogenous variables			
$UserVolume_{it}$	-0.001(.00)	0.005(.01)	-0.008(0.01)
$UserRating_{it}$	0.102*(.06)	0.150**(.06)	0.008(.01)
$CriticRating_{i}$	0.578**(.30)	-0.239(.15)	0.018(.03)
$Screen_{it}$	0.001***(.00)	0.001***(.00)	0.001***(.00)
Interaction Term			
*UserRating*CriticRating*	-0.017*(.01)		
*UserRating*Adv*		-0.002***(.00)	
*CriticRating*Adv*		0.004**(.00)	
*UserRating*PlatformRelease*			-0.010(.01)
*CriticRating*PlatformRelease*			0.187***(.08)
Control variables			
PlatformRelease			-0.744(.52)
$gpgpg13_{i}$	-0.101(.12)	0.050(.10)	0.047(.06)
r_{i}	-0.077(.11)	0.09(.08)	0.105**(.05)
Adv_{it}*(thousands, weekly)*	0.001*(.00)	0.035(.03)	0.002***(.00)
$Newfilm_{it}$	-0.011***(.00)	-0.011***(.00)	-0.010***(.00)
Age_{it}*(weeks)*	0.015*(.01)	0.002(.01)	-.006(.01)
Action	0.118**(.05)	0.163**(.07)	0.075(.06)
Comedy	0.095**(.04)	0.076(.05)	0.078***(.03)
Drama	0.225**(.10)	0.062(.07)	0.144***(.05)
Romance	0.097*(.05)	0.158**(.07)	0.078(.05)
Thriller	0.021(.04)	0.033(.05)	0.014(.04)
N	1970	1970	1970
F-value	183.22	122.02	269.41
R-Sq.	.802	.739	.898
Week fixed effects	Yes	Yes	Yes
Studio fixed effects	Yes	Yes	Yes
Tests for Endogeneity: Relevance and Exogeneity of Instruments			
1st Stage F-Statistic (average)	57.15	26.46	29.43
Hansen J-Statistic (p-value)	0.91(.82)	4.67 (.86)	6.40 (.17)

***significant at .01 level; ** significant at .05 level; * significant at .10 level. Standard errors are in brackets.

Table 6. Robustness Checks With Lagged Endogenous Variables - the dependent variable is weekly revenues.

	Model 1 OLS	Model 2 OLS	Model 3 GMM + Auto-Correlation	Model 4 GMM+ Auto-Correlation+ Heteroskedasticity	Model 5 GMM+ Auto-Correlation+ Heteroskedasticity 2nd WEEK
Endogenous variables					
Lagged UserVolume	0.003***(.00)	-0.0003(.00)	-0.025**(.012)	-0.003***(.00)	-0.015*(.01)
Lagged UserRating	0.002**(.00)	0.002***(.00)	0.014(.01)	0.004***(.00)	0.027(.02)
Lagged CriticRating	0.067***(.01)	0.068***(.01)	0.064***(.02)	0.044***(.003)	0.166***(.04)
Screen	0.001***(.00)	0.001***(.00)	0.001***(.00)	.001***(.00)	0.001***(.00)
Control variables					
gpgpg13		0.040(.03)	0.055(.08)	.013(.02)	0.165(.27)
r		0.026(.03)	0.078(.06)	.020(.02)	0.426(.27)
Adv (thousands, weekly)		0.002**(.00)	0.002***(.00)	0.001***(.00)	0.004*(.00)
Newfilm		-0.009***(.00)	-0.009***(.00)	-0.007***(.00)	-0.024**(.01)
Age (Weeks)		-0.001(.00)	-0.003(.00)	-.002(.00)	-0.046(.04)
Action		0.129***(.03)	0.064(.05)	0.088***(.02)	0.170(.13)
Comedy		0.053***(.02)	0.039(.04)	0.027***(.01)	0.098(.12)
Drama		0.045***(.02)	0.082*(.05)	0.040***(.01)	0.139(.14)
Romance		0.040(.03)	0.029(.06)	0.027(.02)	0.140(.23)
Thriller		-0.003(.02)	-0.003(.04)	-.006(.01)	0.062(.12)
N	1800	1791	1773	1773	197
R-Sq.	.911	.922	.866	.912	.886
F-value	4568.54	439.17	6801.48		
Wald Chi-Sq. (Prob>Chi-Sq.)				20119.27 (.00)	1192.91 (.00)
Movie Fixed Effects	No	Yes	No	Yes	No
Week fixed effects	No	Yes	Yes	Yes	Yes
Studio fixed effects	No	Yes	Yes	Yes	Yes
F-test (p-value) for testing CriticRating>UserRating	174.62 (.00)	167.96 (.00)	4.48 (.03)	172.93(.00)	7.29(.00)

*** significant at .01 level; ** significant at .05 level; * significant at .10 level. Standard errors are in brackets.