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Anita Elberse
Bharat Anand

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Anita Elberse

Assistant Professor
Harvard Business School
Soldiers Field
Boston, MA 02163, USA
Phone: 617 495 6080
Fax: 617 496 5853
Email: aelberse@hbs.edu

(Corresponding Author)

Bharat Anand

Professor
Harvard Business School
Soldiers Field
Boston, MA 02163, USA
Phone: 617 495 5082
Fax: 617 496 5859
Email: banand@hbs.edu

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Abstract

What is the effect of pre-release advertising on the demand for a product? And does the magnitude of that effect vary according to the quality of the good? We empirically examine these questions in the context of the motion picture industry. We make use of a unique, proprietary data set that covers weekly television advertising expenditures, weekly expectations of the market performance, and quality measures for a sample of nearly 300 movies. The focus on expectations creates a valuable advantage: our measure of expectations, which is derived from a stock market simulation, is an accurate predictor of sales; however, while sales data are only available after the product launch, we can observe the dynamic nature of expectations before the release, and relate those to dynamics in the advertising allocation process. We find that advertising affects the updating of market-wide expectations prior to release, and that this effect is stronger the higher the product quality. The latter suggests that advertising plays an informative—and not simply a persuasive—role.

Keywords: marketing, effect of advertising, role of advertising, expectations, econometric modeling, motion picture industry

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Companies often spend hefty sums on advertising for new products prior to their launch. That is particularly true for products in creative industries such as motion pictures, music, books, and video games (Caves 2001), where the lion's share of advertising spending typically occurs in the pre-launch period. Consider the case of motion pictures. Across the nearly 200 movies released by major studios in 2005, average advertising expenditures amounted to over $36 million, while average production costs totaled about $60 million (MPAA 2006). On average, about 90% of advertising dollars were spent before the release date. In addition, fueled by an intense competition for audience attention, studios have significantly increased advertising expenditures: average advertising spending per movie jumped about 50% between 1999 and 2005. Of this, television advertising represented the largest cost—accounting for 36% of total advertising expenditures for new releases in 2005. As a result, film executives are under pressure to address the soaring costs of advertising, particularly television advertising. Universal Pictures Vice Chairman Marc Schmuger commented "It is a little startling to see spending skyrocket across the board. Clearly the industry cannot sustain a trend that continues in that direction" (Variety 2004).

This paper aims to provide insights into this debate by focusing on two related questions: What is the effect of pre-release advertising on the demand for motion pictures? And does the magnitude of that effect vary according to the intrinsic quality of the product? As such, our effort addresses two important – ongoing – debates in the literature on the impact of advertising. The first concerns the question of *whether* advertising works; the second the informative versus persuasive effect of advertising that addresses the question of *how* it works.

Instead of examining the impact of advertising on sales, we examine how advertising affects the updating of sales *expectations* in the pre-release period. Our measure of sales expectations is derived from a popular online stock market simulation, the Hollywood Stock Exchange (HSX), which allows players to bet on the box-office performance of motion pictures. The measure of expectations creates a valuable advantage. As empirical examinations reveal, market-wide expectations are an accurate predictor of sales. However, while sales data are only available after the product launch, we can observe the dynamic nature of expectations before the release, and relate those to dynamics in the advertising allocation process.

Incidentally, in exploiting the idea that market simulations can aggregate information that traders privately hold, we follow the growing number of researchers who have turned to such simulations to gauge market-wide expectations or identify 'winning concepts' in the eyes of consumers (e.g. Chan, Dahan, Lo and Poggio 2001; Dahan and Hauser 2001; Forsythe, Nelson, Neumann and Wright 1992; Forsythe, Rietz and Ross 1999; Gruca 2000; Hanson 1999; Spann and Skiera 2003; Wolfers and Zitzewitz 2004, also see Surowiecki 2004).[1]

We use data on weekly pre-release expectations for a sample of 280 movies that were widely released from 2001 to 2003, and obtain data on weekly pre-release television advertising expenditures for that same set of movies from Competitive Media Reporting (CMR). We estimate a partial-adjustment hierarchical linear model to examine the relationship between advertising and market-wide expectations, and test whether advertising significantly impacts the updating of expectations.

Research on the relationship between advertising and sales is typically handicapped by the simultaneous nature of that relationship: advertising not only affects sales, but also (at least partly) depends on sales (Berndt 1991). The joint endogeneity of advertising and sales has long been recognized (e.g., Quandt 1964, Schmalensee 1972, Bass and Parsons 1969, Berndt 1991, and

Bagwell 2003).[2] The problem also impacts existing research on advertising's impact on motion picture box-office receipts. For example, Prag and Casavant (1994), Zufryden (1996; 2000), Lehmann and Weinberg (2000), Moul (2001), Elberse and Eliashberg (2003), and Basuroy, Desai and Talukdar (2006) all find evidence for a positive relationship between advertising and (weekly or cumulative) revenues. Ainslie, Drèze and Zufryden (2005) recently found a positive relationship between total advertising expenditures and box office revenues. However, as Lehmann and Weinberg (2000) indicate, a key problem with these studies is that the direction of causality remains unclear. It is plausible that movies that are expected to be popular receive more advertising (also see Einav 2006; Krider et al. 2006). To address the endogeneity problem, first, we adopt a first-differenced specification to remove any time-invariant unobserved heterogeneity that affects both advertising and expectations. Second, drawing on insights from interviews with executives about the advertising process, we perform a set of robustness tests to assess the appropriateness of our assumptions concerning time-varying sources of variation in unobserved movie-specific factors.

In addition to examining *whether* advertising works, we explore the nature of its impact—the question of *how* advertising works. On the one hand, conventional wisdom dictates that the larger the amount of the advertising expenditures, the more consumers are persuaded to go see a movie—i.e. that advertising has a *persuasive* effect. On the other hand, it seems reasonable to expect that advertising for a low-quality movie, by revealing information about the quality (indeed, television commercials for movies typically are clips from the movie itself), might turn off consumers who would otherwise have wanted to watch it. In that case, advertising is *informative* about product quality. Anand and Shachar (2004) refer to this possibility as the consumption-deterrence effect of advertising in their study of the effectiveness of previews for television programs; see Ackerberg (2001; 2003), Anand and Shachar (2002; 2004), Byzalov and

Shachar (2004) and Shachar and Anand (1998) for other recent contributions.[3] We examine whether the impact of advertising varies across motion pictures of different quality. This in turn sheds light on the informative versus persuasive nature of advertising.[4] We use two measures of movies' inherent quality or appeal obtained from Variety and Metacritic.

Our conceptual model is summarized in **Figure 1**. It depicts two key hypotheses: (1) pre-release advertising affects the updating of market-wide expectations, and (2) product quality moderates the effect of advertising on market-wide expectations. Hypothesis (1) captures a general effect of advertising, while hypothesis (2) specifies an informative effect of advertising. We find support for both hypotheses: advertising positively impacts the updating of market-wide expectations prior to release, and this effect is more pronounced the higher the product quality. The latter finding suggests that advertising is informative—not simply persuasive. Our model estimates reveal pronounced differences in the returns to advertising for movies with different levels of quality, and imply that studios are likely to benefit from reducing advertising budgets for low-quality movies.

While our data set is unique, our approach of using data on customer expectations to inform marketing strategies can be applied in a broader context, and our findings contribute to the general body of work on the returns to advertising. The majority of existing research on advertising response considers the packaged goods industry, and empirical generalizations in our discipline therefore are largely based on that industry (e.g. see Hanssens, Parsons and Schultz 2001). By focusing on the motion picture industry or, more generally, the media and entertainment sector—where advertising campaigns typically largely take place before the release, are short-lived, and account for a relatively large share of the total marketing expenditures for new products—we help broaden the scope of research on the returns to advertising.

1. DATA AND MEASURES

Our data set consists of 280 movies released from March 1, 2001 to May 31, 2003. This sample is a subset of all 2246 movie stocks listed on the HSX market in this period; we only use movies (a) that are theatrically released within the period, (b) which initially play on 650 screens or more (which classifies them as 'wide releases' for the HSX), (c) for which we have at least 90 days of trading history prior to their release date, and (d) for which we have complete information on box-office performance. **Table 1** provides descriptive statistics for the key continuous variables.

1.1. Advertising

Our advertising measure covers cable, network, spot, and syndication television advertising expenditures as collected by Competitive Media Reporting (CMR). We have access to expenditures at the level of individual commercials, but aggregate those at a weekly level – a common unit of analysis for the motion picture industry. Our data confirm that advertising is a highly significant expenditure for movie studios.[5] For our sample of movies, on average, just over \$11 million was spent on television alone – a share of 56% of the \$20 million allocated across major advertising media (covering television, radio, print and outdoor advertising). Nearly \$10 million (88%) of television advertising was spent prior to the movie's release date. The variance is high: the lowest-spending movie, *The Good Girl*, has a pre-release television budget of just under \$250,000, while the highest-spending movie, *Tears of the Sun*, spent over \$24 million on television advertising. Overall media budgets range from a mere \$3 million to nearly \$64 million.

We note that these figures, although obtained from a different source, are in line with official industry statistics published by the Motion Picture Association of America (MPAA 2004). Judging from those statistics, television, radio, print and outdoor advertising together roughly equal 75% of total advertising expenditures (the remaining 25% cover trailers, online advertising, and non-media advertising, among other things). MPAA reports average advertising expenditures per movie of $27 million over 2001 and 2002; our average of $20 million is roughly 75% of that total as well.

Figure 2 depicts temporal patterns in television advertising expenditures across the sample of movies. It is clear that median weekly advertising expenditures sharply increase in the weeks leading up to release, from just over $100,000 twelve weeks prior to release to $4 million the week prior to release. Of the total of $3.3 billion spent prior to release by the 280 movies in the sample, 99% is spent in the last twelve weeks prior to release. Only 8 movies (3%) advertised more than twelve weeks prior to release.

1.2. Market-Wide Expectations

Our source for data on market-wide expectations, the Hollywood Stock Exchange (HSX, www.hsx.com), is a popular Internet stock market simulation that revolves around movies and movie stars. HSX has over 520,000 active users, a 'core' trader group of about 80,000 accounts, and approximately 19,500 daily unique logins. New HSX traders receive 2 million 'Hollywood dollars' (denoted as "H$2 million") and can increase the value of their portfolio by, among other things, strategically trading 'movie stocks'. The trading population is fairly heterogeneous, but the most active traders tend to be heavy consumers and early adopters of entertainment products, especially films. They can use a wide range of information sources to help them in their decision-making. HSX stock price fluctuations reflect information that traders privately hold (which is only likely for the small group of players who work in the motion picture industry) or information that is in the public domain – including advertising messages. Despite the fact that the simulation does not offer any real monetary incentives, collectively, HSX traders generally produce relatively good forecasts of actual box office returns (e.g. Elberse and Eliashberg 2003, Spann and Skiera 2003; also see Servan-Schreiber et al 2004). According to Pennock et al (2001a; 2001b), who analyzed HSX's efficiency and forecast accuracy, arbitrage opportunities on HSX [6] are quantitatively larger, but qualitatively similar, relative to a real-money market. Moreover, in direct comparisons with expert judges, HSX forecasts perform competitively.

We illustrate the trading process for the movie *Vanilla Sky* – referred to as *VNILA* on the HSX market – in **Figure 3.** HSX stock prices reflect expectations on box office revenues over the first four weeks of a movie's run – a stock price of H$75 corresponds with four-week grosses of $75 million. Trading starts when the movie stock has its official initial public offering (IPO) on the HSX market. This usually happens months, sometimes years, prior to the movie's theatrical release; *VNILA* began trading on July 26, 2000, for H$11. Each trader on the exchange, provided he or she has sufficient funds in his/her portfolio, can own a maximum of 50,000 shares of an individual stock, and buy, sell, short or cover securities at any given moment. Trading usually peaks in the days before and after the movie's release. For example, immediately prior to its opening, over 22 million shares of *VNILA* were traded.

Trading is halted on the day the movie is widely released, to prevent trading with perfect information by traders that have access to box office results before the general public does. Thus, the *halt price* is the latest available expectation of the movie's success prior to its release. *VNILA*'s halt price was H$59.71. Immediately after the opening weekend, movie stock prices are adjusted based on actual box office grosses. Here, a standard multiplier comes into play: for a Friday opening, the opening box office gross (in $ millions) is multiplied with 2.9 to compute the *adjust price* (the underlying assumption is that, on average, this leads to four-week totals). *VNILA*'s opening weekend box office was approximately $25M; its 'adjust' price therefore was 25*2.9=H$72.50. Once the price is adjusted, trading resumes (as the four-week box office total is still not known at this time). Stocks for widely released movies are delisted four weekends into their theatrical run, at which time their *delist price* is calculated. When *VNILA* delisted on January 7, 2002, the movie had collected $81.1 million in box office revenues, therefore its delist price was H$81.1.

Figure 4, which depicts temporal trading patterns on the HSX market, demonstrates that the average number of accounts trading rises in the months and weeks leading up to movies' release dates (as was also the case for *VNILA* in **Figure 3**). The average closing price across all movies trends upwards only slightly, and settles on an average price of nearly H$49 in the week prior to release. **Figure 5** plots the relationship between HSX halt and adjust prices. The correlation is strong, with a Pearson coefficient of 0.94, and mean and median absolute prediction errors of 0.34 and 0.23, respectively. Data for our sample of movies thus confirm that our measure of market-wide expectations is a good predictor of actual sales—a critical observation in light of our modeling approach.

1.3. Quality

We distinguish two different dimensions of a movie's "quality" or appeal, namely its critical acclaim (measured by critical reviews) and its popular appeal (measured by total theatrical box office revenues). Our reason for employing two quality measures reflects the idea that the perfect measure of quality does not exist, and more generally that assessing the "objective quality" of an experience product like movies is extremely difficult, even after the product's market release. Our first measure has the disadvantage that critics' views do not necessarily reflect the quality perceptions of the general public. Our second measure has the shortcoming that commercial performance depends on factors related to the release strategy (including, importantly, the advertising strategy) and competitive environment. Realized sales therefore are not necessarily on par with a movie's inherent appeal. Nevertheless, we believe that each measure represents a relevant dimension of quality.

Critical Acclaim. Data obtained from *Metacritic* (www.metacritic.com) form the basis for our critical acclaim measure. Metacritic assigns each movie a "metascore," which is a weighted average of scores assigned by individual critics working for nearly 50 publications, including all major U.S. newspapers, Entertainment Weekly, The Hollywood Reporter, Newsweek, Rolling Stone, Time, TV Guide, and Variety. Scores are collected and, where needed, coded by Metacritic. The resulting "metascores" range from 0-100, with higher scores indicating better overall reviews. Weights are based on the overall stature and quality of film critics and publications.

A range of studies have examined the relationship between critical acclaim and commercial performance, and most of those studies have found evidence for a positive relationship between reviewers' assessments of a movie and its (cumulative or weekly) box office success while controlling for other possible determinants of that success (e.g. Elberse and Eliashberg 2003, Jedidi et al. 1998, Litman 1982, Litman and Kohl 1989, Litman and Ahn 1998, Prag and Casavant 1994, Ravid 1999, Sawhney and Eliashberg 1996, Sochay 1994, and Zufryden 2000). In a study focused entirely on the relationship, Eliashberg and Shugan (1997) demonstrated that critical reviews correlate with late and cumulative box office receipts but do not have a significant correlation with early box-office receipts. Our use of critics' reviews as an indication of a movie's inherent "quality" or enduring appeal as opposed to its opening-week "marketability" (see Elberse and Eliashberg 2003) fits with this empirical finding.

Popular Appeal. In addition to our measure of "quality as assessed by experts," we employ a measure of a movie's popular appeal or commercial performance, constructed using weekly box office data from trade magazine Variety. Our measure, "cumulative box office revenues," is the most straightforward and the most widely used in the industry. It is the total revenues across all weeks in a movie's theatrical run. Because admission prices are uniform across movies, this measure directly reflects the total number of tickets sold.

Box office dynamics for our sample of movies are depicted in **Figure 6**. It shows that weekly revenues typically decrease over time; from an average of just over $20 million in the opening week to below $5 million in week four, and below $1 million after week eight. Just over 50% of the movies in our sample play at least twelve weeks, while about 5% play at least twenty-four weeks.

Vanilla Sky, which featured in our description of HSX, received a metascore of 45, opened at $33 million, and collected a total of $101 million over the course of 20 weeks. Its values for the two quality measures therefore are 45 (critical acclaim) and 101 (popular appeal). Across the sample, the quality measures have a reasonably strong correlation: the Pearson correlation coefficient is 0.39 ($p<0.01$).

1.4. The Allocation of Advertising: Additional Observations

Before moving to a description of the modeling approach, we point to some additional observations regarding the data that are relevant to our chosen approach and overall research objectives.

Production Costs. Although the variable does not feature in the model we will discuss below, it seems useful to relate the key variables used in this study to production costs—the primary source of expenditures for movie studios. A movie's production cost is often a good indicator of the creative talent involved (high-profile stars such as Tom Cruise, Tom Hanks, and Julia Roberts can weigh heavily on development costs) or the extent to which the movie incorporates expensive special effects or uses elaborate set designs. An analysis with data obtained from the Internet Movie Database (IMDB) shows that average production costs for movies in our sample are just over $43 million (with a standard deviation of $30 million), and vary from $1.7 million to $142 million.

From statistics published by the MPAA (2004), we can assess that television advertising comprised about one third of the average of $30 million spent on theatrical marketing.[7] Given an average production budget of $43 million and average cumulative box office revenues of $56 million (see **Table 1**), it follows that the average movie *loses* approximately $17 million in the theatrical window. The outcome for studios is particularly grim if we consider that they bear all production and advertising costs, but share box-office revenues with theater exhibitors.[8] While the subsequent video and television revenue "window" are typically more profitable, these figures suggest that studios should welcome any opportunity to save on advertising expenditures.

Determinants of Advertising. The correlation matrix for the key variables in this study as well as production costs are displayed in **Table 2**. A few insights regarding the determinants of advertising are worth highlighting. First, advertising expenditures show a stronger correlation with quality as measured by popular appeal (Q_{PA_i}) than with quality measured by critical acclaim (Q_{CA_i}). The latter does not explain a significant amount of the variance in advertising. Second, advertising expenditures are positively correlated with initial expectations. That is, the factors that determine market-wide expectations prior to the start of the advertising campaign (which may include the story concept, the appeal of the cast and crew, seasonality, and the likely competitive environment, among other things) are related to advertising levels. This is an intuitive result, as studios can be expected to base their advertising allocations at least partly on the same set of factors. A simple linear regression analysis (not reported here) reveals that initial expectations explain close to 30% of the variance in pre-release advertising levels, and the effect does not disappear when we control for production costs. Together, initial expectations and production costs explain nearly 50% of the variance in cumulative advertising levels.

These observations beg the important question whether our data suffer from the endogeneity problem that also hinders research on the relationship between advertising and sales. An experimental setting allows the researcher the greatest degree of control in eliminating this problem (e.g. Simester, Hu, Brynjolfsson and Anderson, 2005), but that is not feasible in our setting. Here, we address the problem in two related ways. As discussed in the next section, first, we adopt a model specification that removes time-invariant unobserved heterogeneity. This does not rule out the possibility that weekly changes in advertising and expectations are both correlated with *time-varying* movie-specific unobserved factors. However, based on in-depth interviews with managers, there are strong reasons to believe that our results may not suffer from these concerns. That is, certain features of the institutional context suggest that week-to-week changes in advertising are plausibly exogenous. As explained in more detail later, we go further by testing the robustness of our results in settings where we—drawing on insights provided by the interviewees—would expect that the exogeneity assumption is likely to be violated.

We conducted interviews with three studio executives directly responsible for domestic theatrical marketing strategies as well as two executives at a media planning and buying agency. The central and consistent observation that emerges from these interviews is that studio executives have limited flexibility in adjusting a movie's advertising campaign in the weeks leading up to the release, as they receive updated information about the movie's potential, or as changes in the competitive environment occur. Studios typically buy the vast majority of television advertising—as much as 90 to 95%, according to the studio executives—in the "up-front" advertising market, i.e. at least several months prior to movies' releases. The need to buy in the up-front market is enhanced by studios' preference for advertising time in prime time and on certain days (mostly advertisements air on Wednesday, Thursday, and Friday), and is particularly pressing in periods characterized by high advertising demand, most notably the Christmas period. It is difficult and expensive for studios to buy additional television advertising time on the so-called "opportunistic marketplace" (see Sissors and Baron 2002). Supply on this opportunistic market is affected by the extent to which networks have delivered on the ratings implied in the up-front market, and by events that cause an unusual increase in ratings, such as sports broadcasts and award shows. Late campaign adjustments are particularly problematic for studios that are not part of media conglomerates with television arms (such as News Corporation with Twentieth Century Fox and Fox Television). Finally, although one might think the large number of movies released by major studios gives them more flexibility, the major studio executives we interviewed mentioned they rarely swapped advertising time between movies during our sample period. Naturally, swapping time is not a viable option for studios that release only a few movies each year.

The interviews suggest that, while HSX traders can almost instantaneously reflect revised views about a movie's potential in their expectations, studio executives are somewhat limited in their ability to adjust advertising campaigns. This is consistent with assumptions underlying our modeling framework. However, as mentioned, we take additional steps to assess how robust our estimates are. Specifically, the interviews shed light on at least a handful of contextual factors that affect how much room for maneuver studio executives and their media planners have. We apply these insights in a set of empirical analyses designed to understand whether an endogeneity bias might exist in our findings. We describe these tests in the "Robustness Checks" section that follows the discussion of our main findings.

2. Modeling Approach

We discuss our modeling approach in three sections. We start by describing how one might want to examine our hypotheses within the context of a static model. The pitfalls of such an approach motivate a dynamic model specification, which we discuss next. We conclude this section with an overview of specific estimation issues.

Hereafter, we denote advertising expenditures for movie i in week t by A_{it}, and market-wide expectations for movie i in week t by E_{it}. We consider the period from the start of a movie's television advertising campaign, $t = a$, to its theatrical release, $t = r$. Consequently, market-wide expectations at the start of the advertising campaign and at the time of release are denoted by E_{ia} and E_{ir}, respectively. We refer to *cumulative* advertising expenditures at the time of release as A_{ir}^{*}. We denote a movie's quality assessment (hereafter, we simply refer to this as "movie quality") by Q_i; our two specific dimensions of quality are denoted by Q_{CA_i} (critical acclaim) and Q_{PA_i} (popular appeal). (See **Table 1** for an overview of the key variables and their notation).

2.1. A Static (Cross-Sectional) Model

In studying the effect of advertising on expectations, one might begin by specifying a simple linear regression model that expresses "updated" expectations as a function of both "initial" expectations and cumulative advertising expenditures:

$$E_{ir} = \alpha + \beta A_{ir}^{*} + \gamma E_{ia} + \varepsilon \tag{1}$$

where ε captures unobserved transitory and movie-specific effects.[9] Equation (1) expresses the relationship between advertising and expectations.[10] To assess whether quality moderates the impact of advertising, one could augment equation (1) in the following manner:[11]

$$E_{ir} = \alpha + \beta_0 A_{ir}^{*} + \beta_1 Q_i + \beta_2 Q_i A_{ir}^{*} + \gamma E_{ia} + \varepsilon \tag{2}$$

In the above equation, E_{ia} includes unobserved time-invariant movie-specific factors that affect product quality (and possibly advertising expenditures) and are known at time $t = a$. One example of such a factor is whether the movie's cast includes a well-known actor. However, the specification in equation (2) does not allow one to control for unobserved factors that might affect both market-wide expectations and the amount of advertising that is allocated. Consider a case in which a producer of an independent movie has managed to convince an Oscar-winning actress to join the cast: that information may cause high expectations and may prompt the studio to set aside a higher advertising budget than it normally would for a movie of that type. Ignoring these unobserved effects can result in a spurious effect of advertising on expectations.

Incorporating the dynamics of advertising and expectations over the sample period allows us to control for such additional time-invariant unobserved factors.

2.2. A Dynamic (Panel) Model

Advertising and Expectations. We can extend equation (1) by expressing relevant relationships in a dynamic fashion:

$$E_{it} = \alpha + \beta A_{it} + \gamma E_{i,t-1} + \upsilon_i + \varepsilon_{it} \qquad \text{Where } \varepsilon_{it} \sim N\left(0, \sigma^2\right) \tag{3}$$

where υ_i reflects unobserved time-invariant movie-specific factors. Equation (3) is a form of the so-called *partial-adjustment model*, a commonly used specification to examine the impact of marketing efforts on sales. In our context, the partial-adjustment model allows for a carryover effect of advertising on expectations beyond the current period. The short-run (direct) effect of advertising is β, while the long-run effect is $\beta/(1-\gamma)$.[12]

The shape of sales response to marketing efforts, holding other factors constant, is generally downward concave (Hanssens, Parsons and Schultz 2001). However, if the marketing effort has a relatively limited operating range, a linear model often provides a satisfactory approximation of the true relation (Hanssens, Parsons and Schultz 2001). Exploratory tests suggest that this is the case for our setting as well – we find no evidence of non-linear effects.

The term υ_i captures unobserved time-invariant movie-specific factors that might influence both advertising expenditures and sales expectations.[13] Ignoring these factors would lead to biased and inconsistent estimators of β. The availability of panel data allows first-differencing to remove this unobserved heterogeneity (e.g. Wooldridge 2002). We can rewrite equation (3) as follows:

$$(E_{it} - E_{i,t-1}) = \beta(A_{it} - A_{i,t-1}) + \gamma(E_{i,t-1} - E_{i,t-2}) + \mu_{it} \qquad \text{Where } \mu_{it} = (\varepsilon_{it} - \varepsilon_{i,t-1}) \tag{4}$$

The economics behind this approach are fairly straightforward: whereas υ_i affects the *level* of advertising expenditures for movie *i*, (for example, whether a studio spends $20 million or $50 million advertising a movie), it should not affect *changes* in advertising from week to week.[14]

The Role of Quality. The panel structure of the data also allows for a richer approach to assessing the informative versus persuasive effect of advertising. Recall that this effect can be captured by adding an interaction term $Q_i A^*_{ir}$ in the static model (equation 2). For the dynamic specification, we can turn to a "hierarchical linear" or "random coefficients" modeling approach (e.g. Bryk and Raudenbush 1992, Snijders and Bosker 1999). Specifically, if we regard our movie cross-sections as "groups" (in hierarchical linear modeling terms) and distinguish weekly variations within those groups from variations across groups, we can gain a richer understanding of how group-specific characteristics (such as movie quality) affect the relationship between the independent and dependent variables (here advertising and expectations). We first allow the parameters in equation (4) to randomly vary across movies, denoted by i:

$$(E_{it} - E_{i,t-1}) = \beta_i (A_{it} - A_{i,t-1}) + \gamma_i (E_{i,t-1} - E_{i,t-2}) + \mu_{it} \tag{5a}$$

$$\text{where } \mu_{it} = (\varepsilon_{it} - \varepsilon_{i,t-1})$$

Next, the slope parameters are expressed as outcomes themselves. Particularly, in line with our conceptual framework, β_i is expressed as an outcome that depends on quality and has a cross-section-specific random disturbance. In addition, since variations in the persistence of expectations are likely to be stronger across than within cross-sections, we express γ_i as an outcome with a cross-section-specific disturbance as well. These "slopes as outcomes" models (Snijders and Bosker 1999) can thus be stated as follows:

$$\beta_i = \beta_0 + \beta_1 Q_i + \delta_{1i} \qquad \text{where } \delta_{1i} \sim N(0, \tau_1) \tag{5b}$$

$$\gamma_i = \gamma_0 + \delta_{2i} \qquad \text{where } \delta_{2i} \sim N(0, \tau_2) \tag{5c}$$

Substitution leads to:

$$\begin{aligned}(E_{it} - E_{i,t-1}) = \; & \beta_0 (A_{it} - A_{i,t-1}) + \gamma_0 (E_{i,t-1} - E_{i,t-2}) + \beta_1 Q_i (A_{it} - A_{i,t-1}) \\ & + \delta_{1i} (A_{it} - A_{i,t-1}) + \delta_{2i} (E_{i,t-1} - E_{i,t-2}) + \mu_{it} \end{aligned} \tag{6}$$

$$\text{where } \mu_{it} = (\varepsilon_{it} - \varepsilon_{i,t-1})$$

The terms with β and γ denote the *fixed* part of the model, while the terms with δ and ε together denote the *random* part of the model. This is a relatively straightforward form of a hierarchical linear model (e.g. Snijders and Bosker 1999). Notice that this modeling approach "automatically" leads to the interaction term, $\beta_1 Q_i (A_{it} - A_{i,t-1})$, that tests whether quality moderates the effect of advertising on expectations. For instance, a positive β_1 would imply that advertising for higher-quality movies has a stronger effect on market-wide expectations than advertising for lower-quality movies—an *informative* effect of advertising. If β_0, the parameter belonging to $\left(A_{it} - A_{i,t-1}\right)$, is also significant, the sheer level of weekly changes in advertising has an impact on expectations as well—a *persuasive* effect of advertising.

2.3. Estimation Issues

Given the methodological shortcomings of the cross-sectional model (equations 1 and 2), we only report estimates for the dynamic (panel) specification.[15] We estimated the simple first-differenced partial adjustment model (equation 4) for the twelve-week period prior to release, using ordinary least-squares. Reported standard errors are heteroskedasticity robust (MacKinnon and White 1985).[16] Diagnostic tests did not reveal any evidence of collinearity (we examined the condition indices, see Belsley, Kuh and Welsch 1980) and first-order autocorrelation (we used the Durbin-Watson test). We estimated the dynamic hierarchical linear model (equation 6), again for the twelve-week period prior to release, using the MIXED procedure in SAS. It uses restricted maximum likelihood (REML, also known as residual maximum likelihood), a common estimation method for multilevel models (Singer 1998).[17] We assessed model fit using a variety of common metrics: –2RLL, AIC, AICC, and BIC.[18]

Three issues are worthwhile to note in relation to the dynamic model expressed in equation (6). First, in line with the assumption underlying our modeling approach that advertising expenditures drive expectations but the reverse does not necessarily hold, exploratory linear and non-linear dynamic regression analyses show that changes in market-wide expectations in any given week do *not* explain a significant amount of the variance in changes in advertising spending in the next week. Second, we have tested whether the effect of advertising varies according to the specific week in which it takes place. We note that weekly advertising generally sharply increases in the weeks leading up to the launch date (see **Figure 2**), and it seems reasonable to assume that its effectiveness might depend on the period under investigation. We tested this hypothesis by including two interaction terms (in which we multiply the existing variables with the number of weeks prior to release). The results do not support the view that the effectiveness of advertising is affected by the timing of advertising. Second, explorations using a wide variety of alternative model specifications did not reveal support for non-linear effects of advertising or non-linear effects of lagged expectations.

3. FINDINGS

In presenting the findings, we start with the parameters that describe the relationship between advertising and expectations, and then move to the relationship between advertising, expectations, and product quality. The model estimates are captured in **Table 3**.

3.1. Advertising and Expectations

Table 3 presents estimation results for the first-differenced partial-adjustment model (equation 4). Model I expresses weekly expectations as a function of lagged weekly expectations only; Model II includes weekly advertising as a second independent variable.

The model estimates strongly suggest that advertising positively impacts the updating of expectations before release: in Model II, the coefficients for both the direct effect of advertising (β =0.32) and the carryover effect of advertising (γ =0.40) are statistically significant at the 1% level.[19] The estimate for β implies that, on average, in any given week prior to product release, and controlling for market-wide expectations, a $1 increase in television advertising leads to a $0.32 direct increase in expectations in the same week. Similarly, the estimate for γ indicates that, controlling for advertising expenditures, a $1 increase in expectations in the previous week (due to television advertising or other factors) leads to a $0.40 increase in expectations in the current week. Together, the estimates reflect that, on average, a $1 increase in advertising thus appears to lead to an increase of nearly $0.55 in sales expectations over the course of a number of weeks (note that the long-run effect is $\beta/(1-\gamma)$).

Thus, while television advertising expenditures positively and significantly influence the updating of expectations, the point estimates sketch a gloomy picture of the returns to advertising, and suggest that "across-the-board" spending levels are too high. It is important to recognize that a full characterization of optimal advertising levels should take into account two additional factors. First, whereas box-office revenues are shared between studios and exhibitors, advertising costs are borne solely by studios. Although studios typically receive the lion's share of revenues (particularly in early weeks, when the effects of advertising are also likely to be the strongest), factoring in that studios do not fully capture the returns to advertising makes the low returns to advertising appear even bleaker. Ignoring this feature of the industry is likely to lead to an *overestimation* of the optimal levels of advertising. Second, multiple revenue windows, such as theatrical, home video, and television, have become the norm in the motion picture industry. Even though pre-theatrical-release advertising cost (still) make up the lion's share of total advertising costs, ignoring revenues from non-theatrical windows probably leads to an *underestimation* of the optimal levels of advertising.

3.2. Advertising, Expectations, and Quality

The remaining columns in **Table 3** display estimates for equation (6), which expresses the hypothesis that market-wide expectations are sensitive to the quality of the product reflected in the advertising. Model III presents a simple random coefficient model in which both the coefficient for weekly lagged expectations (γ_0) and the coefficient for weekly advertising (β_0) are allowed to randomly vary across movie cross-sections. Models IV and V are the full specifications captured in equation (6) in that they also allow the advertising coefficient to vary with movie quality (β_1 is the coefficient for the interaction term)—model IV for the "critical acclaim" quality measure, and model V for the "popular appeal" quality measure. Several important insights emerge from the Table.

The estimates for model III provide evidence in support of the random coefficients specification: τ_1 and τ_2 are statistically significant at the 1% level. These imply that the slopes of the advertising coefficient (β_0) and the slopes of the lagged expectations coefficient (γ_0) differ significantly across movies (τ_1 =0.94 and τ_2 =0.03, respectively). Within the context of a partial-adjustment framework, both short-run and long-run effects of advertising on expectations therefore differ significantly across movies. Overall, nearly 10% ((10.65-9.74)/10.65) of the residual variance is attributable to movie-to-movie variation.

Models IV and V provide support for the key hypothesis regarding the role of product quality—coefficients for the interaction terms (β_1) are positive and significant both for the model with Q_{CA_i} (critical acclaim) and for the model with Q_{PA_i} (popular appeal). Using the coefficients for β_1, we can assess the effectiveness of advertising at different levels of product quality:

- For the model with Q_{CA_i} (critical acclaim), $\Delta\left(E_{it} - E_{i,t-1}\right)/\Delta\left(A_{it} - A_{i,t-1}\right) = 0.009 * Q_i$. Accounting for both direct and carry-over effects, the estimates imply that the impact of advertising on expectations (at current levels of advertising) is negative if 0.009*Q_i <(1-γ_0), that is if Q_i <70. Since expectations are strong predictors of actual box office receipts, this implies that current advertising levels for movies with Metacritic scores roughly below two-thirds of the maximum score of 100 do not seem justified.

- For the model with Q_{PA_i} (popular appeal), $\Delta(E_{it} - E_{i,t-1})/\Delta(A_{it} - A_{i,t-1}) = 0.012 * Q_i$. The impact of advertising on expectations (at current levels of advertising) is negative if $0.012 * Q_i < (1 - \gamma_0)$, that is if $Q_i < 50$.

Although the parameter estimates themselves are robust to changes in model specification, the assessments of "optimal" levels of advertising are quite sensitive to small changes in parameter estimates. As such, they should be interpreted with caution. Nevertheless, the core finding that quality moderates the impact of advertising on expectations is strong—for both quality measures. The overall goodness of fit improves significantly when we account for the moderating effect of product quality on advertising (i.e. when we compare model III with models IV and V).[20]. This conclusion is confirmed when we examine the estimates for the fixed components of the models IV and V.

Figure 7, which depicts trends in advertising and expectations for the six weeks before release, graphically illustrates this finding in the raw data. The figure captures the returns to advertising for two groups of movies – the 10% with the *lowest* quality scores, and the 10% with the *highest* quality scores. It displays two graphs – one for the "critical acclaim" quality measure, and one for the "popular appeal" quality score. Although the effect is more pronounced in the "popular appeal" graph, both graphs reinforce the key finding: high-quality movies appear to benefit more from advertising than low-quality movies.

3.3. Robustness Checks

As mentioned, research on the effectiveness of advertising is typically susceptible to the endogeneity problem—that is, the problem that they are simultaneously determined. In our setting, the use of our HSX-based measure of market-wide sales expectations rather than sales in itself may not help to fully overcome the problem. We indicated that unobserved factors could influence both expectations generated on the HSX and advertising expectations, and that first-differencing can remove time-invariant unobserved heterogeneity. However, one might argue that certain relevant unobserved factors are not fixed across time, and therefore not addressed with first-differencing. In other words, unobserved time-varying movie-specific effects may be correlated with both changes in advertising and expectations, and not accounting for these factors could result in inconsistent estimates of the relationship between advertising and expectations.

We perform several robustness checks to assess whether these endogeneity issues may bias our results. The logic behind these tests is relatively straightforward. As described earlier, our interviews with executives from studios and advertising agencies suggest that changes in the planned sequence of advertising expenditures within the twelve-week window prior to a movie release are generally difficult to execute—advertising money is primarily allocated in the "upfront" market, and trades in the "opportunistic" marketplace are typically negligible for various institutional reasons. However, changes are possible in some cases. We identify these settings by considering key characteristics that drive a studio's ability or need to change its advertising allocation decisions: studio characteristics, television ratings "events", and release date changes. We then examine whether the dynamics of the advertising process, and the relationship between advertising and expectations, is statistically different in these cases. In effect, we estimate the relationship between advertising and expectations for two samples separately: one where the sequence of advertising expenditures is plausibly exogenous, and another for which a studio's ability or necessity to adjust the sequence of advertising expenditures within the twelve-week window is arguably greater. We find that while the dynamics of the advertising process are indeed somewhat different in the two samples, the estimates of the effectiveness of advertising are not statistically different across both samples. We provide details below.

Studios. Interviews with industry executives suggest that the ability to adjust advertising expenditures may vary according to studio characteristics. For example, (a) a studio that releases a large number of movies each year (typically the major studios) may have more flexibility since multiple releases may facilitate the exchange of time purchased on TV, (b) a studio whose parent company also owns a television network may receive favorable treatment in the opportunistic marketplace, and (c) a studio that operates on a large budget may be better able to cope with high prices for one movie that required opportunistic buys. As such, advertising expenditures for movies released by studios without these characteristics (i.e., mostly the smaller, independent studios) are plausibly exogenous within the twelve-week window.

Our specific test considers a revised version of a Model III (see **Table 3**) nested in equation (6):

$$\begin{aligned}\left(E_{it}-E_{i,t-1}\right)= \quad & \beta\left(A_{it}-A_{i,t-1}\right)+\gamma\left(E_{i,t-1}-E_{i,t-2}\right)+\varphi X\left(A_{it}-A_{i,t-1}\right) \\ & +\delta_{1i}\left(A_{it}-A_{i,t-1}\right)+\delta_{2i}\left(E_{i,t-1}-E_{i,t-2}\right)+\mu_{it}\end{aligned} \tag{7}$$

where X represents the test variable, and φ represents the coefficient of the interaction of the test variable and the weekly changes in advertising. [21] We consider two test variables: (1) X_{1i}, a set of dummy variables that take on a value "1" if movie i is released by a major studio, and (2) X_{2i}, which represents the number of other movies released by the studio in the twelve-week window before the focal movie i's release date. We find that both variables are weakly positively correlated with weekly changes in advertising, confirming that the dynamics of the advertising process are indeed different for these observations. However, as reflected as Model I and II in **Table 4**, estimates for the interaction coefficients φ are insignificant in Model I and II. The estimated advertising coefficients β are very close to the estimate reported in Model III in **Table 3**. Our conclusions about the effectiveness of advertising therefore are not affected.

Ratings Events. Both the availability and price of advertising time on the "opportunistic" market critically depend on program ratings in a given period. For example, certain sports broadcasts (e.g., the Olympics or World Series) and award shows often result in unusually high ratings. On those days, a studio's ability to buy additional advertising time (or otherwise adjust its television advertising campaign) may therefore be lower. Also, in February, May, July and November of each year Nielsen Media Research collects detailed viewing data. Known as the "sweeps", the viewer data is key to future advertising sales, so television broadcasters usually offer their best programming in these periods, which results in relatively high ratings, and likely less availability and higher prices on the "opportunistic" market. Again, we examine whether the advertising process, and the relationship between advertising and expectations, is significantly different in these periods, compared with times when advertising adjustments are perhaps more feasible.

In order to assess the occurrences of a-typical ratings, we collected Nielsen ratings data for each evening in the sample period, for each of the major networks (ABC, CBS, NBC, FOX, PAX, UPN, and WB). Across all 822 days in the sample, there were 334 days (41%) on which at least one network had a rating that is one standard deviation higher than its mean for that weekday. Similarly, there were 96 days (12%) on which at least one network had a rating that is two standard deviations higher than its mean for that weekday. We again estimate equation (7) for three different test variables: (1) X_{3t}, a variable that reflects the weekly number of days with "one-SD ratings events," (2) X_{4t}, the weekly number of days which are "two-SD ratings events," and (3) X_{5t}, a dummy that is "1" for weeks that fall in sweep periods, and zero otherwise.

Our analyses show that advertising spending is indeed significantly lower (in unit and dollar terms) on days characterized by ratings events. However, incorporating these "ratings events" variables hardly affects the advertising effectiveness estimates. As reflected in Model III, IV and V in **Table 4**, the φ coefficient is insignificant, and the advertising coefficients β do not differ significantly from the corresponding parameter in the benchmark model III in **Table 3**.

Release Date Changes. As a final robustness check, we examine how the advertising process and the relationship between advertising and expectations are impacted by a particular type of time-varying movie-specific effect, namely changes in the planned release date. Release date changes—either for the focal movie or for other movies competing in the focal movie's release window—can significantly alter the competitive environment (e.g., Einav 2003). Because the interviews with studio executives reveal that they often seek to adjust advertising spending for a movie following new information about the expected level of competition, we exploit release date change announcements as exogenous shocks that can impact advertising expenditures.

Specifically, we examine the extent to which advertising expenditures, and the resulting advertising-expectations relationship, are sensitive to such shocks. The results may provide an indication of the extent to which similar—but unobserved—shocks are likely to impact our results. We obtained data from *Exhibitor Relations* to assess the impact of release date changes (see Einav (2003) and Einav (2006) for other applications of this data source). Each week, *Exhibitor Relations* provides an updated release schedule for the US motion picture industry, and highlights changes to the previous report. In our sample period, a total of 2,827 changes to the release schedule were announced. Of those, we selected the announcements that (1) referred to movies released in the sample period, (2) concerned widely or nationally released movies, (3) contained a specific indication of the new release date or weekend, and (4) were made up to 90 days before the new release. This yielded a total of 156 release date changes, involving 116 unique movies, of which 87 also appear in our sample of 280 movies.[22]

Our analyses reveal that release date change announcements indeed are significantly related to changes in advertising in the pre-release period. For example, changes in weekly advertising levels are significantly lower for movies that feature in the release date announcements. Also, the total number of movies with a release date change that a movie encounters in its opening weekend is a weakly significant (p=0.04) positive predictor of the week-to-week changes in advertising spending. As before, we estimate equation (7), with two relevant test variables: 1) X_{6i}, an indicator variable that takes on the value "1" if the focal movie i experienced a release date change, and zero otherwise, and (2) X_{7i}, the number of competing movies, released within a four-week window centered around focal movie i's release date, that experienced a release date change.[23] The results, reported as Models VI and VII in **Table 4**, indicate, once again, that φ is statistically insignificant, and that the change in the estimate of β is negligible compared with the estimate in Model III in **Table 3**.

To summarize, in this section, we extend the model to explicitly accommodate the possibility that, while changes in the sequence of advertising expenditures are plausibly exogenous for some observations, they may not be for others. Our empirical results reveal that the dynamics of the advertising process are indeed somewhat different across these two sets of observations, suggesting that the factors we identified indeed affect the necessity or ability that studios have to adjust weekly advertising expenditures during the sample period. Incorporating these factors in the empirical model, however, has no impact on the estimated coefficients of the relationship between advertising and expectations. Each of these tests individually is not sufficient to rule out that endogeneity plays a role in our study, but taken together, they suggest that our estimates of the effectiveness of advertising are fairly robust to such considerations.

4. Conclusion and Discussion

What is the effect of pre-release advertising on the demand for a product? And does the magnitude of that effect vary according to the quality of the good? In this study, we investigate these questions in the context of the motion picture industry. Instead of examining the effect of advertising on sales, we examine how advertising affects the updating of market-wide sales expectations. The focus on expectations creates a valuable advantage. Our measure of expectations, which is derived from a stock market simulation, is an accurate predictor of sales. However, while sales data are only available after the product launch, we can observe the dynamic nature of expectations before the release, and relate those to dynamics in the advertising allocation process. We find that (1) advertising significantly affects the updating of market-wide expectations prior to release, and (2) this effect is stronger the higher the product quality. This latter finding suggests that advertising plays an informative, and not simply a persuasive, role.

These results have implications for motion picture industry executives seeking to more optimally allocate television advertising budgets. Our estimates suggest that studio executives may benefit from spending less on advertising, particularly for low-quality movies. These results hold for each of our two measures of "quality," critical acclaim or popular appeal. The findings imply that studio executives should refrain from using advertising solely as a persuasive instrument—a "more-advertising-is-better" strategy is unlikely to be optimal.[24]

Our analysis of the impact of advertising on sales exploits the possibility of using the Hollywood Stock Exchange (HSX) data to construct a measure of market-wide sales expectations. Our key findings suggest that HSX can provide clues about the quality of movies and the appeal of initial advertisements for those movies. Stock market simulations, by aggregating potential consumers' beliefs about future outcomes, can be useful test markets for marketing decision variables, and as such might help marketers make more informed decisions. Exploring the value of stock market simulations alongside existing testing alternatives (e.g. Eliashberg, Jonker, Sawhney and Wierenga 2000) seems a particularly fruitful area for further research.

Two caveats of this study might lead to worthwhile research extensions. First, our study presently does not explicitly incorporate the competitive environment for movies.[25] A better understanding of the effect of competition can help studios figure out how they should advertise in the presence of "rivals" (e.g. Berndt 1991), and how the role of the competitive environment affects the strategic recommendations. Second, in drawing inferences about preferred advertising levels, we have assumed that studios aim to run the U.S. theatrical release window in a stand-alone profitable manner. An alternative assumption is that studio executives optimize advertising spending across multiple release windows, particularly across both theatrical and home video. Because home video in recent years has emerged as the most profitable window, studios might regard the theatrical window simply as an advertisement for the home video window—free publicity and other public relations efforts tend to be more effective prior to the theatrical release. One logical extension of this study would be to examine the effectiveness of advertising across both windows while accounting for a carry-over effect.

[1] It is important to realize that our market-wide "expectations" variable differs from the individual-level "expectations" measure as featured in the large body of work within the "confirmation/disconfirmation" or "gap-theory" paradigm, which relates those expectations to observed or advertised product and/or quality satisfaction after trial. Work by Kopalle and Assuncao (2000) and Kopalle and Lehmann (1995, 2001, 2006) is particularly relevant. Unlike those studies, we consider expectations regarding a product's overall market appeal or sales level, and track how those expectations change over time as a result of advertising.

[2] Berndt (1991, p. 375) accurately summarizes the problem: "[I]f relevant elasticities are constant, then advertising budgets should be set so as to preserve a constant ratio between advertising outlay and sales. This implies that advertising is endogenous. On the other hand, one principal reason that firms undertake advertising is because they believe that advertising has an impact on sales; this implies that sales are endogenous. Underlying theory and intuition therefore suggest that both sales and advertising should be viewed as being endogenous; that is, they are simultaneously determined".

[3] Earlier studies by Stigler (1961), Nelson (1970; 1974), Butters (1977), Kihlstrom and Riordan (1984), Grossman and Shapiro (1984), and Milgrom and Roberts (1986), among others, are also relevant to the debate on the persuasive versus informative role of advertising.

[4] We do not explicitly test the consumption-deterrence hypothesis, nor do we attempt to disentangle whether the informative effect is due to a "signaling" or "ad content" effect. Also, our context is one in which most advertising occurs prior to release, the quality of the product is not observable until its release, and consumers tend to be equally unfamiliar with product quality prior to release due to the unique nature of each movie. Consequently, we cannot identify the informative nature of advertising using variation in familiarity across consumers or across products, along the lines of Ackerberg (2001, 2003), Shachar and Anand (1998), and Anand and Shachar (2004).

[5] Advertising expenditures are borne by movie studios or distributors – not by exhibitors (i.e. theater owners or operators).

[6] Pennock et al (2001a) assess the efficiency of HSX by quantifying the degree of coherence in HSX stock and options markets. They argue that in an arbitrage free market, a stock, call option and put option for the same movie must conform to the put-call parity relationship. We do not discuss the HSX options market here; see Pennock et al (2001a) for more information.

[7] This includes the costs of prints.

[8] Revenue-sharing agreements usually are structured in a way that gives the distributor a high share in the first few weeks that declines as the movie proceeds its run in theaters (e.g. the share gradually drops from 80% to 50%).

[9] We have also estimated log-linear models to test for non-linear effects, but since the findings are substantively similar, we only report linear models here.

[10] Because anticipated advertising levels may be incorporated into market-wide expectations formed before the advertising campaign starts, strictly speaking, we should only expect *unanticipated* advertising to affect the updating of expectations after $t=a$.

[11] According to Baron and Kenny (1986), *moderation* exists when one variable (here "quality") affects the direction and/or strength of the relationship between two other variables (here "advertising" and "updated expectations"). If the parameter belonging to the interaction term is significant, a moderation effect exists.

[12] There is an implicit carryover effect to advertising just as in the well-known Koyck model (Koyck 1954), the major difference being that all of the implied carryover effect cannot be attributed to advertising (Clarke 1976, also see Houston and Weiss 1974, Nakanishi 1973), which we believe is an appropriate assumption in our context. Greene (2003) shows that the partial-adjustment model is a reformulation of the geometric lag model. Depending on specific assumptions about the error term, the partial-adjustment model is equivalent to the so-called brand loyalty model (e.g. Weinberg and Weiss 1982).

[13] We acknowledge that first-differencing does not remove time-variant unobserved factors. We return to this issue when we discuss the robustness checks.

[14] In other words, the "exclusivity restriction" here is that motion picture executives do not adjust their advertising expenditures based on movements in HSX stock prices. We believe this is a reasonable assumption for reasons discussed in the concluding paragraphs of the "Data" section.

[15] An unabridged version of this manuscript that includes estimates for the cross-sectional model is available upon request.

[16] Specifically, we correct for heteroskedasticity using MacKinnon and White's (1985) 'HC3' method (Long and Ervin 2000).

[17] SAS PROC MIXED enables two common estimation methods: restricted maximum likelihood (REML) and maximum likelihood (ML). They mostly differ in how they estimate the variance components: REML considers the loss of degrees of freedom resulting from the estimation of the regression parameters, whereas ML does not. Because the existing literature suggests the former is preferable (Snijders and Bosker 1999), we opt for REML.

[18] The results for –2RLL are reported in Table 4. Smaller values are preferred (e.g. Snijders and Bosker 1999).

[19] It is not surprising that advertising plays a relatively small role in explaining the variance in the change in market-wide expectations (the adjusted R^2 shows a modest increase from model I to model II): other factors on which information becomes available in the weeks prior to release (possibly including advertising and public relations messages via other media) likely explain a large part of that variance. Mediation tests confirmed that differences in advertising levels significantly affect the differences in expectation levels. Specifically, Sobel (1982) tests performed using estimates and standard errors reported for Model II in Table 3 lead to a test statistic of 2.97 (p<0.01).

[20] An approximate test of the null hypothesis that the change is 0 is given by comparing the differences in the values for –2RLL to a χ^2 distribution, whereby the degrees of freedom correspond to the number of additional parameters (Singer 1998).

[21] To simplify the discussion of the robustness checks, we only report findings for a model that omits the role of quality, but we have estimated a full model with interaction effects for the test variables:

$$\begin{aligned}(E_{it} - E_{i,t-1}) &= \beta_0 (A_{it} - A_{i,t-1}) + \gamma_0 (E_{i,t-1} - E_{i,t-2}) + \beta_1 Q_i (A_{it} - A_{i,t-1}) + \varphi_0 X (A_{it} - A_{i,t-1}) + \varphi_1 X Q_i (A_{it} - A_{i,t-1}) \\ &+ \delta_{1i} (A_{it} - A_{i,t-1}) + \delta_{2i} (E_{i,t-1} - E_{i,t-2}) + \mu_{it}\end{aligned}$$

where both φ_0 and φ_1 represents coefficients of the interaction terms with X. The results are substantively similar.

[22] The 87 movies that feature in the release date change announcements have lower average production costs ($35 million versus $47 million), opening screens (2,014 versus 2,353), pre-release advertising expenditures ($9 million versus $10 million), and opening week box-office grosses ($24 million versus $14 million) than the 193 movies that do not feature in such announcements.

[23] We explored whether weighting these variables by the MPAA rating of the relevant movies or the type of their distributors made a difference, which was not the case.

[24] One obvious question in light of our recommendation is to what extent studio executives recognize the inherent artistic quality or box office potential of a movie. Demand for movies is relatively uncertain, particularly at the time of development. However, motion picture executives typically have better sense of a movie's potential when the movie is in an advanced editing stage, which generally coincides with the time when theatrical marketing strategies are finalized (also see Ainslie et al. 2005).

[25] Implicitly, expectations as measured by HSX moviestock prices incorporate the competitive environment—HSX players can choose from a large array of movies, and moviestock prices will typically incorporate the strength of likely competitive releases as well as seasonality in demand. Also, our robustness checks cover changes in the competitive environment due to release date changes, which could be the starting point for further research on optimal advertising strategies in different competitive settings (e.g., Einav 2003).

REFERENCES

Ackerberg, Daniel A. (2001). Empirically Distinguishing Informative and Prestige Effects of Advertising. RAND Journal of Economics, 32, 100-118.

Ackerberg, Daniel A. (2003). Advertising, Learning, and Consumer Choice in Experience Good Markets: An Empirical Examination. International Economic Review, 44 (3), 1007-1040.

Ainslie, Andrew, Xavier Drèze and Fred Zufryden (2005). Modeling Movie Life Cycles and Market Share. Marketing Science 24 (3, Summer), 508-517.

Anand, Bharat and Ron Shachar (2002). Risk Aversion and Apparently Persuasive Advertising. Harvard Business School Working Paper Series, 02-099.

Anand, Bharat, and Ron Shachar (2004). Advertising: The Matchmaker. Working Paper.

Bagwell, Kyle (2003). The Economic Analysis of Advertising. In Mark Armstrong and Rob Porter (eds.), Handbook of Industrial Organization, North-Holland: Amsterdam.

Baron, R. M., and Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual , Strategic, and Statistical Considerations. Journal of Personality and Social Psychology, 51(6), 1173-1182.

Bass, Frank M. and Leonard J. Parsons (1969). Simultaneous Equation Regression Analysis of Sales and Advertising. Applied Economics 1 (2, May), 103-124.

Basuroy, Suman, Kalpesh Kaushik Desai and Debabrata Talukdar (2006). An Empirical Investigation of Signaling in the Motion Picture Industry. Journal of Marketing Research 43 (May), 287-295.

Belsley, D.A., E. Kuh and R.E. Welsch (1980). Regression Diagnostics. New York: John Wiley and Sons, Inc.

Berndt, Ernst R. (1991). The Practice of Econometrics: Classic and Contemporary. Reading, MA: Addison-Wesley.

Bryk, A.S. and S.W. Raudenbush (1992), Hierarchical Linear Models, Applications and Data Analysis Methods. Newbury Park, CA: Sage.

Butters, G. (1977). Equilibrium Distributions of Sales and Advertising Prices. The Review of Economic Studies, 44, 465–491.

Byzalov, Dmitri and Ron Shachar (2004). The Risk Reduction Role of Advertising. Working Quantitative Marketing and Economics, 2(4), 283-320.

Caves, Richard E. (2001). Creative Industries: Contracts between Art and Commerce. Harvard University Press, Cambridge: MA.

Chan, Nicholas T., Ely Dahan, Andrew W. Lo and Tomaso Poggio (2001). Experimental Markets for Product Concepts. MIT Working Paper, Center for eBusiness, Paper 149, July 2001.

Clarke, Darral. G. (1976). Econometric Measurement of the Duration of Advertising Effect on Sales. Journal of Marketing Research, 13, 345-357.

Dahan, Ely and John R. Hauser (2001). The Virtual Customer: Communication, Conceptualization, and Computation. MIT Working Paper, Center for eBusiness, Paper 104, September 2001.

Einav, Liran (2003). Not All Rivals Look Alike: Estimating an Equilibrium Model of the Release Date Timing Game. Working Paper, Stanford University, June 2003.

Einav, Liran (2006). Seasonality in the U.S. Motion Picture Industry. RAND Journal of Economics, forthcoming.

Elberse, Anita and Eliashberg, Jehoshua (2003). Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. Marketing Science 22 (3, Summer), 329-354.

Eliashberg, Jehoshua and Shugan, Steven M. (1997). Film Critics: Influencers or Predictors? Journal of Marketing, 61(April), 68-78.

Eliashberg, Jehoshua, Jedid-Jah Jonker, Mohanbir S. Sawhney, and Berend Wierenga (2000). MOVIEMOD: An Implementable Decision-Support System for Prerelease Market Evaluation of Motion Pictures. Marketing Science, 19(3), 226-243.

Forsythe, R., TA. Rietz and TW. Ross (1999). Wishes, Expectations and Actions: Price Formation in Election Stock Markets. Journal of Economic Behavior and Organization, 39, 1999, 83-110.

Forsythe, R., F. Nelson, GR. Neumann and J. Wright (1992). Anatomy of an Experimental Political Stock Market. American Economic Review, 82, 1142-1161.

Greene, W. H. (2003). Econometric Analysis (Fifth Edition). Upper Saddle River: Prentice Hall.

Grossman, G. and C. Shapiro (1984). Informative Advertising with Differentiated Products. The Review of Economic Studies 51, 63-81.

Gruca, Thomas (2000). The IEM Movie Box Office Market: Integrating Marketing and Finance using Electronic Markets. Journal of Marketing Education, 22: 5-14.

Hanson, Robin D. (1999). Decision Markets. IEEE Intelligent Systems 14(3), 16-19.

Hanssens, Dominique M., Leonard J. Parsons, and Randall L. Schultz (2001). Market Response Models: Econometric and Time Series Analysis (Second Edition). International Series in Quantitative Marketing. Boston: Kluwer.

Houston, Franklin S. and Doyle L. Weiss (1974). An Analysis of Competitive Market Behavior. Journal of Marketing Research, 11, 151-155.

Jedidi, K., Krider, R. E., & Weinberg, C. B. (1998). Clustering at the Movies. Marketing Letters, 9(4), 393-405.

Kihlstrom R. and M. Riordan (1984). Advertising as a Signal. Journal of Political Economy 92, 427-450.

Kopalle, Praveen K., and João L. Assunção (2000). When (Not) to Indulge in "Puffery": The Role of Consumer Expectations and Brand Goodwill in Determining Advertised and Actual Product Quality. Managerial and Decision Economics, 21 (6), 223-241.

Kopalle, Praveen K., and Donald R. Lehmann (1995). The Effects of Advertised and Observed Quality on Expectations About New Product Quality. Journal of Marketing Research, 32 (August), 280-290.

Kopalle, Praveen K., and Donald R. Lehmann (2001). Strategic Management of Expectations: The Role of Disconfirmation Sensitivity and Perfectionism. Journal of Marketing Research, 38 (August), 386-394.

Kopalle, Praveen K., and Donald R. Lehmann (2006). Setting Quality Expectations When Entering a Market: What Should the Promise Be? Marketing Science, 25 (1), 8-24.

Koyck, L.M. (1954). Distributed Lags and Investment Analysis. Amsterdam: North-Holland.

Krider, Robert E., Tieshan Li, Yong Liu, Charles B. Weinberg (2005). The Lead-Lag Puzzle of Demand and Distribution: A Graphical Method Applied to Movies. Marketing Science 24(4), 635-645.

Lehmann, Donald R., and Weinberg, Charles B. (2000). Sales Through Sequential Distribution Channels: An Application to Movies and Videos. Journal of Marketing, 64(3) 18-33.

Litman, B. R. (1982). Decision Making in the Film Industry: The Influence of the TV Market. Journal of Communication, 32, 33-52.

Litman, B. R., & Ahn, H. (1998). Predicting Financial Success of Motion Pictures. B. R. Litman. The Motion Picture Mega-Industry. Needham Heights, MA: Allyn & Bacon.

Litman, B. R., & Kohl, L. S. (1989). Predicting Financial Success of Motion Pictures: The '80s Experience. Journal of Media Economics, 2, 35-50.

Long, J.S and L.H. Ervin (2000). Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model. The American Statistician, 54, 217-224.

MacKinnon, J.G. and H. White (1985). Some Heteroskedasticity Consistent Covariance Matrix Estimators with Improved Finite Sample Properties. Journal of Econometrics, 29, 53-57.

Milgrom, P. and J. Roberts (1986). Price and Advertising Signals of Product Quality. Journal of Political Economy 94, 796-721.

Moul, C. C. (2001). Word-of-Mouth and Saturation: Why Movie Demands Evolve the Way They Do. Working Paper, Department of Economics, Washington University.

MPAA (2005). MPAA Market Statistics. [www.mpaa.org].

Nakanishi, Masao (1973). Advertising and Promotion Effects on Consumer Response to New Products. Journal of Marketing Research, 10, 242-249.

Nelson, Philip (1970). Information and Consumer Behavior. The Journal of Political Economy, 78 (2, March/April), 311-329.

Nelson, Philip (1974). Advertising as Information. The Journal of Political Economy, 81 (4, July/August), 729-754.

Pennock, David. M., Steve Lawrence, C. Lee Giles, & Finn Arup Nielsen (2001a). The Power of Play: Efficiency and Forecast Accuracy in Web Market Games. NEC Research Institute Technical Report 2000-168. February 17, 2001.

Pennock, David. M., Steve Lawrence, C. Lee Giles, & Finn Arup Nielsen (2001b). The Power of Play: Efficiency and Forecast Accuracy in Web Market Games. Science, 291(9), 987-988.

Prag, J., and Casavant, J. (1994). An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry. Journal of Cultural Economics, 18, 217-235.

Quandt, Richard E. (1964). Estimating the Effectiveness of Advertising: Some Pitfalls in Econometric Methods. Journal of Marketing Research 1 (2, May), 51-60.

Ravid, S. A. (1999). Information, Blockbusters, and Stars: A Study of the Film Industry. Journal of Business, 72(4), 463-492.

Sawhney, M. S., and Eliashberg, J. (1996). A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures. Marketing Science, 15(2), 113-131.

Schmalensee, Richard (1972). The Economics of Advertising. Amsterdam: North-Holland.

Schmalensee, Richard (1978). A Model of Advertising and Product Quality. The Journal of Political Economy, 86 (3, June), 485-503.

Servan-Schreiber, Emile, Justin Wolfers, David M. Pennock and Brian Galebach (2004). Prediction Markets: Does Money Matter? Electronic Markets, 14(3), 243-251.

Shachar, R., and Bharat Anand (1998). The Effectiveness and Targeting of Television Advertising. Journal of Economics & Management Strategy 7 (3), 363-396.

Simester, Duncan, Yu (Jeffrey) Hu, Erik Brynjolfsson and Eric T. Anderson (2005). Does Current Advertising Cause Future Sales?: Evidence from the Direct Mail Industry. Working Paper, MIT, December 2005.

Singer, Judith, D. (1998). Using SAS PROC MIXED to Fit Multilevel Models, Hierarchical Models, and Individual Growth Models. Journal of Educational and Behavioral Statistics, 24 (4), 323-355.

Sissors, Jack Z. and Roger Baron (2002). Advertising Media Planning. New York: McGaw-Hill.

Snijders, Tom and Roel Bosker (1999). Multilevel Analysis. London: Sage.

Sobel, M.E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equations Models. In S. Leinhart (Editor), Sociological Methodology 1982, 290-312. San Francisco: Jossey-Bass.

Sochay, S. (1994). Predicting the Performance of Motion Pictures. Journal of Media Economics, 7(4), 1-20.

Spann, Martin and Bernd Skiera (2003). Internet-Based Virtual Stock Markets for Business Forecasting. Management Science, 49(10), 1310-1326.

Stigler, G. L. (1961). The Economics of Information. Journal of Political Economy 71, 213-225.

Surowiecki, James (2004). The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations. Random House.

Variety (2004). Can H'w'd Afford Its Tube Touts? Soaring Ad Rates Testing Studios' TV Dependency. April 26, 2004.

Weinberg, Charles B. and Doyle L. Weiss (1982). On the Econometric Measurement of the Duration of Advertising Effect on Sales. Journal of Marketing Research, 19, 585-591.

Wolfers, Justin and Eric Zitzewitz (2004). Prediction Markets. Journal of Economic Perspectives, 18(2), Spring 2004.

Wooldridge, Jeffrey M. (2002) Econometric Analysis of Cross-Section and Panel Data. Boston: MIT.

White, Halbert (1980). A Heteroskedastic-Consistent Covariance Matrix Estimator and a Direct Test of Heteroskedasticity. Econometrica, 48, 817-838.

Wu, De-Min (1973). Alternative Tests of Independence Between Stochastic Regressors and Disturbances. Econometrica 41, 733-750.

Zufryden, F. S. (1996). Linking Advertising to Box Office Performance of New Film Releases: A Marketing Planning Model. Journal of Advertising Research, July-August, 29-41.

Zufryden, F. S. (2000). New Film Website Promotion and Box-Office Performance. Journal of Advertising Research, (January-April), 55-64.

Table 1. Variables, Sources, and Descriptive Statistics [a]

Variable	Notation	N	Mean	Median	SD	Min	Max	Source
Expectation, t=a (in H$ millions)	E_{ia}	280	42.233	30.010	35.570	4.640	262.250	HSX
Expectation, t=r (in H$ million)	E_{ir}	280	48.581	34.365	44.953	8.700	293.120	HSX
Cumulative Advertising, t=r (in $ millions)	A_i^*	280	9.955	9.959	4.533	0.248	24.276	CMR
Quality – Critical Acclaim (0-100)	Q_{AC_i}	280	46.961	48.000	18.496	8.000	95.000	MetaCritic
Quality – Popular Appeal (in $ millions)	Q_{PA_i}	280	56.634	36.431	61.933	3.314	403.706	Variety

[a] The table displays descriptive statistics for the variables in equations (1) and (2).

Table 2. Correlation Matrix [a]

Variable	Notation	C	E_{ia}	E_{ir}	A_i^*	Q_{AC_i}	Q_{PA_i}
Production Cost (in $ millions)	C	--					
Expectation, t=a (in H$ millions)	E_{ia}	.707	--				
Expectation, t=r (in H$ million)	E_{ir}	.694	.889	--			
Cumulative Advertising, t=r (in $ millions)	A_i^*	.674	.513	.524	--		
Quality – Critical Acclaim (0-100)	Q_{AC_i}	.186	.296	.314	.154	--	
Quality – Popular Appeal (in $ millions)	Q_{PA_i}	.550	.802	.842	.472	.386	--

[a] The table displays Pearson correlation coefficients for the variables in equations (1) and (2), and for production costs.

Table 3. Dynamic (Panel) Model: Advertising, Expectations, and Quality [a]

Hierarchical Linear Model										With $Q_i = Q_{CA_i}$			With $Q_i = Q_{PA_i}$		
	I			**II**			**III**			**IV**			**V**		
	Est.	**SE**	**P** [b]	**Est.**	**SE**	**P**	**Est.**	**SE**	**P**	**Est.**	**SE**	**P**	**Est.**	**SE**	**P**
Fixed Component															
β_0 Coefficient of $(A_i - A_{i,t-1})$	--	--	--	0.320	0.074	**	0.352	0.098	**	-0.027	0.016		-0.037	0.143	
β_1 Coefficient of $Q_i(A_i - A_{i,t-1})$	--	--	--	--	--	--	--	--	--	0.009	0.002	**	0.012	0.000	*
γ_0 Coefficient of $(E_{i,t-1} - E_{i,t-2})$	0.410	0.018	**	0.403	0.018	**	0.380	0.023	**	0.370	0.018	**	0.368	0.018	**
Random Component															
τ_1 Variance of δ_{1i}				--	--	--	0.938	0.221	**	0.911	0.226	**	0.953	0.223	**
τ_2 Variance of δ_{2i}				--	--	--	0.032	0.009	**	0.033	0.009	**	0.032	0.007	**
τ_{12} Covariance of δ_{1i} and δ_{2i}				--	--	--	0.037	0.028		0.037	0.027		0.032	0.029	
σ^2 Variance of ε_{it}	11.345	0.262	**	10.645	0.260	**	9.744	0.252	**	9.726	0.255	**	9.719	0.252	**
N	3360			3360			3360			3360			3360		
R^2	0.113			0.141			0.141			0.162			0.168		
Adjusted R^2	0.113			0.141			0.141			0.162			0.168		
Estimation, Restriction	--			--			BW, Unstructured			DBW, Unstructured			BW, Unstructured		
-2RLL	17689			17595			17506			17451			17415		

[a] The table displays hierarchical linear model estimation results, obtained using data for the sample of 280 movies over a twelve-week pre-release period, for models nested within equation (6). The "between/within" ("BW") method was used for computing the denominator degrees of freedom for tests of fixed effects. No structure ("Unstructured") was specified for the variance-covariance matrix for the intercepts and slopes. Only the fixed effects contributed to the calculation of R^2 and Adjusted R^2 (see Snijders and Bosker 1999).
[b] * p=0.05; ** p=0.01

Table 4. Robustness Checks [a]

		I			II			III			IV			V			VI			VII		
		Est.	SE	P [b]	Est.	SE	P	Est.	SE	P	Est.	SE	P	Est.	SE	P	Est.	SE	P	Est.	SE	P
β	Coeff. of $\left(A_i - A_{i,t-1}\right)$	.356	.101	**	.361	.099	**	.350	.125	**	.351	.114	**	.351	.118	**	.353	.117	**	.363	.125	**
γ	Coeff. of $\left(E_{i,t-1} - E_{i,t-2}\right)$	.380	.023	**	.380	.023	**	.381	.023	**	.380	.023	**	.380	.023	**	.380	.023	**	.380	.023	**
φ	Coeff. of $X\left(A_i - A_{i,t-1}\right)$:																					
with	$X_{1.1i}$ (Studio: Fox)	-.457	.347		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	$X_{1.2i}$ (Studio: Buena Vista)	-.563	.356		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	$X_{1.3i}$ (Studio: Paramount)	-.401	.338		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	$X_{1.4i}$ (Studio: Sony)	.027	.312		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	$X_{1.5i}$ (Studio: Universal)	-.113	.383		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	$X_{1.6i}$ (Studio: Warner Bros)	.106	.332		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	X_{2i} (Studio: # of Movies)	--	--	--	-.038	.039		--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	X_{3t} (Ratings Events, 1 SD)	--	--	--	--	--	--	.002	.021		--	--	--	--	--	--	--	--	--	--	--	--
	X_{4t} (Ratings Events, 2 SD)	--	--	--	--	--	--	--	--	--	-.039	.051		--	--	--	--	--	--	--	--	--
	X_{5t} (Sweeps)	--	--	--	--	--	--	--	--	--	--	--	--	0.22	0.53		--	--	--	--	--	--
	X_{6i} (Release Change, Focal)	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	-.040	.216		--	--	--
	X_{7i} (Release Change, Other)	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	-.047	.058	
N		3360			3360			3360			3360			3360			3360			3360		
Adjusted R^2		0.147			0.141			0.145			0.144			0.141			0.139			0.139		

[a] The table displays hierarchical linear model estimation results for equation (9). Only the fixed components are reported. Model III in Table is the benchmark model; see the Table 3 notes for estimation details.
[b] * p=0.05; ** p=0.01

Figure 1. Conceptual Model

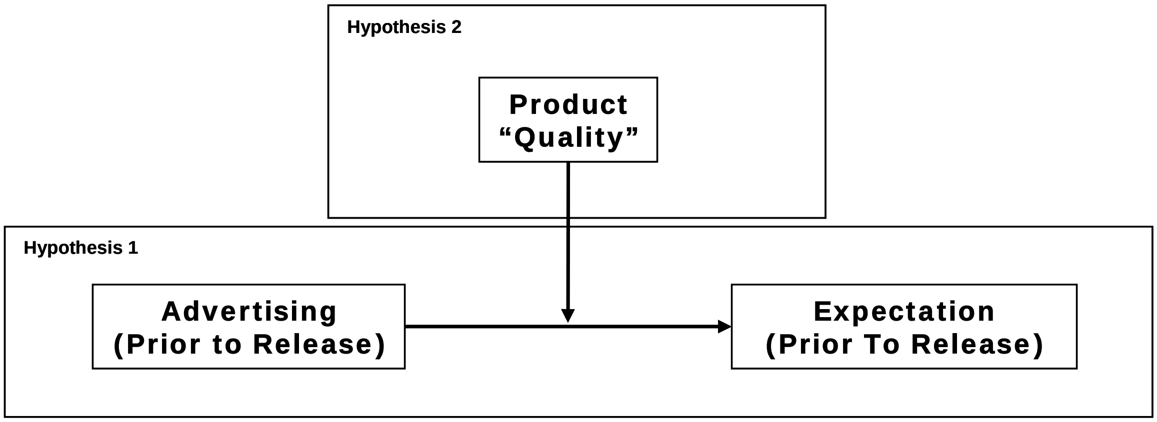
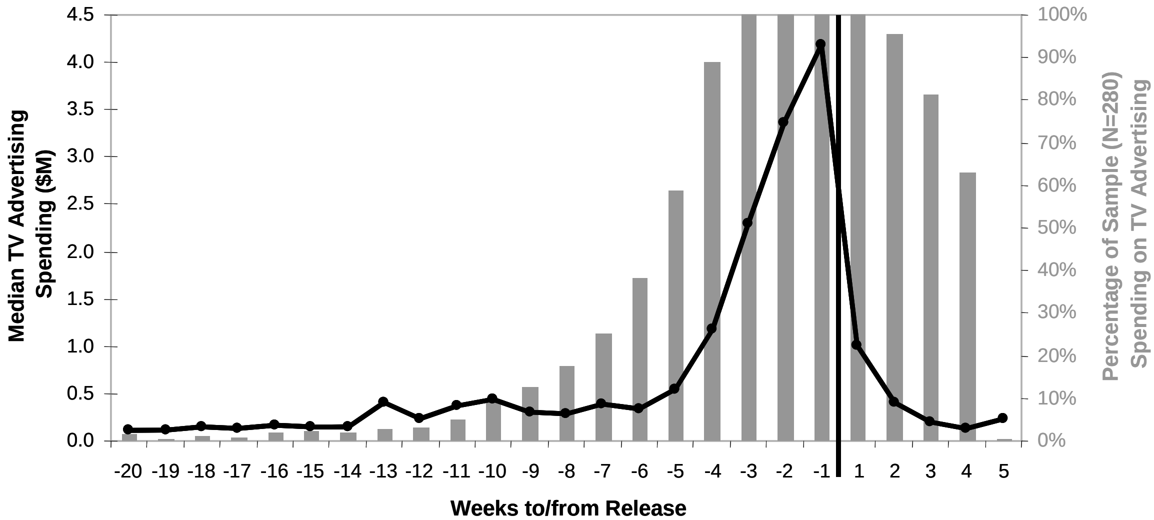
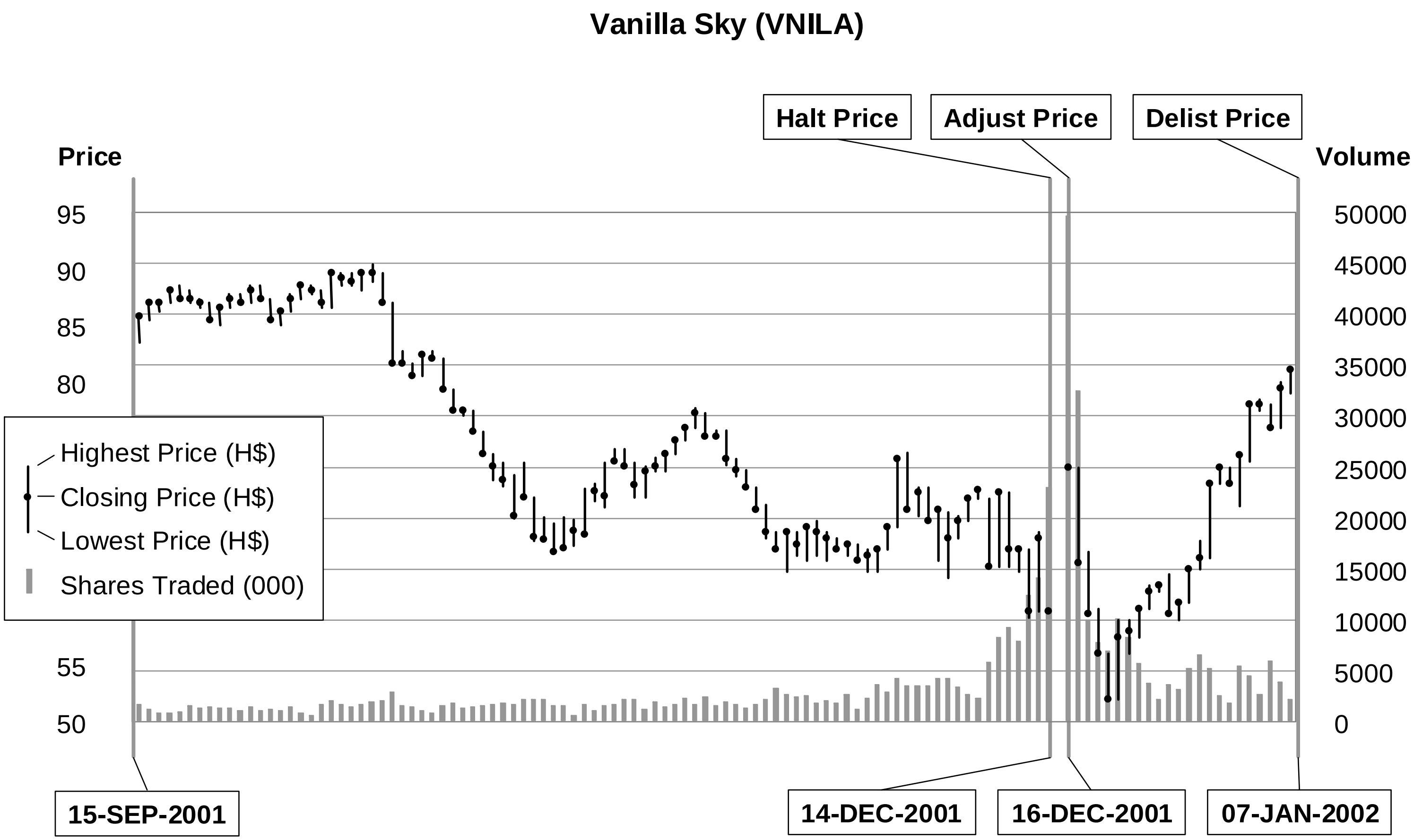


Figure 2. Advertising Expenditures: Temporal Patterns [a]



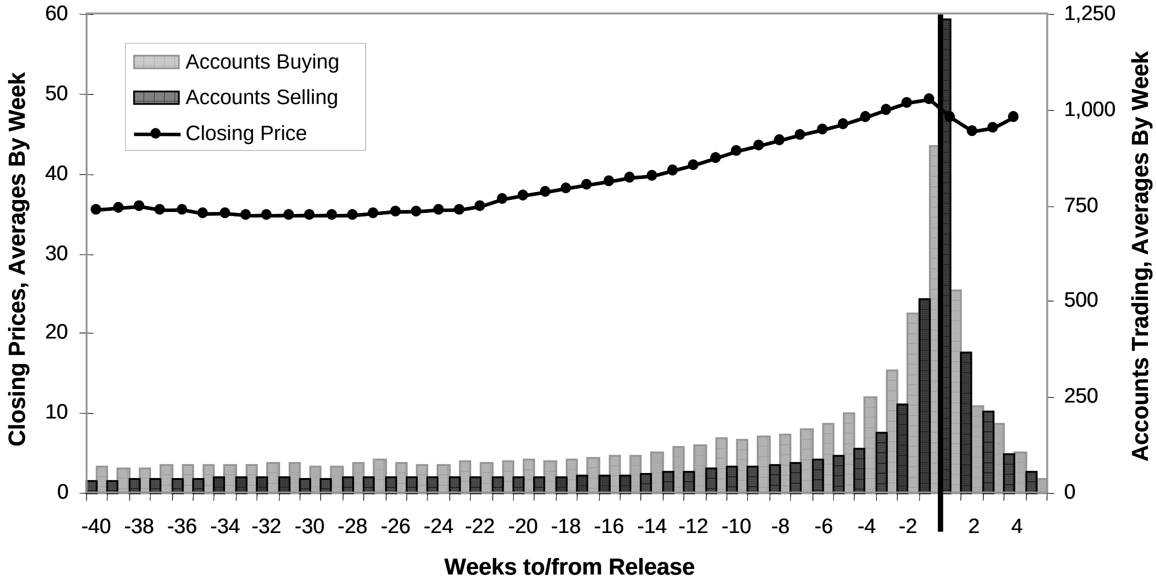
[a] This figure shows, for a period before and after the release of all 280 movies in the sample, (1) the weekly percentage of the movies that are spending on television advertising (depicted by the gray bars), and (2) the weekly median expenditures on television advertising for that set of movies (depicted by the black line).

Figure 3. The HSX Stock Market Illustrated for 'Vanilla Sky' (VNILA) [a]



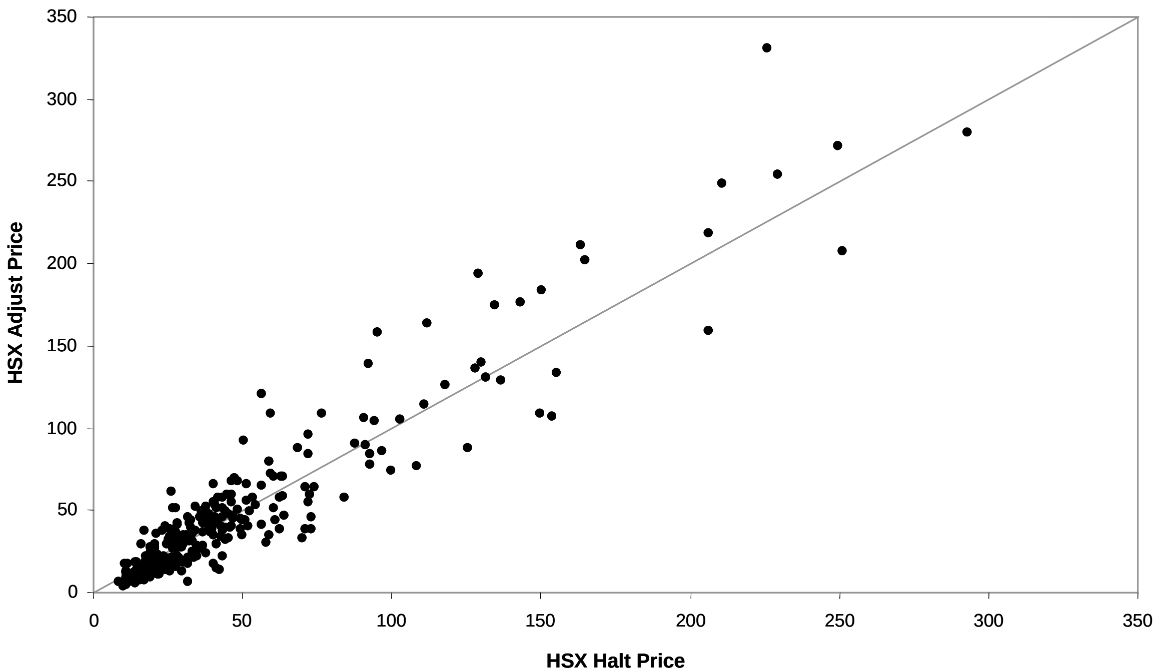
[a] This figure illustrates the HSX trading patterns for one movie, Vanilla Sky, denoted by the symbol "VNILA" on the HSX market. It shows daily lowest, highest, and closing prices (in "Hollywood dollars," denoted by H$, all depicted by the black line), as well as the daily volume of shares traded (depicted by the gray bars), for the three months before the release date, and the four weeks after the release date. The halt price (around H$60) is the price immediately prior to the movie's release, the adjust price (over H$70) is the price based on its opening-weekend grosses, and the delist price (just over H$80) is the price based on its grosses over the first four weeks of release.

Figure 4. HSX Trading: Temporal Patterns [a]



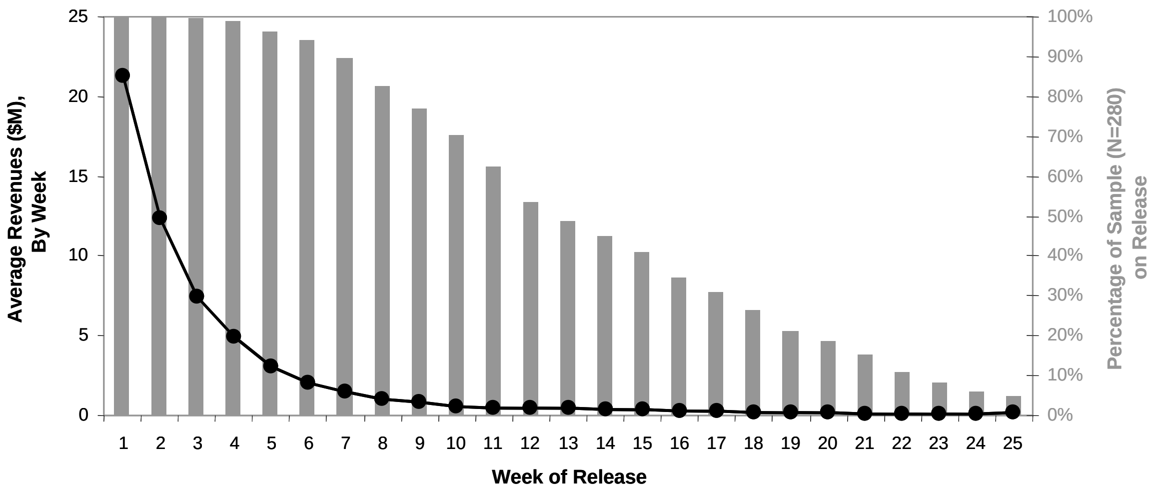
[a] The figure shows, for a period before and after the release of all 280 movies in the sample, the average weekly number of accounts buying and selling (depicted by the light and dark gray bars, respectively), and the average weekly closing price (depicted by the black line).

Figure 5: HSX Halt Prices versus Adjust Prices [a]



[a] The above figure plots all 280 movies according to their halt price, the HSX stock price immediately prior to their release, and their adjust price, the HSX stock price based after their opening week. Because the former is based solely on the trading behavior of HSX players, and the latter on opening-week box-office grosses, the figure plots each movie's predicted versus actual box-office performance. The Pearson correlation coefficient is 0.94, and the mean and median absolute prediction errors are 0.34 and 0.23, respectively.

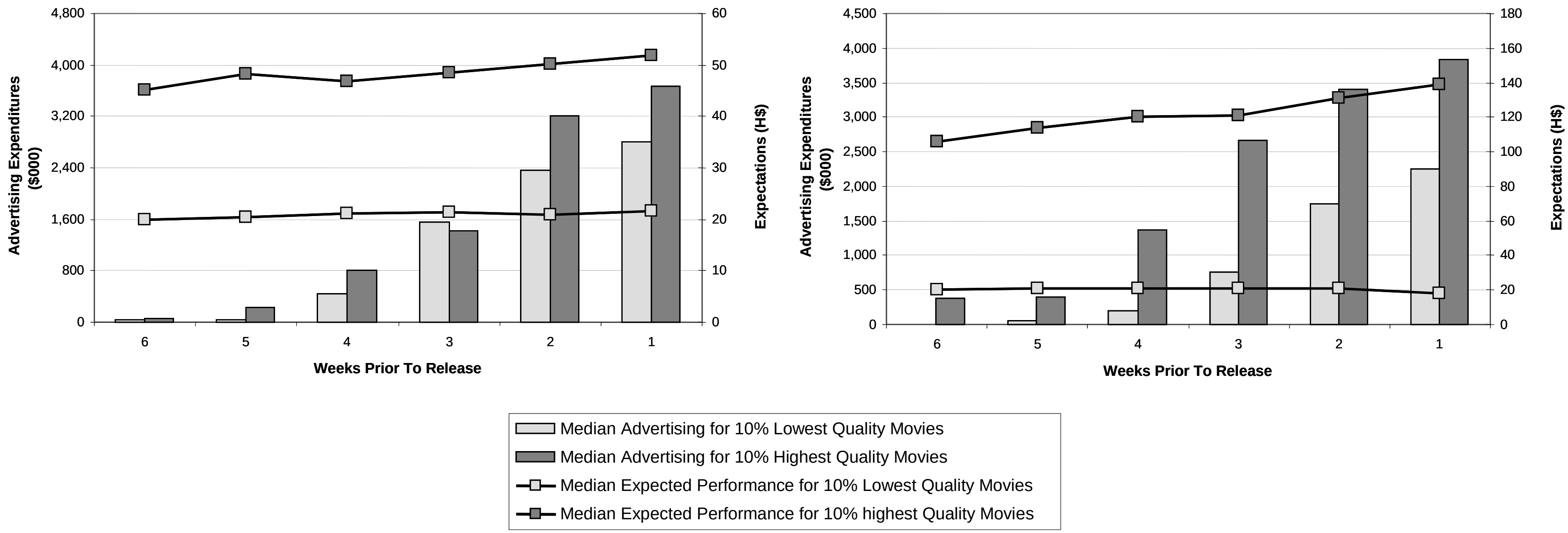
Figure 6. Box Office Performance Dynamics [a]



[a] This figure shows, for all 280 movies in the sample, (1) the weekly percentage of movies playing in theaters (depicted by the gray bars), and (2) the weekly average revenues for that set of movies (depicted by the black line).

Figure 7. The Role of Quality as a Moderating Variable: An Illustration

Quality = Critical Acclaim (Q_{CA_i}) **Quality = Popular Appeal (Q_{PA_i})**



[a] For each of the two quality measures, the above figure depicts the weekly median advertising expenditures for the 10% of movies with the lowest quality scores (depicted by the light gray bars) and the 10% of movies with the highest quality scores (depicted by the dark gray bars), as well as the weekly median expectations, expressed as HSX stock prices, for the 10% of movies with the lowest quality scores (depicted by the light gray lines) and the 10% of movies with the highest quality scores (depicted by the dark gray lines), for the six weeks prior to movies' releases (N=280). The figure shows that, whereas expectations for the low-quality movies remain fairly stable across the six weeks, expectations for the high-quality movies increase as advertising expenditures increase.