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Third-party product reviews (TPRs) have become ubiquitous in many industries. Aided by communication technologies, particularly on the Internet, TPRs are widely available to consumers, managers, and investors. The authors examine whether and how TPRs of new products influence the financial value of firms introducing the products. An event study covering 14 major media and professional reviews of movies released by 21 studios shows that TPRs exert significant impact on stock returns in the direction of their valence. However, the impact comes from the valence of a review that is measured relative to other, previously published reviews and not from the absolute valence of the review itself. The authors further study the dynamics of TPR impact on firm value and find that the impact exists only for prerelease reviews and is the strongest on the product release date, though it

and Hanssens 2009). The marketing function, and the firms overall, constantly strive to better understand the drivers of firm value (Hanssens, Rust, and Srivastava 2009).

At the same time, competition on a global scale has increasingly made innovation and new product development the cornerstone of firm growth. The introduction and success of new products is a critical factor in the financial valuation of firms (Chaney, Devinney, and Winer 1991; Lane and Jacobson 1995). For example, Apple's stock fell sharply after its iPhone had disappointing first-weekend sales (Goldman 2007), and the box office failure of the movie *Alamo* negatively influenced Disney's stock price (Joshi and Hanssens 2009).

Because new products are often associated with high demand uncertainty, investors constantly pay attention to information that could be indicative of product success or failure (e.g., Chaney, Devinney, and Winer 1991). If TPRs can influence and/or predict market demand, they should have the potential to influence investor behavior and, thus, firm value.

Finally, firms constantly manage market information through marketing actions. For example, extant literature indicates that advertising and TPRs may interact with each other (Chen and Xie 2005). An immediate question arises: If TPRs can affect firm value, how can firms deploy advertising strategies to manage such an effect? Therefore, this study embodies four distinctive factors that have strategic implications: firm value, new products, TPRs, and advertising. Examining the relationship among them is particularly relevant in an age when TPR information permeates the Internet.

There is anecdotal evidence that investors pay attention to TPRs in their investment decisions. For example, to meet investors' needs, financial infomediary giant Bloomberg constantly delivers updated TPRs such as movie reviews to brokerage firms through its Bloomberg terminals. Some analysts use video game reviews from review websites such as Metacritic.com to predict stock price (Banerjee 2006). The following quote from the investor community message board on Yahoo! Finance (2008) illustrates the potential impact of critical movie reviews on investors: "reviewer loved it [the movie *Spiderman 2*] ... this will break all box office records ... Sony to \$40 soon."

The literature on how TPRs may influence firm value is limited. A notable exception is Tellis and Johnson's (2007) research, which focuses on product reviews from *Wall Street Journal* technology writer Walt Mossberg and shows that the "reviewed" quality has an immediate effect on stock returns. Our study has several unique characteristics that distinguish it from Tellis and Johnson's work.

First, instead of focusing on a single media outlet or critic and the associated product reviews, we examine the general situation, in which multiple reviews are provided for the same product by different media outlets or critics over time. For example, a new camera or printer typically receives reviews from various mU mU arno

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Last, we used the movie industry for empirical investigation. Compared with other industries such as consumer electronics (Tellis and Johnson 2007), movies provide a more conservative context to study the impact of TPRs on firm value. As Ravid (1999, p. 467) points out, the impact of a movie project on stock price may not be significant, because “the (movie) projects in question, while large, are often not sufficiently significant to warrant discernable changes in stock prices unless the studio is very small. The problem is exacerbated by the fact that studios have been purchased by even larger diversified companies (e.g., Sony).”² Thus, a single product item such as a movie may not be able to influence the financial value of the firm. Moreover, the preference of professional critics and that of regular consumers differ to a greater extent for experiential and hedonic products (e.g., cultural and arts products) than for utilitarian products (e.g., computers, automobiles) (Holbrook 1999).

The movie industry provides an excellent research context for several other reasons. New product introduction is frequent in this highly competitive market (Lampel and Shamsie 2000). According to the Motion Picture Association of America (MPAA), a total of 558 films were released in 2009. Furthermore, professional critics and media regularly provide movie reviews, and these reviews are readily available to readers and researchers through public sources. In addition, several previous studies on TPRs have been conducted in the movie context (e.g., Basuroy, Chatterjee, and Ravid 2003; Eliashberg and Shugan 1997; Reinstein and Snyder 2005).

Before a new product is introduced, the manufacturer and its current and potential investors often face great uncertainty about whether the product will eventually be successful (Sivadas and Dwyer 2000).

Before a new product is introduced, the manufacturer and its current and potential investors often face great uncertainty about whether the product will eventually be successful (Sivadas and Dwyer 2000). Researchers have long recognized that market acceptance of most new products cannot be unambiguously predicted even with extensive marketing research (e.g., Crawford 1977). From the demand side, consumers often lack product attribute information and the expertise to evaluate quality (Alba and Hutchinson 1987); the consequences on consumer choice are twofold: deferred purchase and greater demand variance, both of which further contribute to heightened uncertainty about product sales.

Such demand uncertainty can be particularly high for experiential products such as movies, music, books, and television shows (Lampel and Shamsie 2000). While successful movies could generate substantial revenue in theatrical and alternative sales channels, many fail to recoup their production costs (Vogel 2001). Because movies are experiential products that are consumed for hedonic value,

²Elberse (2007) does not find significant effects of stars joining or leaving movie projects on stock prices. She demonstrates that the value of stars for a movie is approximately \$3 million in theatrical revenue. Consistent with Ravid’s (1999) arguments, \$3 million may not be sufficient to cause stock market reactions.

it is difficult to define “quality” in a straightforward manner (e.g., Linton and Petrovich 1988). As a result, predicting movie box office sales is a challenging task (Sawhney and Eliashberg 1996).

In coping with demand uncertainty and the difficulty of predicting new product sales, firms and investors gather information to aid their assessment. To this end, TPRs provide information about product characteristics and offer a valid composite measure of product quality (Chen and Xie 2005, 2008; Eliashberg and Shugan 1997; Tellis and Johnson 2007). Previous studies have also found a positive correlation between TPRs and consumer opinions. For example, Holbrook (1999) shows that although critics and regular moviegoers could emphasize different attributes in movie evaluation, there is a positive correlation between their assessments. Other researchers such as Basuroy, Chatterjee, and Ravid (2003), Eliashberg and Shugan (1997), Litman and Kohl (1988), Reddy, Swaminathan, and Motley (1998), Reinstein and Snyder (2005), and Wyatt and Badger (1990) find TPRs to be positively correlated with product sales. Therefore, TPRs provide useful information about sales potential. To the extent that the investors understand such predictive value, they should pay attention to TPRs in trading decisions.

However, when multiple reviews are published for a new product over time, it is unclear how investors will treat the value of each review and how the potentially different review opinions are integrated. The impact of TPRs on firm value depends on how investors process different reviews and make inferences about sales potential. In what follows, we discuss two streams of literature that shed light on the information-processing patterns of investors.

Efficient Market Hypothesis

The efficient market hypothesis is one of most established theories in finance (Fama 1970; Samuelson 1965). The basic idea is that stock prices reflect and internalize all relevant information available to the investors. The impact of a piece of information that has just appeared depends on the market expectation that has formed on the basis of previous information, and there is no price movement unless unexpected new information arrives (Fama 1991). This has an important implication: Any new information will not have an impact on stock price unless it contains “newness” that changes market expectations.

Consistent with the efficient market hypothesis, several recent studies in finance and accounting provide evidence that what drives stock returns is whether the expectation, formed from previous information, is met by the new information (e.g., Bartov, Givoly, and Hayn 2002; Burgstahler and Eames 2006; Kasznik and McNichols 2002; Kinney, Burgstahler, and Martin 2002; Lopez and Rees 2002; Skinner and Sloan 2001). For example, Bartov, Givoly, and Hayn (2002) find that firms that beat earning expectations would earn greater stock returns than firms that have the same earnings but fail to exceed the expectation.

In the case of TPRs, as multiple reviews become available over time, the expectation of sales potential is updated continuously in the stock market. In this dynamic process,

the informational value of a particular review will not depend on the review per se but rather on the new information it provides. This predicts that stock returns, or firm value, will respond to how a newly published review differs from previous published reviews.

Behavioral Theoretical Perspectives

A wide range of behavioral research in psychology, consumer research, and finance suggests that cognitive attention is a scarce resource and that the human brain has limited cognitive-processing capacity (e.g., Kahneman 1973; Pashler and Johnston 1998). With respect to investor behavior, recent studies in accounting and finance show that the cognitive attention investors pay to certain information directly influences how the stock market will react to that information (e.g., Huberman and Regev 2001; Peng and Xiong 2006).

Regarding the allocation of cognitive attention, behavior research shows that attention is selective, and people tend to pay more attention to certain types of information than to other types (e.g., Lowe and Steiner 1968). Specifically, the information-processing literature suggests that unexpected information is more arousing and will receive greater attention and cognitive effort (e.g., Kahneman 1973; Metcalfe 1993). For TPRs, these studies imply that the unexpected, incremental information a review possesses relative to existing reviews will receive greater investor attention and cause stock market reactions.

Effects of TPRs on Firm Value

Figure 1 presents a conceptual framework that includes the key factors to be considered—namely, the absolute versus relative valence of TPRs, advertising spending, and the timing of TPRs relative to the new product release date. In many markets, the exact date of product release and the time before that are jointly referred to as “prerelease,” which is distinguished from the postrelease period, when product sales information becomes available. We follow

this typology to examine the impact of prerelease versus postrelease TPRs. In a more thorough investigation of the dynamics of TPRs, we further differentiate prerelease TPRs into those that are published exactly on the release date and those that are published before it.

Effects of TPR valence. Both the efficient market hypothesis and behavior theories suggest that the effect of a TPR lies in the new information it provides over existing reviews. Therefore, to discern the effects of multiple TPRs on firm value, it is necessary to distinguish the opinion of a review and how the review deviates from earlier reviews. We refer to the evaluative opinion of a review itself as absolute valence and the difference between that review and those published previously as relative valence. For illustration, assume that several TPRs assign ratings to a new product. The absolute valence of a review is the rating it assigns. The relative valence of the review can be measured by the difference between the rating assigned by this review and the average ratings assigned by all previously published reviews.

The distinction between absolute and relative valences constitutes an important departure from existing studies that have focused on the opinions of the reviews themselves (e.g., Eliashberg and Shugan 1997; Reinstein and Snyder 2005; Tellis and Johnson 2007). Given the fundamental role of market expectations in driving investor behavior, this distinction is essential to measure how expectations are updated and to understand the impact of TPRs on firm value.

The efficient market hypothesis and the behavior theories predict that investors will react to the relative valence of TPRs. This means that if the stock market has absorbed highly negative information about the product and formed expectations accordingly, a negative TPR that is less negative than the previous reviews will still have a positive effect. Thus, we propose the following hypothesis

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about the effects of absolute versus relative valence of TPRs:

H₁: When multiple TPRs are published for a new product over time, the impact of a particular review on firm value does not come from the absolute valence of the review itself but rather from its relative valence. (a) TPRs that offer a positive (negative) evaluation beyond previously published reviews have a positive (negative) impact on firm value, (b) TPRs that offer product evaluations similar to previously published reviews have no impact on firm value, and (c) the absolute valence of TPRs has no impact on firm value.

Roles of advertising on the effects of TPRs. We now consider how marketing strategies might influence the effects of TPRs on firm value. We focus on the roles of advertising spending, a key element of new product introduction campaigns (Joshi and Hanssens 2009). In theory, advertising has two important but distinctive roles: to persuade (i.e., signal quality and improve confidence) and to inform (i.e., increase awareness and provide information about search attributes) (e.g., Akerberg 2001; Bagwell 2007; Grossman and Shapiro 1984; Stigler 1961).

The persuasion role of advertising is rooted in at least two theoretical foundations. First, research on signaling suggests that, when there is uncertainty about product quality, a high-quality firm may use advertising spending to distinguish itself from low-quality competitors (Erdem and Keane 1996; Milgrom and Roberts 1986; Nelson 1974). Second, in psychology and consumer research, behavioral regularities such as mere-exposure effects point to the benefit of enhanced perception when the product is exposed to target consumers repeatedly (Zajonc 2001). The consequence is similar to a prestige effect (Becker and Murphy 1993): The perceived benefit of a product is enhanced when the firm advertises more. Therefore, when events such as professional reviews occur for a particular product and draw attention from the investors to make trading decisions, more advertising will help induce more positive stock market reaction.

The implications of the awareness role of advertising are more complex. On the one hand, greater awareness and knowledge of a firm and its product may induce greater investor attention to firm- and product-specific news, including TPRs. Thus, the effects of TPRs on firm value will likely be amplified either positively or negatively, depending on the nature of the review. Different from the effect induced by the persuasive role, this essentially predicts an interaction between TPR and advertising on firm value.

On the other hand, recent research in finance and accounting has documented a positive effect of advertising on stock returns through the awareness role. For example, Grullon, Kanatas, and Weston (2004) find that advertising helps increase investors' familiarity with the firm and investors are more likely to buy/own familiar firms. Gervais, Kaniel, and Mingelgrin (2001) show that increased visibility of a stock attracts more new buyers. Furthermore, Hirshleifer et al. (2008) demonstrate that individual investors are net buyers, which helps push up stock returns, after both negative and positive earnings surprises. As Bar-

ber and Odean (2008, p. 7) summarize, "Investors are more likely to buy—and therefore own—stocks that have attracted their attention, whether through unusual events or extensive advertising."

In summary, while the persuasion role uniquely predicts a positive main effect of how advertising influences firm value in the event of third-party reviews, the literature related to the awareness role of advertising suggests both a main effect and an interaction effect. Thus, we propose the following competing hypotheses about the roles of advertising to empirical testing:

H₂: (a) More prereview advertising has a positive impact on firm value in the event of third-party reviews, regardless of review valence. (b) More prereview advertising increases the impact of TPRs on firm value in the direction of review valence.

Dynamics of the TPR effects. The expectation updating process suggests that TPRs should be the most useful to investors when there is high uncertainty about product sales potential. Uncertainty is particularly high before product release but vanishes when the product is released and actual sales information becomes available. As a result, investors do not need to rely on signals such as TPRs to judge sales potential. The effect of TPRs will diminish. Because of these differences, examining the effects of prerelease versus post-release TPRs provides another useful test of the theory that TPRs influence firm value, as doing so provides useful information about sales potential to shape investor expectations.

In the particular case of movies, it is well known that the sales potential of a new movie is revealed quickly after the opening weekend. This happens through two main mechanisms. First, the opening weekend performance in terms of both box office revenue and rankings quickly becomes public through numerous news and entertainment media. Second, the opening weekend revenue not only is an important proportion of total sales but also influences the distribution support that the movie can receive in later weeks (Elberse and Eliashberg 2003; Krider et al. 2005). Therefore, the value of TPRs to investors significantly diminishes after opening. This leads to the following hypothesis about the differential impacts of pre- versus postrelease TPRs. It is consistent with the previous argument that TPRs influence firm value because it provides useful information to shape sales expectations in a dynamic process.

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In the movie industry, given the quick dissemination of sales information after movie release, we expect the effect of TPRs on firm value to diminish quickly and even become nonsignificant.

The pre- versus postrelease differentiation captures the two most distinctive time periods in terms of demand uncertainty and the availability of information about actual sales. Given the unique position that the release date itself occupies in the new product introduction process, it is useful to further distinguish among prerelease TPRs—namely, those that are published exactly on the release date and those that are published before that particular date.

Product release date is a critical event in new product introductions. In many markets, this date is public knowledge due to marketing campaigns and discussions on the Internet. For example, in consumer electronics, in the past, Apple chief executive officer Steve Jobs usually announced new products in the well-attended MacWorld Conference. In movies, release dates of new films often become widely known several months earlier.

As the interest in the new product intensifies on the release date (Huang, Strijnev, and Ratchford 2008), TPRs published on that date are likely to receive greater investor attention, and thus the impact on firm value is stronger. This leads to the following hypothesis about the effects of TPRs on versus before product release date:

H₄: Although both affect firm value, TPRs published exactly on the product release date have a greater impact on firm value than those published before the release date.

New product promotion is a prominent element of the marketing strategy. As competition heightens and product life-cycle is reduced in many product categories, much attention is paid to prerelease promotional activities (Caves 2001). In the movie industry, for example, prerelease advertising accounts for as much as 90% of total advertising spending (Elberse and Anand 2007). Therefore, to shed light on the issues of advertising effectiveness and spending allocation, we further examine the roles of advertising for TPRs published before versus on the product release date.

As we discussed previously, interest in the new product will grow greater on the release date (Huang, Strijnev, and Ratchford 2008), causing third-party information such as TPRs to receive greater investor attention. At the same time, more product information typically becomes available from alternative sources (e.g., media coverage, consumer discussion) as the product release date nears.

From the theoretical base of the persuasion versus awareness roles of advertising, the implications for the effects of advertising are twofold. In terms of persuasion, when alternative information exists and receives more attention, advertising will become less influential (e.g., Chen and Xie 2005). In terms of awareness, it is more difficult for a particular advertising message to be noticed when more information exists in the marketplace.

Thus, both the persuasion and awareness roles suggest that the effect of prereview advertising will abate on the release date. Thus, we propose the following proposition regarding the roles of advertising on versus before product release date:

H₅: The effect of prereview advertising on firm value is greater when the TPR is published before the new product release date than when it is published exactly on that date.

Data and Measures

We collected data on movies released in the United States from February 2005 to April 2006. We obtained movie characteristics such as release time, distributing studio, production budget, genre, MPAA ratings, and sequel from three major movie websites: the Internet Movie Database (IMDb.com), The Numbers (the-numbers.com), and Yahoo! Movies. We obtained movie advertising data from TNS Media Intelligence. To measure firm financial value, we observed movies that were distributed by studios owned by publicly traded companies to obtain stock return data. The movies in our sample were distributed by 21 studios owned by seven companies traded on the New York Stock Exchange. Table 1 lists the studios and their parent companies. On average, each studio released 177 movies, ranging from 9 to 406, from 1995 to 2007. Their box office revenue per movie ranged from \$2.80 million to \$65.49 million, with an average of \$27.76 million. Table 2 reports detailed summary statistics of the sample. We obtained daily stock returns from University of Chicago's Center for Research in Security Prices (CRSP).

For each movie, professional or critical reviews were collected from Metacritic, a member of CNET Networks. Metacritic reports movie reviews from all major critics and the media outlets with which they are associated. Meta-

Parent Company	Studios	Stock Symbol
General Electric Co.	Focus Features Focus/Rogue Picture Universal	GE
Lions Gate Entertainment Corp.	Lionsgate	LGF
News Corporation	20th Century Fox Fox Searchlight	NWS
Sony Corporation	MGM Sony Pictures Sony Pictures Classic Sony/Screen Gems Sony/Tristar Sony/Triumph	SNE
The Walt Disney Company	Buena Vista Miramax Miramax/Dimension	DIS
Time Warner Inc.	New Line Warner Bros. Warner Independent Pictures	TWX
Viacom Inc.	Dreamworks SKG Paramount Pictures Paramount Vantage	VIA

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<i>Chicago Sun Times</i>	93	19	56	18	69.76	0	100	21.37	1.60	4.61		
<i>Entertainment Weekly</i>	121	98	2	21	66.02	0	100	20.97	-.93	3.23		
<i>Hollywood Reporter</i>	94	63	17	14	60.53	10	100	19.31	-3.82	5.96		
<i>Los Angeles Times</i>	105	14	76	15	60.95	20	100	19.83	.27	2.07		
<i>New York Daily News</i>	66	5	53	8	56.24	0	88	20.26	-.03	.66		
<i>New York Post</i>	108	17	76	15	51.17	0	100	24.96	-.19	.95		
<i>The New York Times</i>	112	18	79	15	55.63	0	100	23.47	-.21	.97		
<i>The Onion</i>	119	86	4	29	55.92	0	100	18.34	-.41	3.87		
<i>Premiere</i>	37	15	18	4	59.97	0	100	23.07	-.35	3.34		
<i>Rolling Stone</i>	45	36	4	5	64.33	25	88	17.51	-3.22	8.35		
<i>USA Today</i>	109	101	0	8	66.06	25	100	17.49	-.52	3.46		
<i>Variety</i>	96	87	5	4	59.38	20	100	16.27	-6.39	6.33		
<i>Washington Post</i>	120	10	85	25	54.75	0	100	23.41	1.92	5.24		
<i>The Wall Street Journal</i>	50	0	46	4	56.20	0	100	24.73	.84	3.05		
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Production budget (millions of \$)						43.07	.50	207.00	36.57			
Gross box office revenue (millions of \$)						41.43	.01	380.27	55.43			
Opening screens						1,814	1	3,963	1,360			
St o												
Number of movies released (1995–2007)						177	9	406	141			
Gross box office revenue from all movies (1995–2007, in millions of \$)						5,721	147	17,865	6,339			
Gross box office revenue per movie (1995–2007, in millions of \$)						27.76	2.80	65.49	18.71			

critic.com provides the name of the critic, the media outlet, and the review score for each movie and each review. Metacritic also provides links to the original media outlet's web page, which contains the details of the review and the date when it first appeared online.

We use Metacritic as the main data source for the following reasons. First, it is one of the most comprehensive portal sources of movie reviews. Its coverage and summary of movie reviews are widely acclaimed in the industry.³ Second, the reviews from Metacritic have been increasingly used in recent research (e.g., Elberse and Anand 2007; Huang, Strijnev, and Ratchford 2008; Sun 2009; Wiles and Danielova 2009). Third, Metacritic summarizes each review by assigning a score (named "metascore") ranging between 0 and 100. As specified by Metacritic, a score from 61 to 100 indicates a favorable review and that from 0 to 39 indicates an unfavorable review. A score between 40 and 60 indicates that the review is mixed or neutral. These scores provide researchers with an independently, professionally assessed summary index of review valence.

To further ensure the reliability of the review scores from Metacritic, we cross-checked metascores with the

scores provided by two other influential media: Yahoo! Movies and *Variety* magazine, for the same review. Yahoo! Movies assigns a grade for each review but uses a different format from Metacritic: It uses letter grades ranging from A to F. Following Duan, Gu, and Whinston (2008), we first converted the letter grades to numerical scores so that A = 12, A- = 11, ..., D- = 2, and F = 0. Then, we calculated how metascores correlate with the Yahoo! Movies scores for the same reviews. We found that the scores from the two media are highly consistent; both Pearson and Spearman correlation coefficients are higher than .94 ($p < .01$). *Variety* not only publishes its own reviews but also classifies reviews from other critics as PRO, MIXED, or CONS in its "Crix Picks." Several previous studies, such as Eliashberg and Shugan (1997) and Basuroy, Chatterjee, and Ravid (2003), have used these reviews. We cross-tabulated the favorable, mixed, and unfavorable ratings assigned by Metacritic with the categories assigned by *Variety*. A chi-square test shows that the two categorizations are highly consistent ($\chi^2 = 1368, p < .01$). As an illustration, among all reviews that were assigned as unfavorable by Metacritic, *Variety* gave 98.99% of them a CON rating.

We gathered all movie reviews from 14 major media outlets that were published during the one-month period before movie release and during the two months after release. This covers the most critical time frame for movies

³For more information about the influence of Metacritic in the entertainment industry, see NPR (2008), *Time* (2009), *MTV News* (2008), and Sullivan (2008).

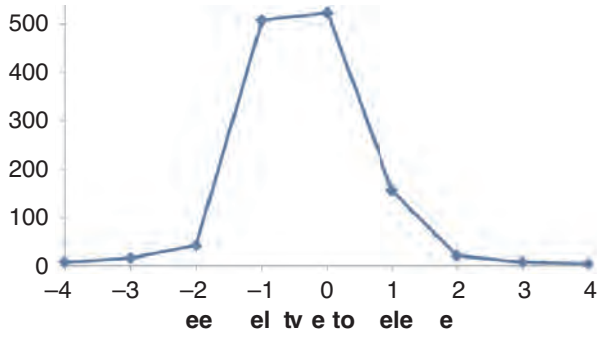
and a majority of media outlets that regularly provide movie reviews (Vogel 2001). Note that TPRs are usually published by two types of media outlets: general media, which provide a wide range of news and information and specialized media, which focus on a particular industry. For example, TPRs of automobiles appear in both general media outlets such as the *Wall Street Journal* and specialized media outlets such as *Car and Driver*. Reflecting this general phenomenon, the 14 media outlets in our data include both general and specialized media. The general media outlets include nine major U.S. newspapers (ranked in order of circulation): *USA Today*, *The Wall Street Journal*, *The New York Times*, *Los Angeles Times*, *The Onion*, *New York Daily News*, *Washington Post*, *New York Post*, and *Chicago Sun Times*. The specialized media include five major entertainment publications: *Entertainment Weekly*, *Rolling Stone*, *Premiere*, *Hollywood Reporter*, and *Variety*. These media are regularly reported on Metacritic and Yahoo! Movies for their reviews and mostly rank among the highest in circulation.⁴

Event Study

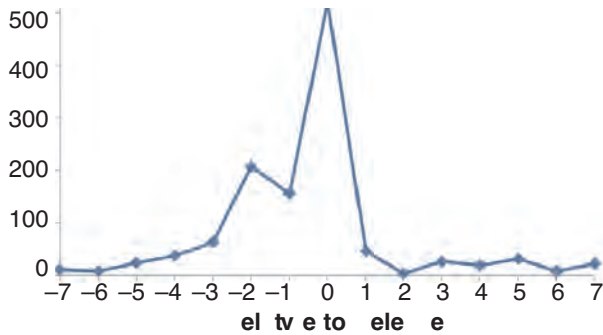
We employed an event study in this research (for excellent examples of event studies in marketing, see Elberse 2007; Joshi and Hanssens 2009; and Tellis and Johnson 2007). By quantifying ARs on the event date when a review is published, we can examine the impact of TPRs on firm value. MacKinlay (1997) and McWilliams and Siegel (1997) review the key features of event study and its applications to economics, finance, and management. Elberse (2007), Einav and Ravid (2009), and Joshi and Hanssens (2009) are recent event studies conducted in the movie context.

A major challenge to event studies is establishing a window that covers the event of interest but is free of confounding events that could prevent the unambiguous attribution of excessive stock returns to the focal event. As McWilliams and Siegel (1997) suggest, a narrow event window makes it easier to control for confounding effects.⁵

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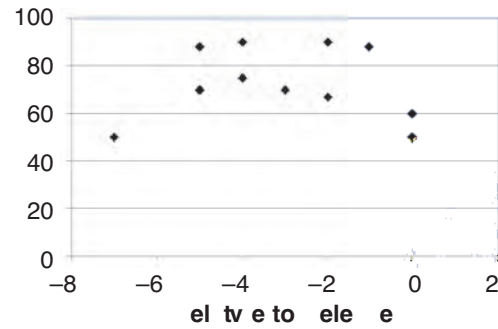


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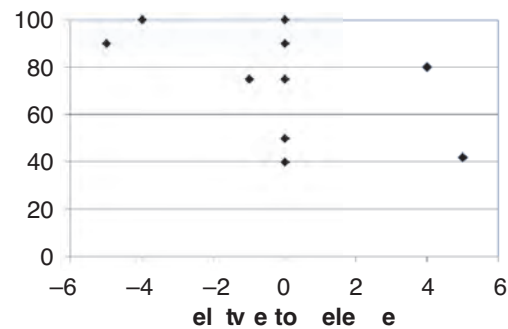


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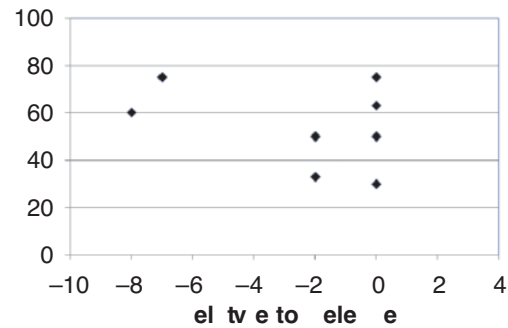
Star Wars: Episode III—Revenge of the Sith



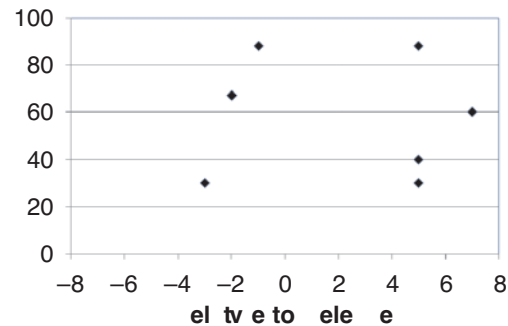
George A. Romero's Land of the Dead



An Unfinished Life



Melinda and Melinda



mate normal returns with the commonly used market model:

$$(1) \quad R_{S_i,t} = \alpha + \beta R_{mt} + \epsilon_{it},$$

where subscript S_i indicates the stock of review event i and $R_{S_i,t}$ and R_{mt} are the returns of stock S_i and the standard market portfolio m on day t . Following the literature, we estimate parameters α and β in the period of approximately 250 trading days before day 0—that is, an estimation window of $t = (-250, -6)$. We use a frequently employed stock market portfolio, the CRSP Equal Weighted Index, for market return.⁷ We then obtain AR for i by subtracting the calculated expected return from the actual return on day 0:

$$(2) \quad \text{AR}_i = R_{S_i,t} - E(R_{S_i,t}) = R_{S_i,t} - \hat{\alpha} - \hat{\beta}R_{m0}.$$

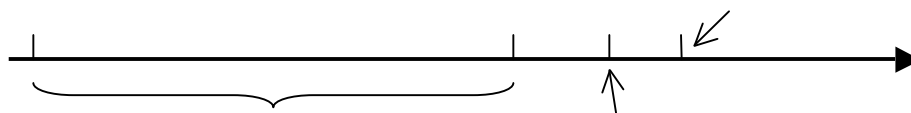
To examine the impacts of TPRs on firm value and how advertising may play a role, we conduct cross-sectional regressions of ARs on TPR valence, other variables of interests, and control variables (Kothari and Warner 2007; MacKinlay 1997; McWilliams and Siegel 1997):

$$(3) \quad \text{AR}_i = \alpha_0 + \alpha_1 \text{VAL}_i + \alpha_2 \text{ADV}_i + \alpha_3 \text{VAL}_i \times \text{ADV}_i + \alpha_4 X_i + \epsilon_i,$$

where VAL denotes the valence of a particular TPR. Depending on specific estimations, VAL is measured by either absolute valence (i.e., the metascore itself) or relative

⁷Other stock market portfolios (e.g., the CRSP value-weighted index, the S&P 500 index) yield similar results.

Notes: The dots indicate the value and the time of occurrence of critical reviews.



valence (i.e., the difference between the metacore of a review and the average score of all previous reviews), and ADV is the cumulative advertising support for the movie before the review event. Following Joshi and Hanssens (2009), ADV measures advertising spending per opening screen to capture the advertising support relative to distribution intensity.

The term X_i includes additional variables that may influence stock market reactions, BUDGET is the movie production budget, and COFINANCE indicates whether a movie is cofinanced by different companies (Joshi and Hanssens 2009). For example, Viacom and Sony cofinanced the movie *The Longest Yard*. To identify cofinanced movies, we follow the approach of Palia, Ravid, and Reisel (2008) to use the LexisNexis academic database and, for each movie, search with keywords that include the movie title; the studio name; and the words “cofinance,” “cofund,” “coproduce,” “coinvest,” or variations of these words. Similarly, CODISTRIBUTE indicates whether a movie is codistributed by different companies. In addition, we include movie characteristics such as movie genre, MPAA

rating, and whether it is a sequel. Finally, following Radas and Shugan (1998), we include whether a movie is released in a peak season to control for seasonality and the degree of competition. Table 3 lists the description and sources of these variables.

Analysis and Results

Among the 485 prerelease review events, 424 have earlier reviews that can be used to construct the relative valence measure. The other 61 are the earliest of all reviews that were published for the particular movies. They can only be used in an analysis of absolute valence. Before turning to the full cross-sectional analyses to estimate how TPRs could influence ARs and how such influence is moderated by advertising, we conducted several statistical tests on ARs of different review events (MacKinlay 1997). These can be used to examine H_1 , the most important proposition regarding TPR valence, and H_3 .

Recall that the absolute valence of each review can be unfavorable, favorable, or mixed. Relative valence can be categorized into similar types: relatively negative, relatively

e r p t o o V r b l e e l

V r b l e	e r p t o	S o r e
VAL	Valence of the TPR. Depending on specific estimations, this is either the absolute valence or relative valence. The exact measure is indicated in each estimation.	Metacritic.com, Yahoo! Movies, Crix' Picks in <i>Variety</i>
ADV	Prereview cumulative advertising expenditure divided by the number of opening screens	TNS Media Intelligence (advertising expenditure), The-numbers.com (opening screens)
BUDGET	Movie production budget	The-numbers.com, IMDb.com
COFINANCE	Whether a movie is cofinanced by different companies	LexisNexis
CODISTRIBUTE	Whether a movie is codistributed by different companies	The-numbers.com, IMDb.com
MPAA dummies	Dummies for MPAA Ratings (e.g., G, PG, R)	The-numbers.com, IMDb.com
Genre dummies	Dummies for movie genre types (e.g., action, comedy, drama)	The-numbers.com, IMDb.com
SEQUEL	Whether a movie is a sequel	The-numbers.com, IMDb.com
PEAKSEASON	Whether a movie is released in a peak season	Radas and Shugan (1998)
NUMREVIEWS	Number of reviews in an event day	Metacritic.com
STDREVIEWS	Standard deviation of reviews in an event day	Metacritic.com
NUM_PREVIOUS	Number of earlier reviews before a review event	Metacritic.com
NUM_POS	Number of positive reviews in an event day	Metacritic.com
NUM_NEU	Number of neutral reviews in an event day	Metacritic.com
NUM_NEG	Number of negative reviews in an event day	Metacritic.com

positive, or relatively neutral. A review is relatively negative (positive) if its review score is lower (higher) than the average score of all earlier reviews. Otherwise, it is relatively neutral.

Table 4, Panel A, presents the results for prerelease movie reviews. On the review event day, the AR is $-.24\%$ when relatively negative reviews occur ($p < .01$) and $.12\%$ when relatively positive reviews occur ($p < .1$). The magnitudes of these effects are broadly comparable to the effects of star announcement (Elberse 2007) and movie opening date changes (Einav and Ravid 2009). Relatively negative TPRs seem to have a greater impact than relatively positive TPRs. This is consistent with the negativity effect Basuroy, Chatterjee, and Ravid (2003) report on movie sales and the notion that firm value can be particularly sensitive to negative news (e.g., Einav and Ravid 2009). The difference in ARs between negative and positive reviews is significant under both the two-sample t-test and the nonparametric Wilcoxon test. The ARs are not significantly different from zero when relative neutral TPRs are published ($p > .96$). Furthermore, when absolute valence is used to measure reviews, the ARs are nonsignificant for either favorable reviews ($p > .90$) or unfavorable reviews ($p > .45$). Table 4, Panel B, presents the results for postrelease reviews. These reviews do not cause significant ARs, regardless of whether they are measured in absolute or relative valence. This holds for all the valence categories (i.e., positive, neutral, or negative) and all tests (i.e., within-category test, two-sample t-test, and the nonparametric Wilcoxon test). Together, these

results provide support for H_1 and H_3 . That is, relative valence of TPRs influences firm value, but absolute valence does not, and the influence is greater during the prerelease period than the postrelease period.

To test if there is information leakage before review publication and if there is systematic delayed review effects, we further examine the magnitude of ARs on adjacent days surrounding the event (day -2 , -1 , $+1$, and $+2$). To eliminate confounding when the ARs on these days are considered, we follow the steps discussed previously to identify and screen out events for which other corporate news occurred. Moreover, to avoid potential contamination by postrelease box office sales information, we include only prerelease reviews that are published one or two days earlier than movie release when calculating ARs for days $+1$ and $+2$. As Table 5 shows, the impact of TPRs is nonsignificant for these days, suggesting there is little information leakage before review publication or systematic delayed review effect, at least for the two-day period surrounding the event day. The potential impact of newly published reviews is the most significant on the event day.

Valence and advertising effects. We now proceed to the cross-sectional analysis with control variables. Table 6 presents the results of prerelease TPRs when relative valence is used to measure valence. The base model includes relative valence, prereview advertising, and their interactions. The full model includes all additional variables from Equation 3, controlling for the effects of various product and market

Impact on Return to Equity					
Prerelease					
Valence Measure	Percentage	Number of Reviews	Change in Return (%)	Two-Sample t-Test	
				Relative	Absolute
Relative valence	Negative	198	$-.24^{***}$	-3.22^{***}	-2.51^{**}
	Positive	214	$.12^*$		
	Neutral	12	$-.02$		
Absolute valence	Negative	37	$-.20$	$-.81$	$-.58$
	Positive	247	$-.03$		
	Neutral	140	$-.06$		
Postrelease					
Valence Measure	Percentage	Number of Reviews	Change in Return (%)	Two-Sample t-Test	
				Relative	Absolute
Relative valence	Negative	63	$.01$	$.34$	$-.24$
	Positive	56	$-.06$		
	Neutral	1	$-.53$		
Absolute valence	Negative	33	$.18$	1.39	1.26
	Positive	41	$-.20$		
	Neutral	46	$-.02$		

* $p < .10$.
 ** $p < .05$.
 *** $p < .01$.

Form I et r	o te t rerele e	So lter tve	S rro	t e v e t
lter tve	ve t, l e ll e bl e o r e o r e	e tve e (%)	o tve e (%)	et ee - te or ere e (t-St t t
Day -2	Release day	.03	-.09	.94
Day -1	Release day	.09	-.08	1.42
Day 0 (review/event date)	Release day	-.24**	.12*	-3.22**
Day +1	Release day-1	-.14	-.02	-.85
Day +2	Release day-2	.02	.02	-.02

* $p < .10$.** $p < .01$.

V r ble	el tve V le e		empor ll o te el tve V le e	
	el tve V le e		l v er el e te	po e t ll e te
	e o el	ll o el		
Intercept	-5.955 (5.447)	10.236 (14.735)	9.860 (14.770)	9.252 (14.789)
VAL (α_1)	.820 (.380)*	.982 (.414)*	.829 (.392)*	.778 (.381)*
ADV (α_2)	36.624 (12.239)**	30.663 (14.167)*	33.867 (13.928)*	34.257 (13.932)*
ADV \times VAL (α_3)	.609 (.569)	.698 (.709)	.375 (.675)	.292 (.684)
BUDGET		-.211 (.191)	-.227 (.192)	-.237 (.192)
BUDGET \times VAL		.008 (.013)	.008 (.013)	.006 (.012)
COFINANCE		-11.984 (19.977)	-10.946 (20.106)	-11.510 (20.143)
COFINANCE \times VAL		-2.146 (1.452)	-1.811 (1.382)	-1.226 (1.302)
CODISTRIBUTE		12.290 (42.467)	11.508 (42.552)	10.955 (42.872)
CODISTRIBUTE \times VAL		-.656 (2.548)	-.215 (2.667)	-.007 (2.779)
MPAA-G		10.828 (26.998)	12.087 (27.035)	12.351 (27.046)
MPAA-PG		-.133 (16.006)	.312 (16.039)	.529 (16.052)
MPAA-R		19.889 (13.542)	19.544 (13.537)	19.836 (13.552)
ACTION		-3.811 (14.684)	-3.023 (14.725)	-2.818 (14.747)
COMEDY		-12.211 (12.330)	-11.660 (12.357)	-11.220 (12.373)
DRAMA		-17.871 (12.978)	-18.046 (12.993)	-17.884 (12.984)
SEQUEL		11.023 (19.257)	10.040 (19.200)	9.505 (19.128)
PEAKSEASON		-24.771 (11.722)*	-24.694 (11.765)*	-24.503 (11.795)*
N	423	423	423	423
R ²	.043	.078	.073	.072
Model selection	MSE	.25	1.26	1.26
	AIC	2.0	114.07	114.88
	BIC	5.0	117.67	118.48

* $p < .05$.** $p < .01$.

Notes: Dependent variable is AR in percentage. Standard errors are in parentheses. To enhance readability, we multiplied all regression coefficients by 100. The values of R² are comparable to the cross-sectional regression models on ARs in the literature (e.g., Asquith and Mullins 1986; Chaney, Devinney, and Winer 1991; Holthausen and Leftwich 1986). The best performing model for each criterion is in boldface.

characteristics. We mean-centered the variables to reduce potential multicollinearity. We further check the variance inflation factors to ensure multicollinearity does not occur.

As Table 6 shows, the relative valence of TPR has a significant, positive impact on abnormal returns in both the base model and the full model. A positive (negative) difference between the focal review and the earlier reviews has a positive (negative) impact. Thus, as we proposed, the relative newness of a TPR beyond earlier reviews determines how it would influence the investors and firm financial value. These support the relative valence hypotheses (H_{1a} and H_{1b}).

Another significant effect shown in both models is the positive effect of prereview advertising expenditure (ADV). However, the interaction between ADV and VAL fails to be significant. These findings support H_{2a}, which we predicted on the basis of both the persuasive and awareness roles of advertising but not H_{2b}, which we predicted on the basis of the awareness role of advertising.

Therefore, in addition to the impact of a TPR's relative valence, firm value will be more positively affected in a review event if the firm has spent more on advertising before the review. Such enhancement exists regardless of whether the review is more positive or negative than earlier reviews. This result has important implications for how

firms could employ marketing strategies to manage the impact of TPRs. That is, they can use advertising proactively to add a positive buffer between TPRs and firm value when the reviews are published.

Note that we measure a TPR's relative valence with the difference between the review score and the average score of all earlier reviews. This is perhaps the simplest measure of relative valence. A more complex measure would be to consider the potential diminishing impact of TPRs over time. For example, the cognitive science literature on memory and information retrieval indicates that the strength of information decays as time passes (Hutchinson and Moore 1984; Sawyer and Ward 1979).

To examine whether such temporal discounting exists and how our results may be influenced, we construct two modified measures of relative valence. The first is an inverse function approach. For a focal review with a score r_0 at time t_0 , if there are n previous reviews with scores r_1, r_2, \dots, r_n at time t_1, t_2, \dots, t_n , a time-weighted average of previous reviews is computed as $\sum_{i=1}^n [(t_0 - t_i)^{-1} / \sum_{i=1}^n (t_0 - t_i)^{-1}] r_i$. The second formulation assumes exponential decay so that the time-weighted average of earlier reviews is computed as $\sum_{i=1}^n [e^{-(t_0 - t_i)} / \sum_{i=1}^n e^{-(t_0 - t_i)}] r_i$.

The last two columns of Table 6 present estimation using these temporally discounted valence measures. The results demonstrate remarkable consistency: Both relative valence and the main effect of advertising are significant, and the parameter estimates remain similar. However, compared with the original relative valence measure, the time-discounted models have lower model fit in terms of R-square. Model selection tests using mean square error (MSE), Akaike information criterion (AIC), and Bayesian information criterion (BIC) all indicate that the original relative valence we propose is the best measure. These results suggest that investors do not seem to discount earlier reviews too much when comparing them with a current review. A possible reason is that investors can access all previous TPRs from portal websites such as Metacritic.com, and thus memory retrieval is less an issue.

How does the absolute valence of TPRs affect firm value? Table 7 presents both the base and full models, showing that absolute valence fails to have a significant impact, in support of H_{1c} . Together with the results in Table 6, these findings show that the opinion of a TPR per se is not what drives the impact of the review. This is consistent with both the efficient market hypothesis and the behavioral literature discussed previously; moreover, it highlights the importance of the incremental difference between a review and the reviews published earlier.

Dynamics of the TPR effects. We now turn to H_3 , H_4 , and H_5 . Table 8 presents the full models including relative valence, advertising, the interaction between valence and advertising, and all other variables. First, different from the significant impact of prerelease TPRs on firm value, the impact of postrelease TPRs is nonsignificant, in support of H_3 . Second, regarding the effects of TPRs published exactly on the product release date versus those published before that, the results in the last three columns of Table 8 support H_4 . That is, the effect of TPRs is stronger on the product

7				
	e o el		ll o el	
	Intercept	-6.341	(5.132)	4.301
VAL (α_1)	.118	(.292)	.058	(.325)
ADV (α_2)	16.063	(18.395)	8.009	(19.322)
ADV \times VAL (α_3)	1.397	(.813)*	1.270	(.920)
BUDGET	-.272	(.190)		
BUDGET \times VAL	.009	(.009)		
COFINANCE	-7.235	(19.603)		
COFINANCE \times VAL	-.246	(1.114)		
CODISTRIBUTE	18.921	(37.740)		
CODISTRIBUTE \times VAL			.723	(2.505)
MPAA-G			18.326	(25.134)
MPAA-PG			-5.556	(14.821)
MPAA-R			22.483	(12.800)*
ACTION			6.891	(13.748)
COMEDY			-13.310	(11.639)
DRAMA			-10.172	(12.103)
SEQUEL			4.385	(16.961)
PEAKSEASON			-28.548	(11.033)**
N		484		484
R ²		.031		.068

* $p < .10$.

** $p < .05$.

Notes: Dependent variable is AR in percentage. VAL is relative valence of TPRs. Standard errors are in parentheses. To enhance readability, we multiplied all regression coefficients by 100.

release date than that of the TPRs published earlier, in terms of both significance level and magnitude. Given that the reviews are published by a wide variety of the 14 media outlets both before the release date and on that date, the results can be attributed to the timing of the reviews and not to any particular media. Third, in support of H_5 , the advertising effect is stronger before the product release date than on that date, when the effect actually becomes nonsignificant.⁸

Alternative measures for the relative valence of TPRs. It could be argued that, rather than previous reviews of the same product, there could be other information bases on which a relative valence measure can be constructed. First, investors might notice how a particular TPR differs from the previous TPRs provided by the same professional reviewer and use this difference to form or update their expectations. In this case, a negative TPR from a critic who is usually positive would indicate a particularly bad product. Second, investors may contrast a particular TPR with the previous TPRs provided by the same media outlet. This is similar in principle to the case of comparing with previous TPRs from the same critic but would be more likely to occur if TPR readers associate the review more closely with the media than with the critic. Third, the relative difference

⁸Because of multicollinearity, we were forced to drop the interaction term ADV \times VAL in Model 2. This should not influence the inference on other variables given that this interaction is never significant in other full models. Moreover, we estimated a comparable model (Model 4) to more directly compare parameter estimates between TPRs on product release date and before that date. For more details, see the notes of Table 8.

m o t e₁ m p t o r - r t α e α e

	o e l (o t r e l e e α e	o e l 2 (α e o t e e l e e t e	o e l (α e e o r e t e e l e e t e	o e l (α e e o r e e l e e t e b t r o p p o ₁ t e r t o
Intercept	-11.835 (24.955)	3.752 (26.815)	9.863 (17.584)	10.053 (17.505)
VAL (α ₁)	-.119 (.743)	2.395 (.985)**	.831 (.479)*	.825 (.469)*
ADV (α ₂)	-4.371 (15.318)	21.958 (19.903)	41.708 (21.572)*	43.752 (17.636)**
ADV × VAL (α ₃)	-.125 (1.080)	—	.222 (.937)	—
BUDGET	-.009 (.493)	.325 (.365)	-.332 (.226)	-.335 (.225)
BUDGET × VAL	-.016 (.040)	.042 (.040)	.010 (.015)	.010 (.015)
COFINANCE	5.482 (48.223)	-19.961 (42.483)	-14.142 (22.907)	-14.162 (22.833)
COFINANCE × VAL	-8.639 (3.687)**	-3.752 (3.026)	-1.725 (1.728)	-1.714 (1.721)
CODISTRIBUTE	-8.900 (65.465)	-27.621 (55.714)	24.272 (53.150)	24.076 (52.439)
CODISTRIBUTE × VAL	1.921 (4.022)	—	-.461 (2.840)	—
MPAA-G	3.452 (77.286)	34.589 (47.055)	5.148 (32.306)	5.057 (32.203)
MPAA-PG	22.017 (43.810)	-6.614 (29.836)	1.264 (18.967)	1.200 (18.896)
MPAA-R	29.699 (24.007)	36.616 (22.954)	12.631 (16.378)	12.188 (16.195)
ACTION	69.376 (28.586)**	-.052 (25.402)	-4.383 (17.816)	-4.206 (17.745)
COMEDY	-18.441 (21.582)	4.212 (22.437)	-13.668 (14.695)	-13.756 (14.643)
DRAMA	-13.877 (25.104)	-30.762 (21.984)	-12.932 (15.936)	-12.916 (15.824)
SEQUEL	45.462 (30.009)	-46.536 (33.682)	31.741 (23.402)	31.797 (23.326)
PEAKSEASON	-41.532 (24.043)*	-.083 (21.605)	-28.953 (13.930)**	-29.036 (13.882)**
N	119	96	327	327
R ²	.226	.176	.090	.089

*p < .10.

**p < .05.

Notes: Dependent variable is AR in percentage. VAL is relative valence of TPRs. Standard errors are in parentheses. To enhance readability, we multiplied all regression coefficients by 100. Model 2 drops two interaction terms due to multicollinearity. Model 4 uses the same data as Model 3 but drops the two interaction terms not included in Model 2. It is estimated to compare parameter estimates between TPRs on product release date and before that date with the same model specification.

may also be constructed as how a particular review of the product differs from reviews of competing products. A review that is relatively positive compared with those of competing products may have a positive effect on the financial value of the firm introducing this product.

To examine whether investors respond to this relative information and whether their response is stronger than to the relative valence we proposed previously, we constructed three alternative relative valence measures and estimated their impact on abnormal stock returns. As Table 9 shows, these measures (based on critic's review history, media history, and reviews of competing products) do not have a significant effect on firm value. Model selections based on MSE, AIC, and BIC all point to the relative measure proposed in the current research—that is, the relative difference

between a TPR and previous TPRs of the same product—the most impactful.

Additional information of TPRs. Our analysis thus far has focused on the valence of TPRs. Although this is a key attribute of reviews, there are other characteristics of TPRs that may serve as heuristics to influence investor behavior. We now measure these characteristics and examine whether investors are influenced by them. Doing so also helps examine the robustness of our main findings.

First, while valence reveals useful information about product quality and sales potential, the sheer number of reviews may also be useful. A product reviewed by more critics could simply be more popular than those that receive less critical attention. Similarly, at any given level of critical rating or review valence, a higher level of variance in the

o m p r o o t e₁ m p t o l t e r t v e e r e o e l t v e V l e e

	v e r e o r e o o t e S m e r o t	v e r e r o m t e S m e r t	v e r e r e b t e S m e e	v e r e o m p e t r o t
Effect on firm value (α ₁)	.2 (.090)	.090 (.370)	.171 (.354)	.408 (.316)
MSE	.250	1.271	1.268	1.267
AIC	05.	111.7	110.8	110.6
BIC	0 .	115.4	114.6	114.3

*p < .05.

Notes: The models in boldface are the best performing for each criterion. We estimated the four relative valence measures with the full model identical to Equation 3 and Table 4. To enhance readability, we multiplied all regression coefficients by 100.

reviews suggests that the professional critics agree less with each other. We thus incorporate the number of TPRs (NUM-REVIEWS) and their standard deviation (STDREVIEWS) on each review event into the main model with relative valence (Table 10, Model 1).

Second, because we constructed relative valence using reviews published earlier, it is useful to determine whether the number of these earlier reviews matters. For a given level of average valence, a larger number of earlier reviews may have attracted more investor attention and makes the deviation from it less impactful (i.e., a stronger anchor). Model 2 in Table 10 estimates the effects of the number of earlier reviews (NUM_PREVIOUS).

Third, investors could consider the absolute valence of a TPR (VAL_ABSOLUTE), together with its relative valence in forming expectations. Empirically, because we have shown that absolute valence itself does not have a significant impact on firm value, it is useful to examine whether the significance of relative valence and the insignificance of absolute valence would change when they are included together (Table 10, Model 3).

Finally, instead of relying on valences (either relative or absolute valence), investors could simply utilize the numbers of positive, negative, and neutral reviews as the heuristic to form expectations. Note that such a heuristic is essentially a mix of volume and valence of TPRs. As Liu (2006) suggests, using these measures does not clearly separate the valence effect from the volume effect and may produce spurious results when the numbers of different types of messages are correlated. To estimate the effects of these hybrid TPR measures, we include them (NUM_POS, NUM_NEU, and NUM_NEG) in Model 4 of Table 10.

Table 10 shows the following results. First and most important, the effect of relative valence of TPRs remains significantly positive. The main effect of advertising expenditure remains significantly positive too, and the interaction between advertising and TPR valence is always nonsignifi-

cant. These highly robust results confirm our findings regarding TPR valence and advertising strategies reported earlier. Moreover, the information about TPR volume and variance does not have significant effects beyond the relative valence of TPRs (NUMREVIEWS and STDREVIEWS, Model 1). Similar results hold for the number of previous reviews (NUM_PREVIOUS, Model 2) and directly using the numbers of reviews in different categories (NUM_POS, NUM_NEU and NUM_NEG, Model 4). Finally, the absolute valence of TPRs (VAL_ABSOLUTE) is nonsignificant, while relative valence (VAL) remains highly significant when they are included together. This confirms our key proposition that what influences investor expectations is mainly the new information conveyed through incremental differences in TPRs. In Web Appendixes W2 and W3 (www.marketingpower.com/jmr_webappendix), we further show the robustness of our findings to three additional factors (consumer WOM, firm, and media effects) and that absolute valence is more predictable and thus less likely to produce unexpectedness than relative valence.

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Both the amount and accessibility of TPRs has grown rapidly in recent years. Firms have begun to use these reviews in a broad range of managerial activities. For example, in the video game industry, developers such as Electronic Arts, Insomniac Games, and Frontier use professional reviews provided on Metacritic.com to fund and design new products, perform sales forecasting, and develop business strategies (e.g., Banerjee 2006). Our findings provide several specific managerial implications with regard to TPR, firm value, and marketing actions.

First, for the purpose of creating shareholder value, firms should pay attention to TPRs and actively track and utilize them to aid product development and introduction. Marketing actions are increasingly being evaluated for

	to I, orm to o			
	o el	o el 2	o el	o el
Intercept	10.346 (14.763)	10.939 (14.764)	9.943 (14.728)	13.157 (16.926)
VAL	.998 (.418)*	1.037 (.418)*	1.331 (.502)**	
NUMREVIEWS	3.117 (3.609)			
STDREVIEWS	-.673 (1.057)			
VAL_ABSOLUTE			-.493 (.404)	
NUM_PREVIOUS		1.143 (1.483)		
NUM_PREVIOUS × VAL		.090 (.088)		
NUM_POS				3.001 (3.643)
NUM_NEU				.681 (5.553)
NUM_NEG				-2.695 (6.034)
ADV	30.357 (14.206)*	31.222 (14.199)*	32.295 (14.222)*	30.093 (13.380)*
ADV × VAL	.714 (.710)	.719 (.710)	.683 (.708)	
N	423	423	423	484
R ²	.080	.081	.081	.063

* $p < .10$.

** $p < .05$.

Notes: Dependent variable is AR in percentage. VAL is the relative valence of TPRs. Standard errors are in parentheses. To enhance readability, we multiplied all regression coefficients by 100. We included covariates (BUDGET, BUDGET × VAL, COFINANCE, COFINANCE × VAL, CODISTRIBUTE, CODISTRIBUTE × VAL, MPAA-G, MPAA-PG, MPAA-R, ACTION, COMEDY, DRAMA, SEQUEL, and PEAK-SEASON) in all models. Their estimation is similar to those of Table 6, and we do not report them due to space considerations.

financial returns and contributions to firm value. Srinivasan and Hanssens (2009) emphasize the importance of the investors in the design and execution of marketing plans. This study demonstrates that TPRs, as a unique quality signal, constitute an impactful factor embedded in the linkage between marketing strategies and firm value. In developing and introducing new products, the opinions of professional critics should not be overlooked.

Second, managers should understand that, despite the ongoing controversy about the relevance of professional critics in the age of consumer-generated content, the community of critics remains an important factor in the marketplace. Whereas prior research has focused primarily on the effect of TPRs on consumers and sales, we demonstrate the value of critics from a different perspective: Professional critics and their reviews possess the ability to affect investors and the stock market.

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