Mark Lett
DOI 10.1007/s11002-017-9418-5

The impact of advertising content on movie revenues

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Abstract We analyze the contents of print ads in the motion picture industry (e.g., number of reviews quoted in the ad, the presence of a top reviewer, size of the ad, star, director, etc.). We find that external validation (a recommendation by a top reviewer) is more important to revenues than the informative content of the ad.

Keywords Advertising content · External validation · Information · Motion pictures

1 Introduction

This paper tests whether content elements of print advertisements affect product sales, in this case, movie revenues. Bagwell (2007) suggests that advertising can be

[1]For discussions along similar lines in the economics literature, see for example, Abernethy and Franke (1996) and Anderson and Renault (2006).

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Published online: 11 March 2017

persuasive, informative, or complementary.[1] These distinctions were used by Bertrand et al. (2010), and they are very helpful here. More precisely, we classify our variables into external validation variables (critical reviews, awards, etc.) which may be considered persuasive, or "informative" (such as stars, director, or content).

We manually collected advertisements that appeared in page images of the *New York Times* either on the day (or closest to it) of a film opening in New York (most ads are indeed from the opening day and coded the ad content variables). We focus on a single data source, *New York Times*, for several reasons. First, the *Times* is the largest circulation newspaper which regularly runs movie Ads, and it is considered by many to be the leading national newspaper that is read coast to coast. Also, importantly for our work, every Friday, the paper runs a special weekend section on movie reviews and ads (a source not readily available for other outlets). Finally, we had to choose one national newspaper for all ads for comparability, as we use some manual coding as well, but studios often run similar ads across the country.

We code several variables for each advertisement. Since some of the coding involved judgment, two of the authors did the work manually and cross-checked each data point so that any coding disagreements were resolved.

The first item we looked for was whether or not there was any mention of external reviews in the movie advertisement. If such reviews were included, *sellingpoint* was coded as 1. We also counted the number of reviews: "*reviews*" (with an average of about 4 and a range of 0 to 18) (see Table 1). Then we considered whether or not the advertisement mentioned a reviewer who was a "top" reviewer. We used some judgment, and in addition to the *New York Times*, we considered "*topreviewers*" as critics from major city publications and national outlets (*Los Angeles Times*, *Time magazine*, *Ebert*, etc.). If we identified at least one top reviewer in the advertisement, then the variable *topreviewer* received a value of 1; its value is 0 otherwise.

We also coded the advertisement as a star-driven ad, a director-driven ad, content driven, an award-driven ad, or none of the above depending on font sizes. For example, if the film content (*content*) is featured prominently, either in the ad or in the review, *content* is equal to one. We consider films to be content driven only if a specific description of the plot is provided. For example, the movie "Buffalo Soldiers" features the following description (see Appendix): "The Heist- A US Army base. The motive: Revenge. The Motto: Steal all that you can steal." This is specific enough to be coded as "content driven." However, a "sweepingly romantic story" (for the movie "*Latter Days*", also shown in the appendix) does not. Similarly, if a star, some award, or a director is mentioned, we coded dummy variables: *star*, *award*, or *director* as 1. The final element to be coded is the size of the ad (*size*), namely whether or not the ad is full page (then *size* = 1) or smaller (then *size* = 0).

The variables classified as "external validation attributes" are: *topreview, reviews*, *sellingpoint* (reviews are the selling point of the ad), and *award*. The second set is "movie characteristics" (informative): *star*, *content*, and *director*. Our analysis below tests whether external validation attributes (closer to the

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Table 1 Variables and definitions

Dependent variables	Variable definition
box	Box office revenue of film *i* in week *t* in millions of $
totbox	Cumulative box office revenue of film *i* in the dataset in millions of $
openbox	Opening week box office revenue of film *i* in millions of $
Movie ad characteristics	
topreview	=1 if ad was review driven and if one of the reviewers was a top reviewer in *New York Times*, *Los Angeles Times* or *Time* magazine, 0 o/w
reviews	Number of reviews cited in the ad
award	=1 if ad mentions an award, 0 otherwise
sellingpoint	=1 if there is a Selling point of the ad; 0 o/w
star	=1 if ad prominently featured a star or if the reviews highlighted a star, 0 o/w
content	=1 if there is detailed description of the movie content or in the featured review, 0 o/w
Director	=1 if ad prominently featured a director so that the director is the selling point, 0 o/w
Size	=1 if ad is full page, 0 o/w
Control variables	
screens	The number of screens for film *i* in week *t*
totreview	Total number of professional critical reviews (pro + con + mixed) from *Variety* magazine for film *i*
posratio	Ratio of positive reviews to total number of reviews
pg	=1 if the film is PG-rated, 0 otherwise
pg13	=1 if the film is PG13-rated, 0 otherwise
r	=1 if the film is R-rated, 0 otherwise
prevoscar	=1 if any of the cast members have won an Oscar in previous years, 0 otherwise
genre	=1 if the genre is either Comedy, Drama or Action, 0 otherwise
newfilm	Number of new films in the Top 20 per week
totalad	Advertising dollars per week in millions
sequel	=1 if the film is a sequel to a prior film
major	=1 if the film is released from a major studio
weeks	Number of weeks since the film was released
Instrumental variables	
screen_diffrating	Average *screens* per week in time *t* of all other movies that have a different rating from movie *i*
screen_diffrating_budget	Average *screens* per week in time *t* of all other movies that have a similar budget to movie *i* but have a different rating from movie *i*
totreview_diffrating_budget	Average *totreview* per week in time *t* of all other movies that have a similar budget to movie *i* but have a different rating from movie *i*
totreview_diffgenre_budget	Average *totreview* per week in time *t* of all other movies that have a similar budget to movie *i* but have are in a different genre from movie *i*

persuasive effect) or movie characteristics affect revenues, whether both matter or whether neither has any effect on movie going.

2 Data and model specification

Sample We identify a sample of 206 films released in the US market between 2003 and 2004. Our sample covers about a third of the 637 films released in the USA during this period (www.boxofficemojo.com).

We consider all movies surveyed in the CrixPix section of external reviews in *Variety* magazine for this time period (Basuroy et al. 2003; Eliashberg and Shugan 1997) and include those that had at least one professional critical review listed. The lowest grossing movie (a mere $8000) in the sample is *Suspended Animation*, released on October 31, 2003 and the highest grossing movie is *Shrek 2* (earning about $436 million). In 2003–2004, approximately 50% of the 637 movies released were R-rated, 33% were PG13 rated, and the rest (17%) were rated G or PG (see Ravid 1999). Our sample matches this rating distribution quite well (46% are R-rated, 37% PG13, and 14% G or PG (see Table 2).

Movie-specific data We also collected a significant additional information[2] on our sample films. Similar to some other researchers, we purchased additional data from Baseline in California. These data include the studio that released each film, release date, MPAA rating, weekly domestic box office revenues (*box*), and theater counts (*screens*) as well as genres. Following prior work (e.g., Basuroy, Chatterjee and Ravid 2003), from CrixPix, we collect the total number of critical (pro, con, and mixed) reviews (*totreview*) from four cities (New York, Los Angeles, Chicago, and Washington D.C.). We then calculate the percentage of positive reviews (*posratio*).

For star power, we collect the total number of Academy Awards obtained by the actors, actresses, and the directors up to one full year prior to the release of the film and then use a dummy variable, *prevoscar*, that takes the value of 1 if any of the participants had won an Oscar before participating in the current movie, 0 otherwise. Also, a film produced by a major studio is coded as a dummy, *major* (See Elberse and Eliashberg 2003).

Desai and Basuroy (2005) show that, historically, only a few genres such as action, drama, and comedy affect revenues earned (ibid., p. 212). Hence, we code a dummy variable, *genre* that receives a value of 1 if baseline codes the genre of the movies as action, drama, or comedy, and 0 otherwise.

Following Elberse and Eliashberg (2003) and Liu (2006), we include a time-varying measure for competition for a film as the number of newly released films in the top 20 movies (*newfilm*) every week. The larger the number of newly released films in a week, the tougher is the competition.

We use a number of other control variables that have been used in the literature. Prior research shows that G and PG classification may have a significant effect on movie revenues

[2] The size of our data set is comparable to those used in earlier work (e.g., Elberse and Eliashberg 2003, Ravid 1999).

Table 2 Descriptive statistics

	Mean	Standard deviation
Dependent variables		
box	5.311	13.730
[a] *totbox*	39.802	65.371
[a] *openbox*	17.191	29.310
Movie ad characteristics		
topreview	0.517	0.500
reviews	4.152	3.064
award	0.129	0.336
sellingpoint	0.678	0.468
star	0.289	0.454
content	0.187	0.390
director	0.079	0.270
size	0.535	0.499
Control variables		
screens	972.552	1149.622
totreview	12.371	4.961
posratio	0.459	0.320
pg	0.138	0.345
pg13	0.368	0.482
r	0.457	0.498
prevoscar	0.338	0.473
genre	0.651	0.477
newfilm	3.020	1.099
totalad	0.525	0.973
sequel	0.099	0.299
major	0.551	0.498
weeks	4.377	2.279
$weeks^2$	24.350	20.797
Excluded instruments		
screen_diffrating	1025.351	552.065
screen_diffrating_budget	1000.848	967.729
totreview_diffrating_budget	12.193	0.124
totreview_diffgenre_budget	12.198	0.150

[a] See Table 1 for definitions

and rate of return (Ravid 1999; DeVany and Walls 2002; Ravid and Basuroy 2004). Hence, we use the MPAA ratings and code PG, PG13, and R dummies with G acting as the default. Sequels are generally the only "holy grail" in the movie business, as they are high return low risk projects (see Ravid 1999; Palia et al. 2008). Hence, we use a dummy, *sequel*, in our analysis. In addition, we control for the total advertising spending (*totalad*) of each film every week with data separately purchased from Kantar Media.

Table 2 shows that 68% of the films in our sample feature reviews as a selling point, and many of them include a top review. In addition, 29% of the films have a star featured in the ad and 19% of the ads are driven by content (the total is over 100% because ads can include content and a star or a top review and a star). About half the ads are full page.

We find the correlation between total reviews (the total number of critical reviews the film has received) and the number of reviews in the ad (*reviews*) to be very low, 0.03. This is important because it means that including reviews in the ad is a choice variable.

We follow the work of Basuroy et al. (2003), Eliashberg and Shugan (1997), and Liu (2006) and limit the empirical analyses to the first 8 weeks of the theatrical run. Similar to previous studies, the first 8-week period accounts for more than 90% of the box office revenues for the average film.

2.1 Model specification and dependent variables

We estimate the impact of advertising content elements on revenues using the following general model of box office revenue performance for movie i in the tth week of its run:

$$Y_{i,t} = \alpha_i + \beta X_i^1 + \gamma X_i^2 + \delta W_{i,t} + \varepsilon_{i,t} \tag{1}$$

In Eq. (1), $Y_{i,t}$ is the outcome variable, X_i^1 is a vector of time-invariant external validation variables in the advertisement (e.g., the number of reviews displayed, the presence of top reviewers quoted), X_i^2 is a vector of time-invariant informative variables(e.g., director, star, content), $W_{i,t}$ includes various control variables some of which vary with the week, (e.g., number of screens, advertising dollars, etc.), α_i is unobserved movie i specific heterogeneity, and $\varepsilon_{i,t}$ is the error term.

Our data set has an unbalanced panel structure (because we do not observe box office revenues for all movies in all weeks). Our key variables of interest are time invariant, so we employ random effects panel estimation. This allows for separate identification of time-invariant regressors from unobserved movie-specific heterogeneity (α_i) which is modeled as a component of the error term in generalized least squares estimation (Wooldridge 2010). A similar approach is used by Song et al. (2016) in their study of time-invariant movie characteristics in a panel setting. Panel data techniques, which use all observations for all movies, seem preferred to cross-sectional techniques because the additional information in the panel increases the ability to identify the time-invariant regressors separately from idiosyncratic shocks (Wooldridge 2010).

However, an OLS estimation with panel data leads to downward bias in standard errors, resulting in an increase in the probability of type 1 error (Cameron and Trivedi 2005, Greene 2012, and Wooldridge 2010). We address this issue by employing clustered robust standard errors; this ensures that while we use observations for all movies in all weeks, our fit statistics are based on the number of movies (i.e., clusters) in the data. The results are robust to arbitrary error correlation within and heteroscedasticity between movies (Wooldridge 2010;Cameron and Miller 2011).

We also estimate two cross-sectional models with *totbox* (each movie's cumulative box office revenue over the 8-week timeframe) and *openbox* (the opening week box office revenue) as dependent variables to address any concerns with the time-invariant variables in our data. The second regression is interesting, given the importance of the opening week on a movie's run which serves an important role in determining exhibitors' decisions going forward. In these analyses, we drop the *weeks* variable and use instruments for *screens* as explained below.

2.2 Identification and endogeneity

The basic models include OLS regressions. However, OLS estimates may be biased because of two potentially endogenous variables. The first is the number of screens (*screens*) (see Elberse and Eliashberg 2003), and the second is the total number of critical reviews (*totreview*) which is likely to be related to unobserved movie characteristics. For example, movies with greater buzz may receive greater attention from critics. Our challenge is to select proper instruments (Rossi 2014). We use the average number of screens for other films on the market as an instrument for *screens* (see Elberse and Eliashberg 2003 and also Berry 1994 in analyses of differentiated product demand). The idea is that the screens used by these other films will likely reflect various trends that can affect the number of screens allocated for the focal film. However, direct competitors for the focal film may take into account the focal film's strategy or unobserved characteristics when choosing their number of screens. For example, two summer blockbuster superhero (i.e.,action) movies are likely to consider each other's distribution strategy when choosing their own distribution strategy. Therefore, any instrument constructed from direct competitors will likely be correlated with the focal films error term, rendering the instrument invalid (Nevo 2000). In this vein, we use the average number of screens in week *t* for films with a different MPAA rating than the focal film (*screen_diffrating*). This captures industry-wide trends for films in week *t*, so it should help identify *screens* for the focal film. As an additional instrument for *screens*, we also use the average *screens* for movies in the same week with a similar budget and a different MPAA rating to the focal film (*screen_diffrating_budget*).

We use a similar approach to obtain instruments for *totreview*. Direct competitors might draw the same reviewers (and hence, the same number of reviewers). Thus, we create two instruments using films with similar budgets as the focal film, the average *totreview* of films with a different rating than the focal film (*totreview_diffrating_budget*), and the average number of reviews for films (with a similar budget) but in a different genre than the focal film (*totreview_diffgenre_budget*).

The first stage regression results (available from the authors) show that the instruments are strong: They are always significant predictors of the endogenous variables with first stage F-stats always above 10 (Wooldridge 2003). Hansen's J is never significant in any of our estimations, suggesting the instruments are orthogonal to the econometric error term. Thus, both instrument relevance and exogeneity conditions are valid in our case (Wooldridge 2003).

3 Results

In Table 3, we present our results for the weekly dataset. Since the dependent variable (box) is weekly box office revenues, we include the number of weeks the movie is on the market (*weeks*) and its squared term ($weeks^2$) as additional control variables to address the (often non-linear) decrease in weekly box office performance as a movie ages. For each model, we show both random effects and random effects IV estimations.

Models 1 and 2 show a balanced panel of 169 movies that were on the market for all 8 weeks. Model 1 does not account for any possible endogeneity while Model 2 does. In models 3 and 4, we use all observations for 206 movies; model 3 does not account for endogeneity while Model 4 does.

The key result from Table 3 is that the presence of a top reviewer (external validation) featured in an ad significantly increases box office revenues. This is the only ad content variable that is statistically significant in every regression. There is some evidence that the number of reviews featured in an ad may negatively impact revenues; however, the effect disappears when we account for endogeneity. No other ad content variables are significant in any model. The signs and significance of the control variables are consistent across models, and most are similar in sign to prior findings. All genre ratings perform worse relative to G-rated movies (see Ravid 1999), competition from new films decreases box office revenue and screens matter (Elberse and Eliashberg 2003), advertising expenditures increase revenues (see, for example, Basuroy et al. 2003), sequels do better (Ravid 1999; Palia et al. 2008), and box office performance declines precipitously as a film ages.

In Table 4, we present the results of regressions where total revenues and opening week revenues are the dependent variables. We use the same predictor variables in both types of regressions, opening week *screens* and *newfilm* proxy for distribution strategy and competition. Since *totrev* captures revenues over 8 weeks, one may be concerned with the use of opening week variables. However, our results are robust to using different proxies (e.g., total number of screens over the life of the film; total number of new films that enter the market over the life of the film).

In models 5 and 6 in Table 4, *totbox* is the dependent variable, using ordinary least squares (OLS) and generalized method of moments (GMM) IV regressions respectively. Similarly, in models 7 and 8, *openbox* is the dependent variable. Model 7 is OLS, while model 8 is a GMM IV regression. The coefficient of *topreview* is robust across models, suggesting a top reviewer endorsement adds approximately 1.5 million dollars to weekly revenues.

Table 3 Regression of weekly box office revenue over 8 weeks since film release on explanatory variables

	Dependent variable = *box*			
	Model 1: random effects (balanced panel)[b]	Model 2: random effects IV (balanced panel)[b]	Model 3: random effects	Model 4: random effects IV
Movie ad characteristics	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
topreview	1.573 (0.856)*	1.672 (0.832)**	1.219 (0.714)*	1.398 (0.743)*
reviews	−0.251 (0.134)*	−0.193 (0.117)	−0.215 (0.125)*	−0.167 (0.112)
award	−0.768 (0.935)	−0.279 (0.860)	−0.893 (0.865)	−0.569 (0.804)
sellingpoint	0.473 (0.630)	0.263 (0.604)	0.221 (0.510)	0.020 (0.496)
star	−0.735 (0.869)	−1.009 (0.843)	−0.643 (0.750)	−0.865 (0.735)
content	−0.422 (0.750)	−0.814 (0.827)	−0.477 (0.699)	−0.818 (0.759)
director	−1.417 (1.531)	−1.683 (1.524)	−1.119 (1.302)	−1.235 (1.270)
size	0.014 (0.791)	−0.576 (0.782)	0.395 (0.698)	−0.034 (0.692)
Control variables				
screens	0.005 (0.001)***	0.007 (0.002)***	0.004 (0.001)***	0.006 (0.001)***
totreview	0.037 (0.087)	−0.160 (0.182)	0.054 (0.075)	−0.128 (0.164)
posratio	0.850 (1.449)	1.305 (1.330)	1.351 (1.291)	1.553 (1.212)
pg	−4.463 (2.487)*	−4.073 (2.360)*	−4.402 (2.046)**	−4.269 (2.017)**
pg13	−2.511 (2.346)	−1.761 (2.244)	−2.339 (1.839)	−1.746 (1.775)
R	−2.035 (2.157)	−0.977 (2.082)	−1.879 (1.714)	−1.040 (1.671)
prevoscar	0.174 (1.039)	0.548 (1.061)	0.021 (0.913)	0.329 (0.964)
genre	−1.253 (0.619)**	−1.082 (0.591)*	−1.100 (0.556)**	−0.990 (0.507)*
newfilm	−0.545 (0.201)***	−0.578 (0.214)***	−0.450 (0.172)***	−0.486 (0.184)***
totalad	5.298 (1.397)***	4.340 (1.501)***	5.509 (1.309)***	4.773 (1.351)***
sequel	5.688 (2.148)***	5.074 (2.111)**	4.811 (1.901)**	4.191 (1.884)**
major	−2.514 (1.370)*	−3.191 (1.514)**	−2.195 (1.146)*	−2.644 (1.201)**

Table 3 (continued)

	Dependent variable = *box*			
	Model 1: random effects (balanced panel)[b]	Model 2: random effects IV (balanced panel)[b]	Model 3: random effects	Model 4: random effects IV
weeks	−3.279 (0.947)***	−3.506 (1.020)***	−2.442 (0.756)***	−2.502 (0.774)***
weeks^2	0.349 (0.089)***	0.403 (0.109)***	0.267 (0.072)***	0.298 (0.083)***
constant	9.179 (3.680)**	9.136 (3.552)**	6.583 (2.702)**	6.708 (2.733)**
R^2	0.532	0.529	0.524	0.521
Wald Stat (*p* value)	573.29 (<0.000)***	395.36 (<0.000)***	600.26 (<0.000)***	405.92 (<0.000)***
N	1352[b]	1352[b]	1548	1548
Overidentification restrictions				
Hansen's J (*p* value)		1.043 (0.594)		1.133 (0.567)
1st Stage F-Stats				
screens[a]		37.59***		50.55***
totreview[a]		10.25***		11.45***

(cluster robust standard errors in parenthesis) *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively[a] Instruments for *screens* and *totreview* listed with descriptive statistics in Table 2 [b] Estimations based on a balanced panel of 169 movies each on the market for 8 weeks after their initial release. The dataset follows all movies for 8 weeks after initial release; 169 of the 206 movies in the dataset are on the market for all 8 weeks

Table 4 Regression of total box office revenue and opening week box office revenue on explanatory variables

	Dependent variable = *totbox*		Dependent variable = *openbox*	
	Model 5: OLS	Model 6: GMM Second-Stage	Model 7: OLS	Model 8: GMM Second-Stage
Movie ad characteristics	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
topreview	15.982 (7.783)**	18.568 (8.165)*	8.083 (3.496)**	9.584 (3.660)***
reviews	−1.100 (1.171)	−1.251 (1.140)	−0.421 (0.564)	−0.433 (0.536)
award	−4.404 (7.161)	−3.791 (7.521)	−1.577 (3.047)	−1.370 (3.023)
sellingpoint	−2.060 (4.972)	−1.991 (4.698)	−1.704 (2.282)	−1.838 (2.152)
star	−5.438 (7.525)	−6.550 (7.224)	−2.118 (3.132)	−2.823 (3.008)
content	−5.887 (7.159)	−8.997 (7.423)	−3.887 (3.286)	−5.426 (3.382)
director	−8.165 (11.975)	−5.666 (10.984)	−3.663 (5.095)	−3.549 (4.797)
size	1.071 (7.253)	2.005 (7.286)	0.259 (3.174)	0.503 (3.190)
Control variables				
screens	0.030 (0.007)***	0.031 (0.009)***	0.015 (0.003)***	0.016 (0.004)***
totreview	0.887 (0.709)	−0.172 (1.803)	0.203 (0.305)	−0.308 (0.721)
posratio	38.166 (15.156)**	29.818 (11.957)**	12.466 (7.063)*	11.205 (5.599)**
pg	−45.497 (26.621)*	−27.195 (16.989)	−17.822 (7.551)**	−14.265 (6.450)**
pg13	−33.345 (23.661)	−13.841 (12.741)	−10.181 (6.417)	−5.809 (4.878)
r	−23.242 (22.547)	−1.150 (13.354)	−4.646 (6.164)	1.163 (5.254)
prevoscar	7.290 (9.543)	8.971 (10.185)	1.236 (4.228)	2.682 (4.156)
genre	−5.474 (6.243)	−2.873 (5.632)	−2.477 (2.847)	−1.986 (2.418)
newfilm	−5.065 (2.463)**	−6.047 (2.647)**	−2.269 (1.157)*	−2.759 (1.166)**
totalad	8.809 (4.244)**	8.339 (4.241)**	2.188 (1.862)	2.000 (1.777)
sequel	39.391 (20.526)*	37.669 (19.602)*	23.808 (9.803)**	23.79 (9.313)**
major	−29.725 (12.791)**	−31.148 (11.314)***	−12.809 (5.485)**	−13.765 (4.911)***
constant	8.245 (20.183)	5.737 (15.483)	2.783 (6.545)	4.330 (6.218)

Table 4 (continued)

	Dependent variable = *totbox*		Dependent variable = *openbox*	
	Model 5: OLS	Model 6: GMM Second-Stage	Model 7: OLS	Model 8: GMM Second-Stage
R^2	0.569	0.557	0.584	0.577
F Stat (*p* value)	11.73 (<0.000)***		13.49 (<0.000)***	
N	206	206	206	206
Overidentification restrictions				
Hansen's J (*p* value)		1.882 (0.390)		1.141 (0.565)
1st Stage F-Stats				
[a] *screens*		18.85***		18.85***
[a] *totreview*		12.23***		12.23***

(Robust Standard Errors in Parenthesis) *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively[a] Instruments for *screens* and *totreview* listed with descriptive statistics in Table 2

Similar to Table 3, our results in Table 4 show that featuring a top reviewer in an ad significantly enhances movie performance. No other ad content variable is significant. Thus, both Tables 3 and 4 provide strong support to the idea that external validation rather than informative ad content affects sales and revenues. Most control variables have similar signs and significance in both tables. However, here, similar to prior work (See Eliashberg and Shugan, 1997; Holbrook 1999; Basuroy et al. 2003), we also find that positive reviews increase opening week and total box office revenues. This latter finding also supports the role of external validation for movie revenues.

Finally, one potential source of endogeneity that we did not address is a possible correlation between unobserved movie quality (captured in the error term) and the inclusion of a positive quote by a top reviewer. This would lead to a positive bias in our estimated effect for *topreview*. We should note, however, that the correlation between t*opreview* and the quality of reviews is 0.43 so that not all films that received good reviews display them. However, we recognize this as a potential limitation of this analysis.

4 Conclusions and implications

This paper tests whether content elements of print advertisements affect movie revenues. We use data on various characteristics of film advertisements that appeared in the *New York Times*. Controlling for most variables identified in previous work, we find that external validation elements and, in particular, reviews by a top reviewer displayed in the ad are the most significant factor determining movie revenues.

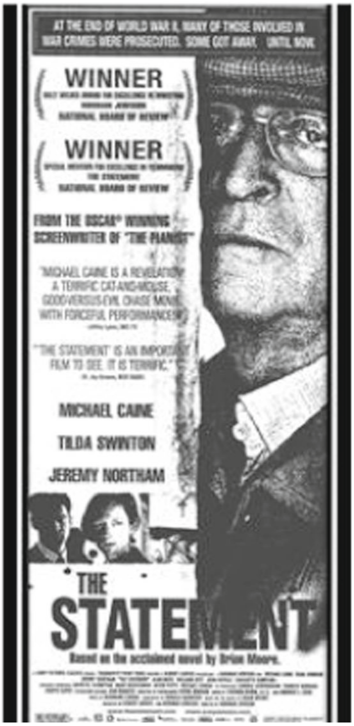
The gist of our findings is consistent with Bertrand et al. (2010), the only other paper that explicitly analyzes and quantifies advertising content. Our findings suggest that featuring stars or other content elements (e.g., director, award) in advertisements may not be a good idea, indicating to readers that the film does not have external validation elements to show.

We discussed these findings with industry professionals, and as anecdotal evidence, we reproduce a conversation we had with Mark Lazarus, a movie producer. Mr. Lazarus produced *The Loved Ones,*a horror movie which won an award at the prestigious Toronto Film Festival. He commented: *...Both star and award featured heavily in our test campaign along with positive reviews and quotes. When the results came back we were extremely surprised - awards and star had meant virtually nothing to our potential audience - instead, we found that the endorsements of well-respected horror experts were the key to convincing people to see the movie*. This paper is based on a sample of 206 movies, but hopefully future research can generalize our findings regarding the importance of external validation in advertising to other industries.

Acknowledgements We thank participants in the UCLA Annual Business and Economics Scholars Workshop in Motion Picture Industry Studies, and participants in SERG (Screen Economics Research Group) conference in Sydney, Australia, for their comments. We thank Jura Liaukonyte for her careful reading of this manuscript and valuable suggestions.

Appendix: How we code the ads.

Statement- 2 reviews; The selling point is not reviews, the ad is star, content , writer and award driven.
Buffalo Soldiers – a tough call, but it has 7 reviews including a top reviewer; content is the selling point.
Latter Days 3 reviews including a top reviewer; reviews are the selling point.
Neither of the ads is a full page ad.



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