The effectiveness of post-release movie advertising

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Frequent new product introductions and short product life cycles lead to unusually high levels of advertising in the movie industry. We study the effectiveness of television advertisements aired after the theatrical opening of a motion picture ('post-release advertising'). We estimate an instrumental variables, lagged effects model using a novel dataset constructed to obviate simultaneity concerns and temporal aggregation biases. We find that post-release movie advertising exhibits a high degree of heterogeneity across films, but generates substantial returns for some movies. Our findings suggest that studios may find it beneficial to experiment with higher post-release advertising budgets. Further, exhibitors may benefit from extended movie life cycles if they share post-release advertising responsibility with studios.

Introduction

Recently, considerable attention has been given to the impact of advertising on returns (e.g. Duhan & Sandvik 2009; van den Putte 2009) and consumption (Wilcox *et al.* 2009). Clearly, research on specific product categories and the return from advertising is needed. The motion picture industry is an area conducive to research on the return from advertising. Movies are experience goods that are typically distributed sequentially across platforms, starting with short periods of theatrical availability. Frequent new product introductions and rapid turnover lead movie studios to advertise heavily. Studios spent US$3.7 billion to advertise their movies in 2003 (TNSMI 2006), leading to $9.5 billion in US box office receipts (Motion Picture Association of America (MPAA) 2005). This

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advertising:sales ratio of 0.39 is among the largest of all US industries (Schonfeld & Assoc. 2006).

About 90% of movie advertising expenditures are incurred before the movie's theatrical release (Elberse & Anand 2007). We refer to such advertising as 'pre-release' advertising. Previous literature has found that pre-release advertising serves four purposes: it informs consumers of the movie's upcoming release and characteristics; it builds 'buzz'; it increases theatrical distribution; and it signals potential studio profitability to investors (Joshi & Hanssens 2009).

The remainder of movie advertising expenditures is incurred after the movie opens in theatres. We refer to this as 'post-release' advertising. Post-release advertising can sustain or grow movie distribution, remind and inform consumers of a film's current availability, provide updated information about critical reviews, and may influence word of mouth. But the critical aspect of post-release movie advertising is that it reaches consumers when the movie is currently available.

Because of rapid changes in new movie availability, consumers may often be unaware of which movies are currently available. Post-release advertising is a reliable tool that studios may use to inform the public of their oft-changing offerings. That studios do relatively little post-release advertising could therefore be regarded as a puzzle. This puzzle, combined with a lack of published papers on the topic, motivates us to study post-release movie advertising.

Our purpose in this paper is to estimate the effects of post-release movie advertising on box office revenues. We do this controlling for theatrical distribution, movie characteristics, critical reviews, rival movie availability and advertising, and demand saturation and time effects.

We find that post-release movie advertising effectiveness is large for about one-third of the movies in our sample. This finding of substantial advertising effectiveness is surprisingly rare among published papers in marketing. However, while these estimated returns are relatively large, they vary widely across movies. Substantial heterogeneity in advertising effectiveness offers one possible explanation for why studios do relatively little post-release advertising. We explore this in depth below.

Our results suggest that studios may be able to expand their post-release advertising budgets profitably, but we do not advocate that this expansion should come at the expense of pre-release advertising. Studios and exhibitors may jointly benefit if they change their contracting terms to encourage more post-release advertising.

Recent literature

Motion pictures have attracted substantial academic attention in recent years. Eliashberg *et al.* (2006) provide an extensive review. We restrict our attention here to the smaller set of recent papers that focus on estimating the impact of movie advertising on movie demand.

Elberse and Eliashberg (2003) find that endogenising movie distribution reduces the estimated effect of a 10% increase in cumulative advertising from 5% of box office revenues to 2.5%. However, they do not observe variation in advertising expenditures over the length of a movie's run. Ainslie *et al.* (2005) estimate a Hierarchical Bayes model of movies' market shares and diffusion. They find that a 1% increase in total advertising increases cumulative box office 6.6%, but they do not observe variation in movie advertising expenditures over time. Moul (2006) finds that omitting advertising from demand estimation overstates the impact of screens on movie admissions, but his measure of advertising is limited to column inches in the *Chicago Tribune*. Elberse and Anand (2007) estimate the returns to pre-release advertising by using a creative instrument to control for advertising endogeneity: revenue expectations set in an online futures market (the 'Hollywood Stock Exchange'). They find that, on average, US$1 million in pre-release advertising leads to US$550,000 in cumulative box office revenues.

A closely related paper is Joshi and Hanssens (2009). These authors use an event study methodology and a large dataset of movies to identify the effects of pre-release movie advertising on studio share prices. They find that movies with above average pre-release advertising expenditures are associated with smaller abnormal returns. Our paper departs from the recent literature in its focus on post-release advertising rather than pre-release; our examination of advertising's effects on box office revenues rather than share prices; and its use of a time series model, which allows for extensive controls for advertising endogeneity.

Data

We estimate our model using market data from several sources. The dataset covers the period 28 April to 25 May 2003. It includes all movies that ranked among the top 20 in box office revenues in any of those four weeks, regardless of whether they advertised or not. Table 1 lists the 29 movies in the data.

Table 1: Observed movie characteristics

Movie	Critical appeal	Star appeal	Director appeal	Runtime	Production budget ($000,000)	Distributor
A Man Apart	34	70.9	44.5	109	36	New Line
A Mighty Wind	78	8.7	9.3	92	6	Warner Bros.
Agent Cody Banks	44	29.5	6.3	110	28	MGM
Anger Management	51	77.1	123.3	101	75	Sony
Bend it like Beckham	68	0	1.0	112	15	20th Century Fox
Better Luck Tomorrow	69	0	0	98	0	Paramount
Bringing Down the House	38	28.8	50.8	105	33	Buena Vista
Bulletproof Monk	39	63.5	0	103	52	MGM
Chasing Papi	36	49.3	0	80	10	20th Century Fox
Chicago	79	62.3	0	107	45	Miramax
Confidence	58	51.9	15.2	98	15	Lions Gate
Daddy Day Care	33	89.7	85.1	92	60	Sony
Down with Love	52	78.7	68.4	101	35	20th Century Fox
Head of State	45	51.5	0	95	35	DreamWorks
Holes	74	48.3	53.9	117	20	DreamWorks
House of 1000 Corpses	30	0	0	88	7	Lions Gate
Identity	63	30.3	38.0	87	28	Sony
It Runs in the Family	43	45.4	2.3	109	40	MGM
Malibu's Most Wanted	42	33.7	33.4	80	15	Warner Bros.
Phone Booth	53	64.0	17.9	81	13	20th Century Fox
Piglet's Big Movie	62	0	0	75	5	Buena Vista
The Core	46	35.2	87.7	136	60	Paramount
The Good Thief	69	8.2	8.3	109	30	20th Century Fox
The Lizzie McGuire Movie	54	0	2.1	90	17	Buena Vista
The Matrix Reloaded	63	55.3	171.5	138	150	Warner Bros.
The Pianist	87	20.6	0	148	35	Focus
The Real Cancun	29	0	0	90	35	New Line
What a Girl Wants	42	48.4	27.1	104	25	Warner Bros.
X2: X-Men United	70	76.0	83.1	134	110	20th Century Fox
Mean	53.5	38.9	32.0	103.1	$35.7	

Data sources and measures

For each of the included movies, we collected box office revenue, distribution and movie characteristics data from the industry website, Box Office Mojo. Distribution is defined as the number of screens on which the movie was shown in a given week. Movie characteristics include genre, MPAA rating, runtime (length in minutes), distributor, production budget, 'director appeal', 'star appeal' and 'critical appeal'. Director appeal is defined as the mean box office revenues of the director's movies in the preceding five years, and star appeal is the average, over the movie's starring actors, of box office revenues of the films in which the actors had starred in the previous five years. Critical appeal was collected from metacritic.com as the weighted average of quantitative assessments of movie critics' reviews in 41 magazines, major newspapers and websites.

Advertising data were recorded by TNS Media Intelligence/CMR. Our measure of advertising is daily prime-time expenditure, by movie, on national broadcast and cable network television. These media accounted for 44.6% of movie advertising expenditures in 2003. We do not observe spending in non-television media, but comprehensive data on spending in all advertising media are seldom available. Table 2 summarises the movie advertising, distribution and revenue data.

Patterns in the raw data and endogeneity

Figure 1 shows raw data for advertising and box office revenues for three movies in the sample. The patterns preview some of our findings and underscore the importance of endogeneity controls. The naked eye can see that box office revenues roughly track advertising expenditures in all three graphs. Among all movies, the correlation between post-release advertising spending on day $t-1$ and box office revenues on day t is 0.499.[1]

These raw patterns can mask more complex relationships. There are three common sources of bias in advertising/sales response function

[1] If we regress box office revenues on weekday dummies, movie dummies and movie-specific time trends, we can remove the effects of pre-release advertising spending, period of the run and cyclical weekday effects. The correlation between the remaining part of box office revenues and previous-day advertising expenditures is 0.099, significant at the 99% confidence level.

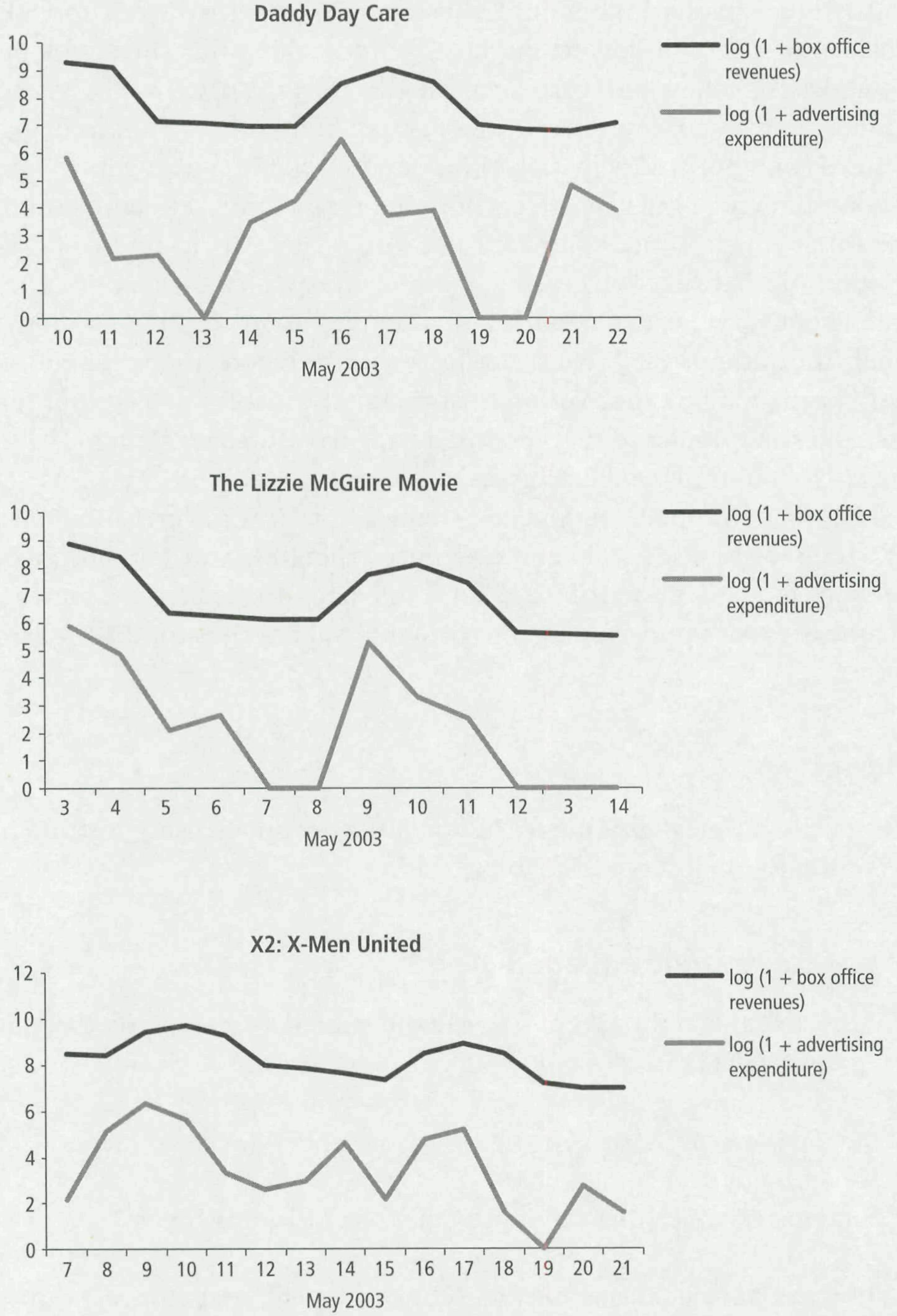
Table 2: Descriptive statistics

Movie	Mean weekly box office revenues	Mean daily advertising	Min. weekly distribution	Mean weekly distribution	Max. weekly distribution
A Man Apart	$636,000	0	89	509	1,235
A Mighty Wind	$2,333,750	$70,255	155	462	770
Agent Cody Banks	$499,250	0	180	1,058	1,422
Anger Management	$10,231,500	$4,144	2,476	3,106	3,656
Bend it like Beckham	$2,001,000	$35,865	421	503	555
Better Luck Tomorrow	$640,500	$1,914	161	326	387
Bringing Down the House	$1,309,500	0	399	990	1,668
Bulletproof Monk	$2,101,000	0	236	1,507	2,955
Chasing Papi	$566,000	0	66	279	584
Chicago	$1,442,500	0	520	829	1,209
Confidence	$3,004,750	$1,349	365	1,324	1,871
Daddy Day Care	$13,785,000	$129,556	0	1,695	3,408
Down with Love	$2,365,500	$136,193	0	531	2,123
Head of State	$456,750	0	116	458	1,006
Holes	$8,295,250	$909	2,232	2,359	2,452
House of 1000 Corpses	$981,750	$1,116	255	555	815
Identity	$11,644,250	$23,562	2,196	2,570	2,733
It Runs in the Family	$1,827,750	0	320	944	1,207
Malibu's Most Wanted	$2,164,500	$239	811	1,916	2,503
Phone Booth	$1,907,250	0	406	1,125	2,113
Piglet's Big Movie	$362,750	0	320	475	744
The Core	$284,750	0	94	516	1,228
The Good Thief	$416,500	0	120	183	222
The Lizzie McGuire Movie	$8,320,000	$35,394	0	2,077	2,825
The Matrix Reloaded	$40,967,250	$213,054	0	1,802	3,603
The Pianist	$413,500	0	141	313	539
The Real Cancun	$944,500	$26,705	0	1,187	2,261
What a Girl Wants	$1,474,000	0	260	1,339	2,450
X2: X-Men United	$44,739,500	$156,296	0	2,745	3,749
Mean	$5,728,155	$28,847	425	1,161	1,803

estimation: simultaneity, omitted variables and time aggregation.[2] The *Lizzie McGuire Movie* graph in Figure 1 illustrates the common simultaneity bias (cf. Erickson 1992 and references therein). Advertising expenditure tracks contemporaneous box office revenues very closely. Because movie advertising on any given day cannot depend on the same day's box

[2] Endogeneity refers to any correlation between an independent regressor and an error term. If left uncorrected, it causes parameter estimates to be biased and inconsistent. Simultaneity is a particular form of endogeneity in which the independent variable is partially caused by the dependent variable; in this context, the concern is that sales may cause advertising due to studios' ad budgeting strategies. Time aggregation is a form of endogeneity that can arise when independent events are measured infrequently (cf. Tellis & Franses 2006).

Figure 1: Log box office revenue and log advertising expenditures



office revenues, since studios do not observe revenues in real time, our data ensure that our estimation is not affected by simultaneity.

All three graphs in Figure 1 illustrate the need to use a model to isolate the effect of advertising on revenues. Box office revenues peak immediately following sharp increases in advertising. This is because studios tend to concentrate advertising expenditures on Wednesday and Thursday nights in anticipation of elevated weekend movie-going. These Wednesday and Thursday effects illustrate the potential effects of omitted variables, which, if not controlled for, would cause us to find a spurious relationship between advertising and box office. This correlation reflects endogenous studio behaviour in that studios tend to advertise movies when the returns are highest, such as shortly before the weekend and early in the movie's run. We use instrumental variables in a control function approach similar to that proposed by Villas-Boas and Winer (1999) to correct for omitted variables biases.

The final common endogeneity concern is time aggregation biases (cf. Tellis & Franses 2006 and references therein). Since a consumer is unlikely to see a prime-time ad for a movie and then see the movie in the theatre that same evening, our data interval obviates time aggregation biases.

Model

We specify a time series model of box office revenues using instruments to control for unobserved variables.

Box office revenue equation

We seek to explain the box office revenue earned by movie j on day t, BO_{jt} using equation (1):

$$BO_{jt} = AdvExp_{jt-1}\alpha^b_{aj} + Dist_{jt}\alpha^b_d + X^b_{jt}\beta_b + \varepsilon^b_{jt} \qquad (1)$$

X^b_{jt} contains variables that influence daily box office revenues:

- observed movie characteristics (critical appeal, star appeal, director appeal, genre, movie rating, runtime and production budget); these have been found by numerous previous studies (e.g. Elberse & Eliashberg 2003) to impact box office appeal

- movie dummies, to control for unobserved movie characteristics and time-invariant pre-release advertising
- day-of-the-week dummies, to control for fluctuations in demand
- days and days-squared since the movie's release, to control for how long the movie has been in the market
- average daily box office revenues, to control for unobserved word of mouth (Liu 2007) and allow for non-linear sales decay (Ainslie *et al.* 2005).

We next discuss our control functions, beginning with advertising.

Advertising and distribution control functions

We specify the advertising expenditure for movie *j* on day *t* in equation (2):

$$AdvExp_{jt} = Dist_{jt}\alpha_d^a + X_{jt}^a\beta_a + Z_{jt}^a\lambda_a + \varepsilon_{jt}^a \tag{2}$$

X_{jt}^a contains factors that can influence both movie advertising and box office revenues: theatrical distribution, movie characteristics, movie fixed effects, weekday dummies, days and days-squared since the movie's release, and average daily box office revenues to date. Z_{jt}^a is a vector of instruments for advertising which we discuss further under the subhead 'Instrumental variables', below.

Our other control function explains theatrical distribution. Distribution typically changes weekly, on Fridays, as exhibitors re-evaluate their screen allotments in consideration of weekend demand, so there is virtually no variation over days within a week. We therefore estimate distribution at the weekly level (w) using equation (3):

$$Dist_{jw} = AdvExp_{jw-1}\alpha_a^d + X_{jw}^d\beta_d + Z_{jw}^d\lambda_d + \varepsilon_{jw}^d \tag{3}$$

The weekly nature of the distribution data limits the degrees of freedom and, consequently, the number of variables we can include. X_{jw}^d includes observed movie characteristics. Z_{jw}^d is a vector of instruments for distribution, which we discuss under the subhead 'Instrumental variables', below.

Instrumental variables

Valid instruments must meet two conditions:

(A1) they must be correlated with the endogenous regressor, and
(A2) they must be uncorrelated with the error term in the second-stage equation.

We use three instruments for advertising expenditure in Z_{jt}^{a}: movie *j*'s percentage change in distribution (Z_{jt}^{a1}), the studio's ads for its *other* movies (Z_{jt}^{a2}) on day *t*, and the movie's gross box office revenue to date (Z_{jt}^{a3}). The first two instruments are motivated by partial rigidities in the television advertising market. Advertising is set by movie studios, which have portfolios of movies to promote. Studios buy nearly all of their TV ad time during the 'upfront' marketplace to procure quantity discounts (Auletta 1992). A total of 80% of networks' commercial inventory is sold during the upfront, which concluded approximately ten months prior to our sample period. The remainder is sold on the scatter market, usually at a premium, up until the time the inventory airs. It is therefore difficult for studios to increase their advertising weight in the short run. But while *quantities* of advertising are difficult to change in the short run, the *creatives* that studios air can be changed very shortly before a commercial airs. Our discussions with industry executives confirm that studios often select which movie to advertise shortly before a purchased ad airs, based on the latest market information available – sometimes even on the air date of the advertisement. The third instrument is included because gross box office revenue to date indicates the level of demand saturation the movie has achieved. Demand saturation is inversely related to unrealised demand, which determines the potential returns to advertising.

Z_{jt}^{a1} should satisfy (A1) if the studio is more likely to allocate its advertising slots to its other movies when movie *j* is faltering. Z_{jt}^{a1} should satisfy (A2) if consumers base movie-going decisions on current distribution levels rather than changes in distribution levels. Z_{jt}^{a2} should satisfy (A1) since the studio has to allocate its purchased time among its extant movies. Z_{jt}^{a2} should satisfy (A2) if movie advertising has primarily category expansion effects rather than business stealing effects. Z_{jt}^{a3} should satisfy (A1) if studios' decisions regarding which advertising creatives to air are influenced by demand saturation. Z_{jt}^{a3} should satisfy (A2) if consumers base movie-going decisions primarily on movies' personal consumption value and do not see a movie multiple times in the theatre.

We use two instruments for distribution in Z_{jw}^{d} distribution growth, as measured by the percentage change in week-over-week box office revenues (Z_{jw}^{d1}), and the average age of the top five grossing movies in week w (Z_{jw}^{d2}) will satisfy (A1) if, as their profit motive suggests, theatres look at recent movie performance to decide whether to add or drop screens for movie j. Z_{jw}^{d1} will satisfy (A2) if the extent to which consumers' movie-going decisions depend on changes in movie performance is adequately controlled by the multiple *daily* measures of changes in box office performance in equation (1) rather than the *weekly* change in box office Z_{jw}^{d1}. Z_{jw}^{d2} will satisfy (A1) because of competition for screens. The longer a movie stays in the top five after its release, the more likely it will retain its 'legs' and its place on exhibitors' screens. Z_{jw}^{d2} will satisfy (A2) if consumers' movie-going decisions are primarily driven by movie characteristics and availability rather than movie age.

The Appendix provides some evidence in support of these assumptions.

Lagged advertising effects

Many prior studies on advertising effectiveness have noted that the effects of advertising may last for multiple periods. The inclusion of multiple lagged advertising effects implies that equation (1) could be rewritten as:

$$BO_{jt} = \sum_{s=1}^{\infty} AdvExp_{jt-s}\alpha_{ajs}^{b} + Dist_{jt}\alpha_{d}^{b} + X_{jt}^{b}\beta_{b} + \varepsilon_{jt}^{b} \qquad (4)$$

In equation (4), the subscript s denotes lags from the current period. This implies that each movie j has a separate advertising effectiveness parameter for each lagged time period (α_{ajs}^{b}). This would dramatically increase the number of parameters to be estimated. As noted by a large literature, an exponential smoothing assumption can decrease the number of parameters required.

$$\sum_{s=1}^{\infty} AdvExp_{jt-s}\alpha_{asj}^{b} = \gamma_{j}\sum_{s=1}^{\infty} \lambda_{j}^{s-1} AdvExp_{jt-s} \qquad (5)$$

Using equation (5), we apply the Koyck transformation to simplify equation (4):

$$BO_{jt} = AdvExp_{jt-1}\gamma_j + \lambda_j BO_{jt-1} + Dist_{jt}\alpha_d^b + X_{jt}^b\tilde{\beta}_b + \varepsilon_{jt}^b \tag{6}$$

where $\tilde{\beta}_b = 1 - \lambda\beta_b$.

To determine whether equation (6) is the appropriate model to estimate, we apply the Griliches (1967) test. We add an additional advertising lag to test whether the lagged box office term sufficiently captures all previous advertising efforts. We estimate equation (7) to check:

$$BO_{jt} = AdvExp_{jt-1}\gamma_1 + AdvExp_{jt-2}\gamma_2 + \lambda BO_{jt-1} + X_{jt}^b\tilde{\beta}_b + \varepsilon \tag{7}$$

According to Griliches (1967), if γ_2 is not significantly different from zero, then lagged box office revenue sufficiently captures previous advertising. If γ_2 is statistically significant, then the lagged effects model is inappropriate for explaining the data. Equation (8) displays selected results, with *t*-statistics in parentheses:

$$\begin{array}{l} BO_{jt} = \underset{(-1.44)}{-4982} + \underset{(3.17)}{11.23}\ AdvExp_{jt-1} + \underset{(0.22)}{0.78}\ AdvExp_{jt-2} + \underset{(7.3)}{0.45}\ BO_{jt-1} \end{array} \tag{8}$$

γ_2 is insignificant. Thus we proceed by including one lag of advertising.

Estimation

We first estimate equations (2) and (3) separately using Feasible Generalised Least Squares (FGLS). The advantage of FGLS over Ordinary Least Squares (OLS) is its allowance for data-driven heteroskedasticity in the errors.[3] We replace advertising and distribution in equation (6) with their fitted values.

A Wooldridge Panel Serial Correlation test indicated first-order autocorrelation in the equation (6) residuals. To correct for this we use quasi-differencing. This is a procedure in which we first estimate a first-order autocorrelation parameter in the residuals, $\hat{\rho}$. We transform the data to

[3] We found FGLS and OLS estimation yield quantitatively similar results. A Breusch-Pagan Lagrange multiplier test rejects the null hypothesis that the errors exhibit constant variance, so we present the FGLS results.

allow for this autocorrelation, using an upper bar to indicate a generalised difference, $\overline{BO}_{jt} = BO_{jt} - \hat{\rho} BO_{jt-1}$. We then use FGLS to estimate the quasi-differenced model in (9):

$$\overline{BO}_{jt} = \overline{AdvExp}_{jt-1}\gamma_j + \overline{BO}_{jt-1}\lambda_j + \overline{Dist}_{jt}\alpha_d^b + \overline{X}^b_{jt}\tilde{\beta}_b + u \tag{9}$$

Canjels and Watson (1997) and Phillips and Lee (1996) show that quasi-differencing obtains efficient estimates and accurate standard errors in the presence of serial correlation in the residuals.

Robustness checks

We subjected our assumptions to a variety of robustness checks to monitor the sensitivity of our results to the assumptions made. We tried replacing the exponential decay assumption with a distributed lag advertising carryover function, and estimated the optimal number of lags to include in the model. This approach, which is used by Tellis *et al.* (2000), involves comparing the likelihood value, c^2 statistic, and significance of the lags to determine which number of lags yields the best fit. We found that including one lag of advertising and one lag of box office revenues in equation (1) was optimal, consistent with the Koyck transformation.

To verify that endogeneity was present, we conducted separate Durbin-Wu-Hausman tests of the null hypotheses that advertising expenditure and distribution were exogenous, using the instruments described under the subhead 'Instrumental variables', above. Both tests rejected the null at the 99% confidence level.

We estimated the model using logs of box office, advertising and theatrical distribution. The results were quantitatively similar. We present model estimates using variable levels rather than logs because levels provided a slightly higher fit.

We estimated a Tobit model in the advertising control function to handle the sparseness of the advertising data. The results were nearly identical to the linear control function results.

Empirical results

The movie industry has attracted substantial recent attention, so we focus on the empirical results of most interest.

Control function estimation results

Distribution parameter estimates (equation 2) are presented in Table 3. The first three parameter estimates are significant and intuitive: distribution falls when box office revenues decline, can be partially supported by advertising expenditures, and becomes more difficult to maintain when stronger competition enters the market. Longer movies tend to be distributed less widely because they reduce theatre turnover without increasing revenues. Most of the studio dummies were not significant. The distribution regression fit the data with a pseudo R^2 of 0.68.

Table 4 presents advertising regression parameter estimates (equation 3). The estimates indicate that past box office revenues are a stronger influence on post-release advertising than distribution. Movies that are close to reaching saturation or that have low daily earnings receive less

Table 3: FGLS distribution equation parameter estimates

Variable	Estimate (std. error)	Variable	Estimate (std. error)
% change in weekly box office	103.81** (32.04)	MPAA rating: PG-13	409.94 (214.02)
Advertisings	2.53** (0.51)	MPAA rating: R	–622.25* (282.82)
Average age of top 5 grossing movies	–68.24** (20.48)	Critical appeal	14.71 (9.69)
Production budget	8.08 (7.72)	Cast appeal	–0.40 (4.44)
Genre: action	–694.05 (413.17)	Director appeal	16.22** (4.03)
Genre: comedy	–1,014** (266.60)	Runtime	–26.96* (11.82)
Genre: drama	388.18 (339.58)	Constant	3,609** (1,181)

Pseudo R^2 = 0.68; Number of observations = 96; *Significant at the 5% confidence level; ** Significant at the 1% confidence level advertising support since they will soon exit the market. Comedies, R-rated movies and long movies receive less post-release advertising than other films, while big-budget and star-studded films are advertised more. Critical appeal tends to increase post-release advertising since positive critical reviews can be featured in commercials. The one potentially counterintuitive result is that post-release advertising tends to fall with director appeal. One possible explanation is that director appeal may act as a proxy for the complexity of a movie's plot, making it difficult to craft advertising messages.

Table 4: FGLS advertising expenditure parameter estimates

Variable	Estimate (std. error)	Variable	Estimate (std. error)
Distribution	2.4E-3 (4.0E-3)	Cast appeal	5.01** (1.06)
% change in distribution	2.39 (2.47)	Director appeal	–2.97** (0.93)
Gross box office revenues to date	–2.9E-3** (6.2E-4)	Runtime	–5.55** (0.93)
Average daily box office revenues to date	–3.2E-2** (5.3E-3)	Days since release	–0.63 (0.43)
% change in box office revenues	–14.75 (9.55)	(Days since release)	4.2E-3 (3.0E-3)
Rival advertising	–1.2E-3 (2.7E-3)	Premiere week	31.98** (9.59)
Distributor ads for other movies	–2.7E-3 (4.6E-3)	Day: Tuesday	–0.69 (4.08)
Production budget	9.98** (1.70)	Day: Wednesday	–0.77 (3.84)
Genre: action	–20.07 (69.25)	Day: Thursday	2.23 (6.53)
Genre: comedy	–219.96** (42.70)	Day: Friday	–1.75 (4.79)
Genre: drama	90.43 (50.49)	Day: Saturday	–3.42 (5.52)
MPAA rating: PG-13	–8.14 (46.47)	Day: Sunday	–2.91 (3.90)
MPAA rating: R	–186.08** (60.09)	Constant	193.89* (88.26)
Critical appeal	4.36** (1.03)		

Pseudo $R^2 = 0.43$; Number of observations = 605; *Significant at the 5% confidence level; ** Significant at the 1% confidence level

Box office revenue results and interpretation

Table 5a displays the movie-specific advertising effectiveness parameter estimates of equation (9). There is substantial heterogeneity in advertising effectiveness across movies. Of the 15 movies that did some post-release advertising, five advertising effectiveness parameters were estimated to be positive and significant. However, the point estimates of the five significant parameters range from 15 to 25. The interpretation of these parameters is the effect of US$1 in post-release advertising spending on next-day box office revenues. Thus the significant effects found indicate large returns to advertising for some movies. However, we found no significant effect for two-thirds of the movies that advertised in the sample; this indicates substantial heterogeneity associated with post-release advertising.

Five advertising effectiveness parameters are negative, but none is close to significant (using two-sided tests). There is no assumption in the model that would prevent a significant negative finding. We think it is unlikely that advertising effects are truly negative, since studios copy-test their advertisements and would rapidly alter their ad creatives if these were found to be reducing demand for a movie.

Table 5a displays the characteristics of advertising movies to provide context for the determinants of post-release advertising effectiveness. In general, significant advertising effects are associated with higher production budgets, greater star power and greater director appeal. Movies with effective post-release advertising had production budgets that were 227% higher than advertising movies without significant effects. They also had 68% more star power and 150% more director appeal. There is little difference in critical reviews, MPAA rating or running time. In general, significant advertising effects are associated with later release dates, indicating that post-release advertising may be maximally effective early in the movie's run, when movie demand is less saturated and the proportion of uninformed consumers is highest.

There is no clear correlation with average advertising spending levels. This suggests three non-exclusive possibilities. Studios may not be fully able to predict their movies' advertising effectiveness, studios may be risk averse, and studios' share of post-release box office revenues may not be high enough to justify maximally efficient advertising expenditures.

Table 5a: Advertising estimates and movie characteristics

	Advertising$_{jt-1}$ estimate (std. error)	Mean advertising elasticity[a]	Release date	Average daily ad spending	Critical appeal	Star appeal ($m)	Director appeal ($m)	Production budget ($m)	Rating	Running time (mins)
A Mighty Wind	–4.8 (32.5)		16/4/2003	$70,255	78	8.7	9.3	6	PG-13	92
Anger Management	32.1 (16.5)		11/4/2003	$4,144	51	77.1	123.3	75	PG-13	101
Bend it Like Beckham	1.8 (1.7)		12/3/2003	$35,865	68	0.0	1.0	15	PG-13	111
Better Luck Tomorrow	–43.6 (42.3)		11/4/2003	$1,914	69	0.0	0.0	0.25	R	98
Confidence	2.1 (8.5)		25/4/2003	$1,349	58	51.9	15.2	15	R	98
Daddy Day Care	25.2 (4.5)**	0.30	9/5/2003	$129,556	33	89.7	85.1	60	PG	92
Down With Love	7.7 (5.3)		16/5/2003	$136,193	52	78.7	68.4	35	PG-13	101
Holes	24.3 (15.0)		18/4/2003	$909	74	48.3	53.9	20	PG	117
House of 1000 Corpses	–9.6 (28.0)		11/4/2003	$1,116	30	0.0	0.0	7	R	88
Identity	23.9 (4.3)**	0.55	25/4/2003	$23,562	63	30.3	38.0	28	R	87
Malibu's Most Wanted	–41.2 (38.3)		18/4/2003	$239	42	33.7	33.4	15	PG-13	80
Lizzie McGuire	24.5 (2.9)**	0.48	2/5/2003	$35,394	54	0.0	2.1	17	PG	90
The Matrix Reloaded	15.3 (6.7)*	0.32	15/5/2003	$213,054	63	55.3	171.5	150	R	138
The Real Cancun	–11.1 (7.7)		25/4/2003	$26,705	29	0.0	0.0	35	R	90
X2: X-Men United	18.1 (5.2)**	0.24	2/5/2003	$156,296	70	76.0	83.1	110	PG-13	134

* Significant at the 5% confidence level; ** Significant at the 1% confidence level

[a] We calculated advertising elasticities for every observation in the sample with a positive advertising expenditure. We report here the mean of those elasticities within each movie with a significant effect

Table 5b: Box office revenues parameter estimates

Variable	Estimate (std. error)	Variable	Estimate (std. error)
Production budget	1.4 (18.6)	Critical appeal	13.1 (39.4)
Distribution	–0.1 (0.1)	Star appeal	–1.8 (17.6)
Days since release	–12.0 (6.7)	Director appeal	5.8 (22.1)
(Days since release)^2	0.1 (0.0)	Runtime	–2.0 (26.0)
Genre: action	68.3 (550.2)	Day: Tuesday	141.9** (45.2)
Genre: comedy	110.9 (442.6)	Day: Wednesday	128.2** (45.4)
Genre: drama	477.2 (2073.3)	Day: Thursday	130.1** (48.9)
MPAA rating: PG-13	–655.7 (1972.3)	Day: Friday	341.9** (51.1)
MPAA rating: R	–221.5 (256.4)	Day: Saturday	459.4** (40.0)
Average daily box office to date	0.0 (0.1)	Day: Sunday	154.7** (42.0)

Pseudo R^2 = 0.8964; Number of observations = 522; * Significant at the 5% confidence level; ** Significant at the 1% confidence level

In Table 5b we report additional results from equation (9). The weekday effects indicate that movie consumption is greatest on Saturday, followed by Friday. The quasi-differencing procedure greatly reduces the explanatory power of time-invariant movie characteristics, though many of these effects are significant when we estimate using levels instead of differences. The pseudo R^2 of the regression was 0.896, indicating that the model explains the data quite well.

Discussion

In this paper we investigated the effectiveness of post-release advertising for motion pictures. We did this using a dataset that obviated simultaneity and temporal aggregation concerns. We controlled for the effects of omitted variables using an instrumental variables approach. We have shown that our results are robust to many changes in our basic modelling assumptions and econometric approach.

Our main findings are that advertising effectiveness is very heterogeneous across movies, and generates large returns for some movies. Only 5 of 15 advertising movies were found to have statistically significant effects of advertising, but those movies' immediate returns to US$1 in post-release advertising ranged from US$15 to US$25. Significant advertising elasticities range from 0.24 to 0.55. These elasticities are larger than most found in the literature; Sethuraman and Tellis (1991) conduct a meta-analysis of 260 empirical advertising studies and report a median advertising elasticity of 0.11. Despite this difference, these large returns for some movies' post-release advertising are credible as this type of advertising constitutes giving viewers a free sample of a new, hedonic experience good that is contemporaneously available. If ever we expect to find large returns to advertising, it should be in a setting such as this.

The heterogeneity in advertising effectiveness across movies shows the risk studios face when setting advertising budgets. In creative industries such as this one, it is notoriously difficult to project which products will succeed and which will fail.

Managerial implications

It is tempting to conclude that our results imply that studios are leaving money on the table in their post-release advertising. While this is certainly possible, and may even seem likely, there are several reasons to hesitate before reaching such a conclusion. Due to the standard contracting terms between studios and exhibitors, studios do not capture all of the theatrical returns of their advertising. Studios receive descending percentages of their films' box office revenues as time passes after release. This gives them substantial incentives to open the movie in as many theatres as possible and to have less regard for the movie's 'legs'. No decisive statement about studios' profitability of current advertising levels is possible without access to confidential studio/exhibitor contracting terms.

Our results may have two implications for practice. First, they may suggest that studios ought to experiment by increasing post-release advertising expenditures. While this is a risky marketing tactic, the potential returns may be high enough to justify additional expenditures. There are two main differences between post-release advertising effectiveness and pre-release advertising. Consumers' memories are limited and studios' messages face substantial competitive clutter, so post-release advertising may be less affected by consumer forgetting. Also, post-release ads may contain stronger calls to action and more credible information (like critical reviews, man-on-the-street interviews, etc.) since the product is currently available.

It is important to note that our results may support experimentation with larger post-release advertising budgets, but this probably should not come at the expense of pre-release advertising budgets. A substantial body of work, including Elberse and Eliashberg (2003) and Joshi and Hanssens (2009), provides strong evidence that pre-release advertising is effective and profitable. Kopalle and Lehmann (2006) find that firms may optimally overstate quality prior to product release in entertainment industries such as movies, suggesting large pre-release advertising budgets.

A second implication of our analysis is that if studios can profitably increase their post-release advertising budgets, exhibitors may benefit from increasing their incentives to do so. Currently, the studio's interest is maximising initial box office revenues with less regard for the movie's 'legs'. The studio's interest in theatrical revenues may be further eroded by the possibility that theatrical demand can cannibalise more profitable demand in secondary distribution channels (e.g. DVD and pay-per-view sales).

This incentive change could be accomplished by two possible modifications to studio/exhibitor contracts. First, exhibitors could take partial responsibility for post-release advertising expenditures. This would be similar to co-op advertising arrangements, in which manufacturers and retailers share retailers' product-specific advertising costs, which are used by thousands of retail brands (Nagler 2006). The second modification that would encourage studios to do more post-release advertising would be to alter the rate at which their share of exhibition revenues declines after the movie's release, holding the studios' total take constant. Reducing the degree to which studios' revenues decline with movie age would strengthen their interest in prolonging the movie's life. However, it must be recognised that this suggestion would also alter the degree of risk borne by exhibitors, an important factor that we have not analysed here.

Research limitations and opportunities

Our study has several limitations that suggest directions for future research. We discuss perhaps the three most profitable of these here. First, we have not investigated how post-release film advertising budgets impact studios' stock prices. Our data are well suited to endogeneity corrections, but poorly suited to event-study analysis of this type. While our measure of sales is limited to box-office revenues, advertising's impact on share price could also capture investors' expectations of its effects on DVD sales, pay-per-view revenues or movie licensing.

Second, it would be interesting to know how movie advertising effects change over time. While our dataset has high periodicity, it is limited to a relatively narrow window of time – the April/May season identified by Joshi and Hanssens (2009) – and a relatively small number of movies. It would be useful to know how post-release advertising effectiveness varies with movie characteristics and seasons of the year, and how it has changed in recent years.

Finally, while our measure of advertising is more detailed than many previous studies, it would be useful to supplement it with word-of-mouth data or ad spending in additional media. Recent work by Liu (2006) and others suggests that word of mouth has a large impact on movie demand. It would be interesting to examine the degree to which different types of post-release advertising appeal influence the volume and valence of consumers' word of mouth.

Appendix

In this Appendix we describe our procedure to test the instruments described under the subhead 'Instrumental variables', above.

To test (A1), we conducted F-tests to gauge the degree to which the advertising instruments and distribution instruments explain the dependent variables in the first-stage control functions. To test (A2), we included the first-stage instruments in the second-stage regression and conducted F-tests to determine whether they jointly explain box office revenues.[4]

[4] These two tests formalise the standard instrumental variable intuition, that an instrument should be correlated with the endogenous regressor, and orthogonal to the error term in the second-stage regression. Another way of viewing this second condition is that excluding the instruments from the second-stage equation does not constitute a specification error.

Table 6: Robustness testing

	First-stage estimate (std. error)	Second-stage estimate (std. error)
Distribution instruments		
% change in weekly box office	103.81** (32.04)	119.07 (113.54)
Average age of top 5 grossing movies	–68.24** (20.48)	–9.81 (16.57)
Joint significance *F*-stat	105.70	2.89
P-value	0.0000	0.2362
Advertising instruments		
% change in distribution	2.39 (2.47)	–20.01 (42.46)
Distributor ads for other movies	–2.7E-3 (4.6E-3)	–0.03 (0.05)
Gross box office revenue to date	–2.9E-3** (6.2E-4)	0.01 (0.01)
Joint significance *F*-stat	23.45	1.09
P-value	0.0000	0.7801

* Significant at the 5% confidence level; ** Significant at the 1% confidence level

Table 6 displays the results of these first two tests. An F-test rejects the null hypothesis that advertising instruments can be excluded from equation (2) at a very high confidence level. An analogous F-test indicates that the distribution instruments cannot be excluded from equation (3) at a similarly high confidence level. The second column of Table 6 presents the estimated effects of the instruments if we include them in the box office revenues equation (1). We reject their inclusion in the second-stage regression as the F-tests fail to reject the null hypothesis that they should be jointly excluded.

Finally, we conducted a Hausman test to compare the instrumental variables estimates to non-IV estimates of the same parameters. FGLS estimates would be preferred to IV on efficiency grounds under the null hypothesis that there is no statistical difference between the two sets of estimates. The data reject the null at a 99% confidence level. We conclude that the IV results are preferred to the non-IV results.

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