

The Effectiveness of Pre-Release Advertising for Motion Pictures: An Empirical Investigation Using a Simulated Market

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Abstract

One of the most visible and publicized trends in the movie industry is the escalation in movie advertising expenditures over time. Yet, the returns to movie advertising are poorly understood. The main reason is that disentangling the causal effect of advertising on movie sales is difficult because of the classic endogeneity problem: movies expected to be more popular (for example, those with a talented director or well-known actor) also receive more advertising. In this study, we use data on a movie's stock price as it trades on the Hollywood Stock Exchange, a popular online market simulation, to study the impact of movie advertising. Since the entire dynamic path of a movie's stock price—a measure of revenue expectations for the movie—prior to release is observed, one can sweep out any time-invariant unobserved factors that affect both advertising and expectations. Furthermore, certain institutional constraints in the advertising allocation process imply that the first-differenced advertising series is plausibly exogenous over the sample period. We find that advertising has a positive and statistically significant effect on expected revenues, but that the effect varies strongly across movies of different “quality.” The point estimate implies that the returns to advertising for the average movie are negative.

Key words: advertising, effectiveness, movies, stock market simulations.

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1 Introduction

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 Schmuget 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 view suggests that the escalation of advertising expenditures may reduce the returns to advertising, even drastically. Furthermore, the effectiveness of advertising is likely to differ across movies according to movie “quality”: if there is any information content in advertising, then advertising a movie of low quality might even drive away consumers rather than attract them.¹ How effective, then, is movie advertising? Are the returns to the marginal advertising dollar positive or negative? And, how does advertising effectiveness differ across movies?

Since advertising is a major instrument of competition in the movie industry, it follows that understanding the impact of movie advertising is central to an assessment of the current and future industrial organization of the movie industry. Unfortunately, disentangling the impact of movie advertising is quite difficult. The main reason is that studying the effect of advertising on box office receipts is confounded by the classic endogeneity problem: movies expected to be more popular also are likely to receive more advertising (Einav 2006, Lehmann and Weinberg 2000).²

¹See Anand and Shachar (2004) for more on the consumption-deterring effect of advertising.

²Prior studies that find a positive relationship between advertising and (weekly or cumulative) revenues include, for example, Ainslie, Drèze and Zufryden (2005), Basuroy, Desai and Talukdar (2006), Elberse and Eliashberg (2003), Lehmann and Weinberg (2000), Moul (2001), Prag and Casavant (1994), and Zufryden (1996; 2000). However, as several of these authors note, the direction of causality remains unclear. Berndt (1991, p. 375) summarizes the general 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”.

In this paper, we attempt to shed light on the effectiveness of movie advertising by pursuing a different empirical strategy. Instead of looking at box office receipts, we look at the impact on a measure of sales expectations in the pre-release period. Our measure is the movie’s “stock price” as it trades on the Hollywood Stock Exchange, a popular online stock market simulation. This measure is sensible since a movie’s HSX stock price is one of the strongest predictors of actual box office receipts. The idea that market simulations can aggregate information that traders privately hold follows work by a growing number of researchers who use such simulations to gauge market-wide expectations or to identify “winning concepts” in the eyes of consumers.³ Beyond that, the HSX measure has two advantages over actual receipts measures. First, one can observe the entire dynamic path of a movie’s stock price (which is a measure of market-wide revenue expectations for the movie) prior to release, and therefore relate these to the dynamics in the advertising process as well. Second, one can sweep out any time-invariant unobserved factors that affect both advertising and expectations, by first-differencing both series. Since changes in the planned sequence of advertising expenditures within the twelve-week window prior to a movie release are difficult to execute for a variety of institutional reasons, one can argue that the first-differenced advertising series is plausibly exogenous over the sample period. We go beyond this by performing a series of robustness tests that examine how sensitive the resulting estimates of advertising effectiveness are to this identifying assumption.

Section 2 describes our data and variables used in estimation. We use data on weekly pre-release expectations, as measured by the HSX stock prices, for a sample of 280 movies that were widely released from 2001 to 2003. We obtain data on weekly pre-release television advertising expenditures for that same set of movies from Competitive Media Reporting (CMR), and measure quality using data from Metacritic.

Section 3 describes our empirical strategy to examine the relationship between movie-level advertising and market-wide expectations of the movie’s success. The model centers around two questions posed earlier. First, does pre-release advertising affect the updating of market-wide expectations? Second, how does this effect vary according to product quality?

The results, described in Section 4, indicate that the impact of advertising on pre-release market-wide expectations is positive and statistically significant. Furthermore, this effect is more pronounced for movies of higher “quality”. However, the model estimates imply that, on average, a one dollar increase in advertising increases expectations of box-office receipts by at most \$0.65. We discuss the implications of these results for the “optimality” of current advertising expenditures in the industry.

³See, for example, 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.

Section 4 also presents a series of tests that examine the robustness of our results, in particular to the assumption that unobserved time-varying movie-specific effects do not bias the point estimates of the impact of advertising on expectations. 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 need to adjust advertising 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 the two samples. Section 5 concludes and discusses some implications for future research.

2 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) that 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.

2.1 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.⁴ For our sample, \$11 million was spent, on average per movie, on television advertising alone – a 56% share of the \$20 million allocated across major advertising media (covering television, radio, print and outdoor advertising). Nearly 88% (\$10 million) 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.

Worth noting is that these figures, though obtained from a different source, are similar to official industry statistics published by the Motion Picture Association of America (MPAA 2005). Judging from those statistics, television, radio, print and outdoor advertising together roughly

⁴Advertising expenditures are borne by movie studios or distributors – not by exhibitors (i.e. theater owners or operators).

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 1 depicts temporal patterns in television advertising expenditures across the sample of movies. As seen there, 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.

2.2 Market-Wide Expectations

Our source of data on market-wide expectations is the Hollywood Stock Exchange (HSX). HSX is a popular Internet stock market simulation that revolves around movies and movie stars. It 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 HSX⁵ are quantitatively larger, but qualitatively similar, relative to a real-money market. Moreover, in direct comparisons with expert judges, HSX forecasts perform very competitively.

Figure 2 illustrates the trading process for the movie *Vanilla Sky* – referred to as *VNILA* on the HSX market. 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

⁵Pennock 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.

million. Grosses during the first four weeks, in turn, comprise on average 85% of total theatrical revenues. 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 \times 2.9 = \text{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 3 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.

Weekly box office revenues typically decrease over time; for our sample of movies, they decline 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 play at least twelve weeks, while about 5% play at least twenty-four weeks.

2.3 Quality

We assess a movie’s “quality” or appeal in terms of its critical acclaim, measured by critical reviews. Obviously, a perfectly accurate measure of quality does not exist, in part because quality is unobservable and movies are an experience good which makes assessing their objective quality difficult even after the products’ market release. Our measure has the disadvantage that critics’ views do not necessarily reflect the quality perceptions of the general public (e.g., Holbrook 1999). Realized

sales therefore do not necessarily correspond with a movie’s critical acclaim. Nevertheless, we think the measure represents a relevant dimension of quality.

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.

Several prior studies have examined the relationship between critical acclaim and commercial performance. Most find a positive relationship between reviewers’ assessments of a movie and its (cumulative or weekly) box office success, controlling for other possible determinants of 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). Recently, Basuroy, Desai and Talukdar (2006) provide empirical evidence for interactions between advertising expenditures, critics’ reviews, and box office revenues. In a study focused entirely on the relationship between critical acclaim and box office success, Eliashberg and Shugan (1997) demonstrate that critical reviews correlate with late and cumulative box office receipts but do not have a significant correlation with early box-office receipts. Holbrook (1999) also shows some convergence in tastes of critics and ordinary consumers. 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 these empirical findings.

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 value for the quality measure therefore is 45. Across the sample, our critical acclaim measure of quality is reasonably strongly correlated with popular appeal as reflected by movies’ total theatrical box office revenues: the Pearson correlation coefficient is 0.39 ($p < 0.01$).

2.4 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.

2.4.1 Production Costs

Production costs represent the biggest cost 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 production costs for movies in our sample are just over \$43 million on average (with a standard deviation of \$30 million), and vary from \$1.7 million to \$142 million. Furthermore, since television advertising comprised about one third of total theatrical marketing costs for a movie (from MPAA statistics, 2005)⁶, it follows that on average a movie’s theatrical marketing costs are approximately \$30 million. Average (cumulative) box office revenues per movie were \$56 million in 2004 (see **Table 1**). This implies that the average movie *loses* approximately \$17 million in the theatrical window. The outcome for studios is particularly grim if one considers that they bear all production and advertising costs, but share box-office revenues with theater exhibitors.⁷ 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.

2.4.2 Determinants of Advertising

A few observations concerning advertising determinants are worth mentioning. First, advertising expenditures are positively correlated with our measure of quality, but not particularly strongly: the Pearson correlation coefficient is only 0.15. Second, advertising expenditures are positively correlated with initial expectations, with a coefficient of 0.51. 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 hint that, as one might expect, both advertising and sales expectations might be driven by unobserved movie-specific factors—the movie’s budget, the presence of a particular actor or director, the storyline, genre, etc. As explained later, we tackle this problem in several different ways. First, we first-difference both series to sweep out movie-specific time-invariant unobserved heterogeneity. Second, we describe below certain institutional features behind the advertising allocation process that imply that week-to-week changes in advertising are plausibly exogenous. In

⁶This includes the costs of prints.

⁷Revenue-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%).

other words, the central identifying restriction is that weekly changes in advertising and expectations are both uncorrelated with *time-varying* movie-specific unobserved factors. Third, we go beyond this by testing the sensitivity of model estimates across sub-samples where the maintained identifying restriction is more likely to be violated.

Our assumption behind the exogeneity of changes in advertising during the pre-release period draws from interviews we conducted with three studio executives directly responsible for domestic theatrical marketing strategies, and two executives at a media planning and buying agency. The central observation from these interviews is that once advertising budgets have been allocated and expenditures allocated across media outlets, studio executives have very 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. The main reason for this is that 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 very 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.

While HSX traders can almost instantaneously respond to new information or revised views about a movie’s potential, the interviews, confirming prior descriptions of the advertising allocation process, suggest that studio executives are quite limited in their ability to adjust advertising campaigns. Our maintained assumption that unobserved movie-specific time-varying factors are uncorrelated with changes in television advertising for a movie reflects this hypothesis. However, as mentioned, we take additional steps to assess how robust our estimates are to this assumption. Specifically, the interviews do shed light on certain contextual factors that affect how much room studio executives and their media planners have to maneuver ex-post. We apply these insights in a set of empirical tests that are designed to examine how sensitive our model estimates are to this

assumption. We describe these tests, and their results, in section 4.3 (Robustness Checks) after the discussion of our main findings.

3 Estimation Strategy

We present our modeling approach in three parts. We start by describing our hypotheses within the context of a static model, and the pitfalls associated with such a specification. This discussion motivates a dynamic model specification, which we discuss next. We conclude this section with an overview of specific estimation issues.

The notation hereafter is as follows. 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 . (See **Table 1** for an overview of the key variables and their notation).

3.1 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.⁸ Equation (1) expresses the relationship between advertising and expectations.⁹ To assess how quality moderates the impact of advertising, one can augment equation (1) as:¹⁰

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

⁸We 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.

⁹Because 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 $t=a$.

¹⁰According 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.

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 $t = a$. 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 inconsistent estimates 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.

3.2 A Dynamic (Panel) Model

3.2.1 Advertising and Expectations

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

$$E_{it} = \alpha + \beta A_{it} + \gamma E_{i,t-1} + v_i + \varepsilon_{it} \quad (3)$$

where $\varepsilon_{it} \sim N(0, \sigma^2)$, and v_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 $\beta/(1 - \gamma)$. The specification is common in the marketing literature and reflects a situation in which, for example, not every person is instantly exposed to or persuaded by advertising.¹¹

The shape of sales response to marketing efforts, holding other factors constant, is generally downward concave. 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.¹²

¹¹There 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). Notice that the carry-over effect implies that advertising expenditures need not be evenly distributed across the twelve weeks in order to generate the highest impact.

¹²Over a broader operating range, diminishing returns to advertising are likely. In other words, the effects of advertising with values well outside the range of our sample should be approached with care.

The term v_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:

$$(E_{it} - E_{i,t-1}) = \beta(A_{it} - A_{i,t-1}) + \gamma(E_{i,t-1} - E_{i,t-2}) + \mu_{it} \quad (4)$$

where

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

The economics behind this approach are fairly straightforward: whereas v_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

Equation (3) corresponds with recent work in behavioral finance on “momentum pricing” (Jegadeesh and Titman 1993; also see Chan, Jegadeesh and Lakonishok 1996, Jegadeesh and Titman 2001). Those papers show that—contrary to the random walk hypothesis—movements in individual stock prices over a relatively short period tend to predict future movements in the same direction. Momentum profits can arise from various types of biases in the way that investors interpret information (for example, “self-attribution” or “conservatism”; see Jegadeesh and Titman 2001 for a discussion).¹⁵

3.2.2 The Role of Quality

The panel structure of the data also allows for a richer approach to assessing how quality impacts the returns to advertising. Recall that this effect can be captured by adding an interaction term $Q_i A_{it}^*$ in the static model (equation 2). For the dynamic specification, one 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

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

¹⁴In 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.

¹⁵The findings reported in Table 2 provide empirical support for this “momentum model” specification. Similar evidence obtains from a regression of a given week’s percentage *returns* on the previous week’s percentage *returns* (the coefficient is 0.39, with a standard error of 0.02).

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:

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

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:

$$\begin{aligned} \beta_i &= \beta_0 + \beta_1 Q_i + \delta_{1i} & \text{where } \delta_{1i} &\sim N(0, \tau_1) \\ \gamma_i &= \gamma_0 + \delta_{2i} & \text{where } \delta_{2i} &\sim N(0, \tau_2) \end{aligned}$$

Substitution leads to:

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

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. If β_0 , the parameter belonging to $(A_{it} - A_{i,t-1})$, is also significant, the sheer level of weekly changes in advertising has an impact on expectations as well.

3.2.3 Estimation Issues

Given the methodological shortcomings of the cross-sectional model (equations 1 and 2), we only report estimates for the dynamic (panel) specification.¹⁶ We estimated the dynamic hierarchical

¹⁶An unabridged version of this manuscript that includes estimates for the cross-sectional model is available upon request.

linear model (equation 6) and the nested first-differenced partial adjustment model (equation 4) 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 Reported standard errors are heteroskedasticity robust (MacKinnon and White 1985).¹⁹ 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 also confirmed that an ordinary least-squares estimation approach yielded a similar result for equation (4).

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 1**), 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. Third, 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. Fourth, importantly, one could argue that HSX traders should only respond to advertising to the extent it is "unexpected," in other words expenditures not already incorporated into expectations at the time the advertising campaign starts, and thus that the dependent variable in our model should be a measure of such unanticipated advertising expenditures. This is a valid concern, which we address in our "Robustness Checks" section.

¹⁷SAS 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. We report results for REML.

¹⁸The results for $-2RLL$ are reported in Table 4.

¹⁹Specifically, we correct for heteroskedasticity using MacKinnon and White's (1985) 'HC3' method (Long and Ervin 2000).

4 Results

We start by presenting the parameters that describe the relationship between advertising and expectations, and then move to describing the role of quality on this relationship. The model estimates are presented in **Table 2**.

4.1 Advertising and Expectations

Table 2 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 reveal that advertising changes have a positive and significant impact on the updating of expectations before release: in Model II, the coefficients for both the direct effect of advertising ($\beta=0.32$) and the carryover effect of advertising ($\gamma=0.40$) are statistically significant at the 1% level.²⁰ The point estimate for β implies that, on average, in any given week prior to product release, and controlling for market-wide expectations, a \$1 million increase in television advertising leads to a H\$0.32 direct increase in the HSX price in the same week. (Recall that one HSX dollar is roughly equivalent to \$1 million in receipts in the first four weeks). Similarly, the estimate for γ indicates that, controlling for advertising expenditures, a H\$1 increase in the HSX price in the previous week (due to television advertising or other factors) leads to a H\$0.40 increase in the price in the current week. Together, the estimates reflect that, on average, a \$1 million increase in advertising result in a long-run increase of nearly H\$0.55 in the HSX price (note that the long-run effect is $\beta/(1 - \gamma)$). Last, since four-week grosses comprise on average 85% of total theatrical revenues, this means that a \$1 increase in advertising results in a long-run increase of approximately \$0.65 (i.e., $(1/0.85) * 0.55$) in expected revenues.

Taken literally, these estimates imply that while increases in television advertising expenditures increase expected receipts, the returns to the marginal dollar of advertising are negative, in turn suggesting that “across-the-board” spending levels are too high. 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

²⁰It is not surprising that advertising plays a relatively small role in explaining the variance in the change in market-wide expectations (the adjusted R² 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 ($p<0.01$).

do not fully capture the returns to advertising would imply that the returns to advertising are even lower. Ignoring this feature of the industry is likely to lead to *overestimate* 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 one to *underestimate* the optimal levels of advertising.

4.2 Advertising, Expectations, and Quality

The remaining columns in **Table 2** display estimates for equation (6), which express hypotheses that concern the impact of movie quality on advertising effectiveness. Model III presents a simple random coefficients model in which both the coefficient for weekly lagged expectations (γ_0) and the coefficient for weekly changes in advertising (β_0) are allowed to randomly vary across movie cross-sections. Model IV is the full specification captured in equation (6), and allows the advertising coefficient to vary with movie quality (β_1 is the coefficient for the interaction term).

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 ($\tau_1=0.94$ and $\tau_2=0.03$, respectively). Within the context of a partial-adjustment framework, both short-run and long-run effects of advertising on expectations therefore also differ significantly across movies. Overall, nearly 10% $((10.65-9.74)/10.65)$ of the residual variance is attributable to movie-to-movie variation.

Model V provides support for the hypothesis that movie quality impacts advertising effectiveness; the coefficient for the interaction term (β_1) is positive and significant for the model with Q_i . Using the point estimate for β_1 , one can assess the effectiveness of advertising at different levels of product quality. Specifically, for the model with Q , $\Delta(E_{it} - E_{i,t-1}) / \Delta A_{it} - A_{i,t-1} = 0.009 * Q_i$. Accounting for both direct and carry-over effects, the estimates imply that the impact of advertising on the HSX price (at mean current levels of advertising) is negative if $0.009 * Q_i < (1 - \gamma_0)$, that is if $Q_i < 70$. This implies that current advertising levels for movies with Metacritic scores roughly below four-fifths of the maximum score of 100 do not seem justified.²¹

Although the parameter estimates themselves are robust to changes in model specification, the assessment of the “optimal” advertising level is quite sensitive to small changes in parameter estimates. As such, it should be interpreted with caution. Nevertheless, the core finding that quality moderates the impact of advertising on a movie’s stock price is strong. The overall goodness of fit improves significantly when one accounts for the moderating effect of product quality on advertising

²¹Recall that the “exchange rate” between HSX price and actual receipts is roughly 1 HSX dollar=\$1 million in receipts during the first four weeks, which represents 85% of total revenues.

(i.e., comparing model III with model IV).²² This conclusion is confirmed when we examine the estimates for the fixed components of model IV.

Figure 4, which depicts trends in advertising and expectations for the six weeks before release, illustrates that these patterns are visible even in the raw data. The figure illustrates the returns to advertising for two groups of movies – the 10% with the *lowest* quality scores, and the 10% with the *highest* quality scores. The graph reinforces the finding that high-quality movies appear to benefit more from advertising than low-quality movies.

4.3 Robustness Checks

As mentioned, our use of the HSX-based measure of market-wide sales expectations (instead of data on actual sales) allows one to control for movie-specific time-invariant unobserved factors that may affect both the HSX measure and advertising levels for each movie. To the extent that such unobserved shocks are time-varying, one might still worry about the consistency of the estimates. In this section, we perform several checks to assess the robustness of our results to these concerns. 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, as described, 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: namely, particular 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.

As a final robustness check, we address the concern that changes in advertising expenditures may be anticipated. For example, if studios tend to increase advertising expenditures each week during the sample period, then, rationally, HSX market participants should incorporate this

²²An 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).

into their expectations upfront. In that case, only the *unanticipated* component of changes in advertising expenditures should affect market expectations during the twelve-week period under investigation. In section 4.3.4, we estimate our model incorporating a measure of “surprises” in advertising expenditures. While the point estimates are slightly different, the results confirm both the economic and statistical significance of our earlier findings.

4.3.1 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 2**) nested in equation (6):

$$(E_{it} - E_{i,t-1}) = \beta(A_{it} - A_{i,t-1}) + \gamma(E_{i,t-1} - E_{i,t-2}) + \varphi X(A_{it} - A_{i,t-1}) + \delta_{i1}(A_{it} - A_{i,t-1}) + \delta_{2i}(E_{i,t-1} - E_{i,t-2}) + \mu_{it}. \quad (7)$$

where X is a vector of test variables, and φ represents the coefficients on the interaction of the test variables and the weekly changes in advertising.²³ 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 3**, estimates for the interaction coefficients φ are insignificantly different from zero in both models. Furthermore, the estimated advertising coefficients β are very close to the estimate reported in Model III in **Table 2**.

²³To 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:

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

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

4.3.2 Ratings Events

Both the availability and price of advertising time on the “opportunistic” market 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 therefore lower 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 other periods when advertising adjustments are perhaps more feasible.

In order to assess the occurrences of atypical 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 3**, the coefficient φ is not statistically different from zero, and the advertising coefficients β do not differ significantly from the corresponding parameter in Model III in **Table 2**.

4.3.3 Release Date Changes

As another 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.²⁴

Our analyses reveal that changes in advertising in the pre-release period are indeed significantly related to release date change announcements. For example, changes in weekly advertising levels are 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 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.²⁵ The results, reported as Models VI and VII in **Table 3**, 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 2**.

To summarize, we extended the model in this section 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 need for or ability of studios to adjust weekly advertising expenditures during the sample period. However, incorporating these factors in the empirical model has negligible impact on the estimated coefficients of the relationship between

²⁴The 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.

²⁵We 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.

advertising and expectations. To that extent, these results provide confidence in both the identifying restrictions and the robustness of our earlier findings on the effectiveness of advertising.

4.3.4 Anticipated Advertising

Figure 5 indicates that advertising expenditures increase monotonically during the twelve-week pre-release period. But then, rational market participants should incorporate expected changes in advertising expenditures into their price forecasts upfront.²⁶ Here, we address the robustness of our results to this possibility.

It is worth noting at the outset that the aggregate patterns depicted in figure 5 mask substantial movie-to-movie variation in the advertising process. Indeed, whereas advertising dynamics follow that pattern for certain movies, it does not for many others. Notwithstanding this, we incorporate expectations regarding ad budgets explicitly into forecasts of market participants here.

In order to derive a measure of expected advertising expenditures, we first regress movie-specific weekly advertising expenditures on several variables that are thought to determine ad budgets:

$$A_{it} = \varsigma + \varsigma_1 C_i + \varsigma_2 W_i + \varsigma_3 \sum_{i=1}^{t-1} A_{it} \quad (8)$$

where C_i denotes the production budget (which in turn is correlated with the presence of stars, the use of special effects, and other movie attributes that are often thought to be relevant to setting advertising budgets; see, for example, Elberse and Eliashberg 2003 and Einav 2006), W_i reflects a vector of indicator variables for each week under investigation (we normalize the variable for the last week before release to be zero), and $\sum_{i=1}^{t-1} A_{it}$ denotes cumulative advertising expenditures for that movie to date. We estimate this model using ordinary least squares and retain the predicted values, denoted by \hat{A}_{it} . The model has an R^2 of 0.46, and returns significant parameter estimates for each variable.²⁷

Next, we create a measure of “unanticipated” advertising, \tilde{A}_{it} , as the difference between actual and predicted advertising expenditures, i.e. $\tilde{A}_{it} = (A_{it} - \hat{A}_{it})$. Finally, we re-estimate equations (4) and (6) using the first-differenced weekly *unanticipated* advertising expenditures, $(\tilde{A}_{it} - \tilde{A}_{i,t-1})$, as the relevant regressor (rather than changes in actual advertising expenditures, $(A_{it} - A_{i,t-1})$).

²⁶Note that an estimation problem arises only if weekly *changes* in movie-specific advertising expenditures are anticipated, not levels of advertising expenditures in general. For example, the fact that a “star-filled” movie has a larger ad budget that is also rationally anticipated by market participants upfront should not, by itself, create an estimation problem unless week-to-week changes in ad expenditures were somehow correlated with this factor.

²⁷The coefficient estimate for ς_1 is 0.005 (standard error 0.000), and the estimate for ς_3 is 0.174 (standard error 0.008). Estimates for the parameter vector ς_2 can be obtained from the authors.

In equation (4), the resulting coefficient for the first-differenced lagged expectations, $(E_{i,t-1} - E_{i,t-2})$, is 0.41 (standard error 0.02) and is statistically significant (at a 1% level). The coefficient on first-differenced unanticipated advertising, $(\tilde{A}_{it} - \tilde{A}_{i,t-1})$, is 0.28 (standard error 0.08). While the point estimate is slightly lower than the corresponding estimate reported earlier (0.35 versus 0.28), the results reinforce both the economic and statistical significance of our earlier findings, as well as the conclusion that advertising levels are too high “across the board.” A similar pattern emerges for equation (6): coefficient estimates for the model with quality as a moderating variable on the advertising effect are very similar to those reported in Model IV in **Table 2**, confirming the result that spending levels are disproportionately high for low-quality movies.²⁸

5 Conclusion

What is the effect of pre-release television advertising on movie box office receipts? And does the magnitude of that effect vary according to the quality of the movie? Analyzing the returns to advertising is central to understanding the long-run impact of competition on advertising escalation, and is of direct interest to movie studios. However, it is hard to disentangle the causal effect of advertising on sales using data on actual box-office receipts. In this study, we use data from a simulated market, the Hollywood Stock Exchange, to examine these questions. A movie’s virtual stock price is, in effect, a measure of expected box-office receipts, and turns out to be strong predictor of sales. In addition, these data have two major advantages. While sales data are only available after the product launch, we can observe the entire dynamic path of movements in expectations pre-release, and relate those to dynamics in the advertising allocation process. Furthermore, various institutional constraints on the advertising allocation process suggest that changes in pre-release advertising from week to week are plausibly exogenous. Our results indicate that (1) advertising has a positive and statistically significant impact on market-wide expectations prior to release, and (2) this impact of advertising is lower for movies of lower quality. The point estimate implies that the return to advertising for low-quality movies is negative. These results have implications for motion picture industry executives seeking to optimally allocate television advertising budgets and maximize their profits. The findings also have a welfare optimality implication to the extent that advertising draws customers who otherwise would have opted for other movies.

Two caveats of this study might lead to worthwhile research extensions. First, our analysis does not explicitly incorporate the competitive environment for movies.²⁹ A better understanding

²⁸The R^2 for both models with the “unanticipated” advertising measures is 0.10, lower than for the models reported in **Table 2**.

²⁹Implicitly, 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

of the effect of competition can help studios figure out how they should advertise in the presence of “rivals” (e.g., Berndt 1991), and what this implies for 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.

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).

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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 (0-100)	Q_{AC_i}	280	46.961	48.000	18.496	8.000	95.000	MetaCritic

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

Table 2. Dynamic (Panel) Model: Advertising, Expectations, and Quality ^a

Hierarchical Linear Model	I			II			III			IV		
	Est.	SE	P ^b	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	
β_1 Coefficient of $Q_i(A_i - A_{i,t-1})$	--	--	--	--	--	--	--	--	--	0.009	0.002	**
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	**
Random Component												
τ_1 Variance of δ_{1i}				--	--	--	0.938	0.221	**	0.911	0.226	**
τ_2 Variance of δ_{2i}				--	--	--	0.032	0.009	**	0.033	0.009	**
τ_{12} Covariance of δ_{1i} and δ_{2i}				--	--	--	0.037	0.028		0.037	0.027	
σ^2 Variance of ε_{it}	11.345	0.262	**	10.645	0.260	**	9.744	0.252	**	9.726	0.255	**
N	3360			3360			3360			3360		
R ²	0.113			0.141			0.141			0.162		
Adjusted R ²	0.113			0.141			0.141			0.162		
Estimation, Restriction	--			--			BW, Unstructured			DBW, Unstructured		
-2RLL	17689			17595			17506			17451		

^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 R² and Adjusted R² (see Snijders and Bosker 1999).

^b * p=0.05; ** p=0.01

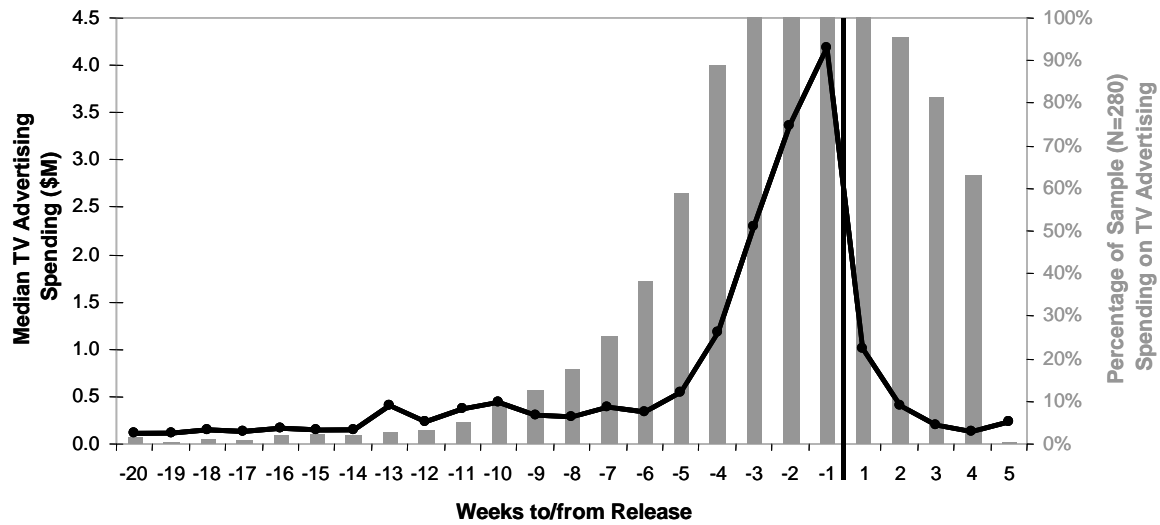
Table 3. Robustness Checks ^a

		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 $(A_i - A_{i,t-1})$.356	.101	**	.361	.099	**	.350	.125	**	.351	.114	**	.351	.118	**	.353	.117	**	.363	.125	**
γ	Coeff. of $(E_{i,t-1} - E_{i,t-2})$.380	.023	**	.380	.023	**	.381	.023	**	.380	.023	**	.380	.023	**	.380	.023	**	.380	.023	**
φ	Coeff. of $X(A_i - A_{i,t-1})$:																					
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.

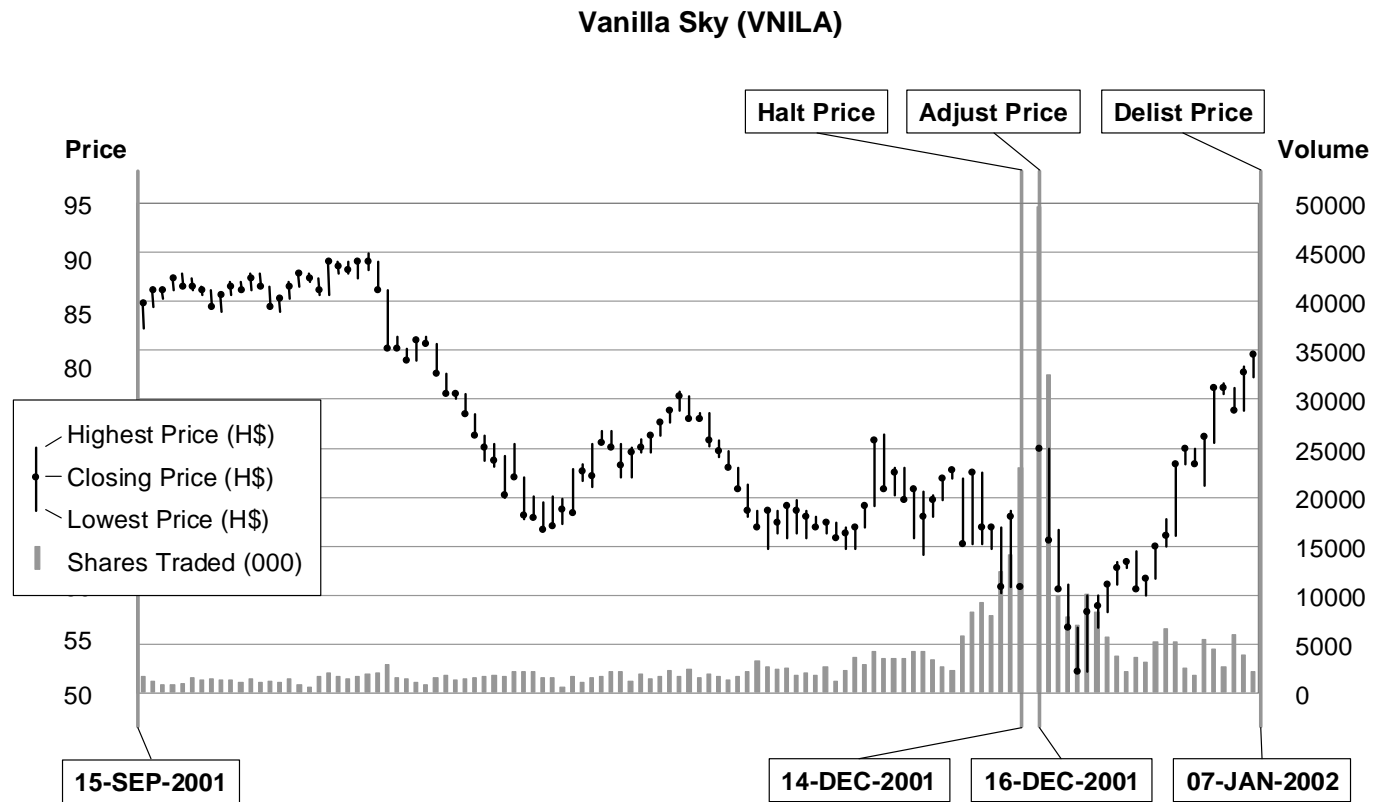
^b * p=0.05; ** p=0.01

Figure 1. Advertising Expenditures: Temporal Patterns ^a



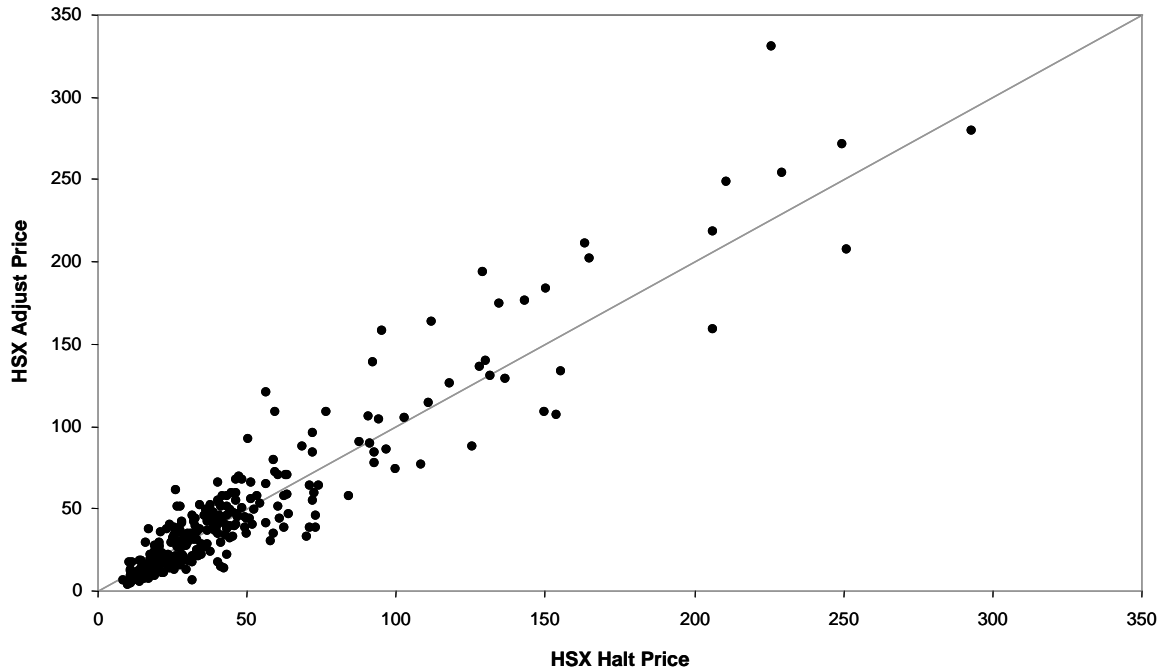
^a This figure shows, for a period before and after the release of all 280 movies in the sample, (1) the weekly percentage of the movies that are spending on television advertising (depicted by the gray bars), and (2) the weekly median expenditures on television advertising for that set of movies (depicted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

Figure 2. The HSX Stock Market Illustrated for 'Vanilla Sky' (VNILA) ^a



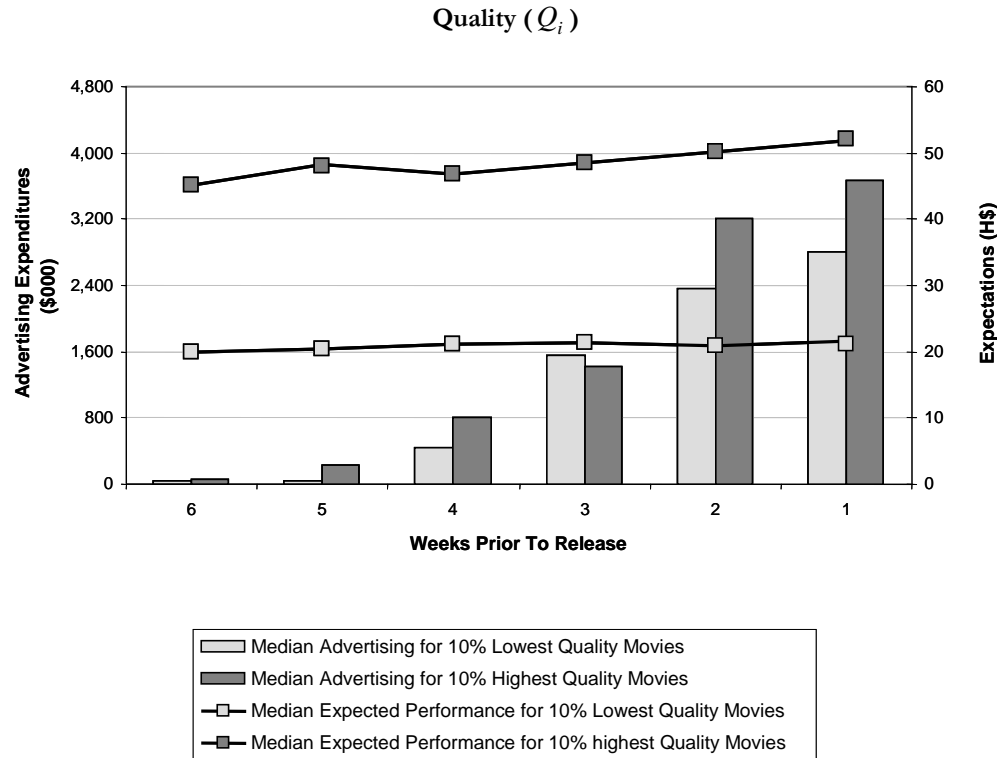
^a This figure illustrates the HSX trading patterns for one movie, Vanilla Sky, denoted by the symbol "VNILA" on the HSX market. It shows daily lowest, highest, and closing prices (in "Hollywood dollars," denoted by H\$, all depicted by the black line), as well as the daily volume of shares traded (depicted 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 3: 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 4. The Role of Quality as a Moderating Variable: An Illustration



^a 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.