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Does Advertising Indicate Product Quality?
Evidence from Pre- and Postlaunch Advertising in the Movie Industry

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Abstract

Literature on the informative role of advertising indicates that advertising quantity can serve as an indicator of product quality. As product life cycles grow shorter, firms in many industries spend significant amounts on advertising during the prelaunch period to create large initial demand. Thus, the role of prelaunch advertising may differ from that of postlaunch advertising, and a proper understanding of these differences is important. This study provides an empirical investigation of whether advertising is a reliable indicator of quality before and after product launches, using the data from the movie industry. Analyses of 1,078 movies released during 2003–2011 show that postlaunch advertising is a reliable quality indicator and increases revenues, whereas prelaunch advertising is not a reliable quality indicator, even if it leads to higher revenues.

Keywords: advertising, informative role, product quality, entertainment marketing

1. Introduction

Is advertising a reliable indicator of product quality, in prelaunch and postlaunch periods? Despite a rich stream of literature on advertising and quality signals (e.g., Milgrom and Roberts 1986), most studies examine the role of advertising only after a product has been introduced; a limited number of studies address the changing roles of advertising over time (e.g., Basuroy, Desai, and Talukdar 2006). Yet in many product categories, including movies, video games, music, and high technology products, firms devote significant expenditures to prelaunch advertising. For example, large movie studios typically spend more than 80% of their total advertising budget in the prelaunch period (Elberse and Anand 2007). Because the life cycles of these product categories are short, firms rely on prelaunch advertising to create large initial demand and enhance their returns on investment. In this sense, it is important to understand the role of prelaunch advertising and distinguish it from the role of postlaunch advertising to help firms effectively allocate their advertising budgets.

We empirically test the relationship between the amount of advertising and product quality in prelaunch and postlaunch periods, using data from the movie industry, which represents a good empirical setting for this study. Movie studios allocate vast advertising budgets to the prelaunch period, so the impact of prelaunch advertising is particularly interesting. We anticipate that after a movie is released, a studio with a high quality product, which we refer to as the high quality firm, advertises more than a studio with a low quality product, because consumers can gather information about movie quality from various sources, including critical reviews or word of mouth. In contrast, we are uncertain of the direction of the relationship between prelaunch advertising and movie quality. Before a movie is released, consumers remain uninformed about the movie quality, so the high quality firm spends to signal its movie quality, but the low quality firm also has an incentive to boost its advertising to exaggerate its movie quality and attract more consumers. In this context, prelaunch advertising might not be a reliable indicator of product quality, because consumers cannot differentiate a low quality movie from a high quality one on the basis of advertising expenditures. Yet perhaps it is not cost effective for the low quality firm to spend more on advertising during the prelaunch period, because it might not be able to recover its investments, if consumers believe the product quality fails to live up to the promise issued by the intensive advertising. In this case, the low quality firm may be reluctant to follow the example of the high quality firm, such that the amount of advertising in the prelaunch period would be a reliable signal, similar to postlaunch advertising, even if less information is available to consumers.

We examine the relation between the amount of advertising and movie quality in two ways. First, we test whether pre- and postlaunch advertising expenditures relate positively to product quality, using regression analyses. The results show that prelaunch advertising is not significantly associated with quality, but postlaunch advertising is positively and significantly associated with it. Second, we test whether advertising changes the effect of product quality on revenues when we include both advertising and a quality indicator in regression analyses. If advertising truly represents product quality, the effect of quality in the regression models should be weakened by the inclusion of advertising; advertising, as an additional quality measure, would account for some portion of the explanation by the true quality measure (e.g., Kennedy 2008). Our results show that the effect of quality on revenue does not change when we include prelaunch advertising, whereas this effect is weakened when we include postlaunch advertising.

Therefore, according to the consistent results from these empirical analyses, postlaunch advertising is a more reliable indicator of quality than prelaunch advertising. Even if prelaunch advertising is not a reliable indicator of quality, it is still effective in raising demand though. Thus, firms use prelaunch advertising for other purposes, such as providing direct information about the product's existence or changing consumers' attitudes toward the product (e.g., Boulding, Lee, and Staelin 1994). The positive relationship between postlaunch advertising and product quality is consistent with prior literature such as Tellis and Fornell (1988) who find the relationship between advertising and quality is stronger during the latter stages of the product life cycle. However, prior studies has largely focused on the effect of advertising *after* a product launched. In addition, the insignificant relationship between prelaunch advertising and quality is new. Our results suggest that the high quality firm cannot effectively signal its product quality through the amount of its advertising during the prelaunch period.

Our findings also offer managerial implications. If firms sell products for which consumers cannot judge the quality before consumption (Nelson 1974), and initial revenues play an important role in creating subsequent demand, firms should allocate their advertising budgets according to the distinct purposes of advertising in the prelaunch and postlaunch periods. For high quality products, firms should allocate their advertising budget in the prelaunch period to increase awareness or affirmative attitudes, instead of signaling quality, because low quality firms can effectively interfere with the quality signal by increasing their advertising, making it impossible for consumers to distinguish high and low quality products on the basis of advertising expenditures. Instead, high quality firms can use advertising as a quality signal in the postlaunch period, when it is difficult for low quality firms to imitate this advertising strategy.

2. Literature Review and Theoretical Background

Advertising literature suggests three roles of advertisements: informative, persuasive, and prestige (Bagwell 2007). In its informative role, advertising provides consumers with either direct information that is vital to their purchase decision (e.g., Eckard 1991) such as price and style details or indirect information such that its quantity may serve as an indicator of product quality. We focus on the indirect form of information, because the direct information conveyed by advertising can be evaluated by consumers prior to purchase and less controversial.

Nelson (1970, 1974) explains that advertising can indicate quality, because it is costly, and in turn, various scholars have investigated the relationship between the amount of adverting and product quality (e.g., Kihlstrom and Riordan 1984; Kirmani 1990; Milgrom and Roberts 1986). Many studies show that higher quality firms advertise more than lower quality firms, because not only the direct costs of advertising can be large, but also the significant potential costs occur if the product's revealed quality does not match the promise of the advertising.

Therefore, consumers infer that highly advertised products possess better quality than less advertised products; if the amount of advertising does not relate to product quality, this inference becomes erroneous.

A few studies have examined how consumers use advertising in their purchase decisions over time; for example, Basuroy, Desai, and Talukdar (2006) note that consumers rely less on advertising to assess product quality once an independent source of information becomes available. With the assumption that marketing efforts are true signals of quality, Narayanan, Manchanda, and Chintagunta (2005) find that marketing communication has primarily an informative effect early after introduction, but the persuasive effect subsequently dominates. Ackerberg (2001) reveals a positive effect of advertising on inexperienced consumers’ purchase probabilities but no effect among experienced consumers, suggesting an informative role of advertising. Chandy et al. (2001) find that argument-based appeals, expert sources, and negatively framed messages are particularly effective in new markets compared to older markets. Through a meta-analysis, Sethuraman, Tellis, and Briesch (2011) find that advertising elasticity is higher in the early stage than the mature stage of the product life cycle.

All these studies, however, examine the effectiveness of advertising during the postlaunch period with an exception of Basuroy, Desai, and Talukdar (2006). Unlike these prior studies, we attend to the role of advertising in both prelaunch and postlaunch periods, rather than just the role of advertising after products have launched. In particular, rather than assuming that advertising provides full and truthful information about product quality, we test the relationship between advertising amounts and product quality, to investigate whether advertising offers a reliable indicator of quality in pre- and postlaunch periods.

Advertising provides a reliable indicator of quality only if high quality firms find it profitable to invest in advertising and low quality firms do not (Kihlstrom and Riordan 1984). In the postlaunch period, because alternative sources of information about quality become available, consumers can distinguish high quality firms from low quality ones. So, it is not profitable for low quality firms to mimic high quality firms’ advertising strategy and erroneously signal their high quality. Rather, high quality firms alone should find it profitable to invest in advertising, to differentiate themselves from low quality firms.

In contrast, it is not clear *ex ante* whether low quality firms are better to mimic the advertising strategy of high quality firms during prelaunch periods. Some theories of the relationship between advertising and product quality suggest that the amount of advertising does not relate strongly to product quality during the prelaunch period. First, product quality information is minimal in the prelaunch, compared with the postlaunch period. Because substantial advertising can stimulate initial demand, even low quality firms should have an incentive to overstate their product quality through advertising in the prelaunch period (Kopalle and Lehmann 2006). Therefore, both high and low quality firms may spend similar amounts on advertising, a scenario that Kirmani and Wright (1989) refer to as “immunity”: The firm's payoff remains high, even though the advertised product's benefits are overstated.

Second, the purpose of adverting may vary between periods. The prelaunch period requires awareness advertising, and this need is not necessarily correlated with product quality (Zhao 2000). Another purpose of prelaunch advertising is to increase product availability (Desai, 2000; Jones and Ritz 1991). Distributors and retailers are more likely to carry and promote sales for products that already receive high advertising support, which in turn increases consumer demand (Ho, Dhar, and Weinberg 2009). Thus, firms have an incentive to spend on prelaunch advertising to secure strong distribution intensity. This incentive is not necessarily correlated with product quality, so it could encourage even low quality firms to increase their advertising spending during the prelaunch period.

Yet other studies suggest that low quality firms avoid investing to advertise low quality products during the prelaunch period. First, when repeat purchases matter, it is not cost effective for low quality firms to use advertising to signal quality. Firms have an incentive to overstate the quality of experience goods when consumers cannot check their false claims before purchase, but this strategy works only for trial purchases (Nelson 1974). Because high quality firms attract more repeat purchases than low quality firms, low quality firms may find it costly to advertise their low quality products heavily. Second, low quality firms that spend substantial amounts on prelaunch advertising may not recover their investments if that prelaunch advertising raises consumers' expectations too much, and the ultimately revealed quality does not satisfy their heightened expectation (Kopalle and Lehmann 1995). Joshi and Hanssens (2009) show that movies with higher than average prelaunch advertising suffer lower postlaunch stock returns than movies with below-average prelaunch advertising, due to the effects of increased expectations. Elberse and Anand’s (2007) finding of negative returns to a marginal dollar of advertising supports this line of reasoning. The strategy of falsely indicating high quality through advertising thus might not work for low quality products, even in the prelaunch period.

In summary, we anticipate that postlaunch advertising is an indicator of quality, but considering the two competing views, we leave the relationship between prelaunch advertising and product quality as an empirical question.

3. Empirical Estimation

We test whether prelaunch and postlaunch advertising indicate quality in two ways. First, we examine whether prelaunch and postlaunch advertising are associated with product quality (advertising–quality models). The association should be positive if high quality firms spend more on advertising than low quality firms. Second, we determine whether the effect of quality on revenue changes when we add prelaunch and postlaunch advertising (two potential quality indicators) as independent variables (revenue–quality models). If advertising is a reliable quality indicator, the effect of quality on revenues should differ when we include advertising, in addition to the quality measure, because advertising will account for a significant portion of the effect of quality on revenue.

3.1. Model

3.1.1. Advertising–quality model

To investigate the effect of movie quality on both prelaunch and postlaunch advertising amounts, we set up the two equations:

$$\ln PREAD_m = a_0 + a_1 QUALITY_m + \sum_{j=2}^{J} a_j X_{1j,m} + u_{1m} \tag{1a}$$

$$\ln POSTAD_m = b_0 + b_1 QUALITY_m + b_2 FIRSTWKREV_m + \sum_{k=3}^{K} b_k X_{2k,m} + u_{2m} \tag{1b}$$

where m represents the product (movie). We assume the error terms follow a bivariate normal distribution, $N(0, \Sigma_u)$ and have a non-zero covariance.

In Equation 1a, we regress the log of prelaunch advertising expenditures on quality and other control variables, as denoted by X_1. This equation suggests that product quality affects prelaunch advertising spending though decisions about prelaunch advertising expenditures also may occur before the product is completed and available on the market. We assume that as the experts in their fields, the firms possess reasonable estimates of the quality of the products they produce. In Equation 1b, we regress the log of postlaunch advertising expenditures on quality, first-week revenues, and other control variables, denoted by X_2. We include first-week revenues in the second equation because movie studios likely adjust the level of postlaunch advertising they undertake after they observe initial demand.[1]

If higher quality firms advertise more expecting that advertising serves as a quality indicator, quality will be positively associated with advertising. That is, the coefficients of quality (a_1 and b_1) in Equation 1 are positive. We use a seemingly unrelated regression (SUR) model, because prelaunch and postlaunch advertising expenditures can be affected by common unobserved factors, such as the financial conditions of producers. There are some unique variables in each equation, which should help increase estimation efficiency in the SUR model.

3.1.2. Revenue–quality model.

In the revenue–quality models, we examine the effect of quality on the revenues in the first and subsequent weeks by comparing models with and without advertising amount. For the revenue-quality model of the first week, we use the cross-sectional data of the first week and compare the two equations in Equation 2.

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[1] In the prelaunch advertising equation, we include competition and seasonality in the first week; the postlaunch advertising equation instead includes average competition, seasonality over the subsequent weeks.

$$lnFIRSTWKREV_m = \alpha_0 + \alpha_1 QUALITY_m + \sum_{j=2}^{J} \alpha_j X_{3j,m} + \varepsilon_{1m} \qquad (2a)$$

$$lnFIRSTWKREV_m = \beta_0 + \beta_1 QUALITY_m + \beta_2 PREAD_m + \sum_{k=3}^{K} \beta_k X_{3k,m} + \varepsilon_{2m} \qquad (2b)$$

where the error terms follow a bivariate normal distribution, $N(0, \Sigma_\varepsilon)$, and have a non-zero covariance.

We regress the log of revenue on quality in Equation 2a and on quality and prelaunch advertising expenditures in Equation 2b. By comparing the coefficients of quality α_1 and β_1, we examine whether prelaunch advertising changes the effect of quality on revenues of the first week. We also include the common control variables, denoted by X_3, in both equations.

For the revenue-quality model of subsequent weeks, we use the panel data from the second week to the last week and compare the two equation in Equation 3.

$$\ln OTHERWKREV_{mt} = \gamma_{0m} + \gamma_1 QUALITY_m + \sum_{j=2}^{J} \gamma_j X_{4j,mt} + \eta_{1mt} \qquad (3a)$$

$$lnOTHERWKREV_{mt} = \delta_{0m} + \delta_1 QUALITY_m + \delta_2 PREAD_m + \delta_3 POSTAD_{mt} + \sum_{k=4}^{K} \delta_k X_{4k,mt} + \eta_{2mt} \qquad (3b)$$

where *t* represents time in week and the error terms follow a bivariate normal distribution, $N(0, \Sigma_\eta)$, and have a non-zero covariance. γ_{0m} and δ_{0m} are movie-specific fixed effects that reflect unobserved factors such as true product quality. The control variables, denoted by X_4, include both time-invariant (e.g., production budget) and time-varying variables (e.g., revenues from previous weeks).

We regress the log of revenue on quality in Equation 3a and on quality, pre- and postlaunch advertising in Equation 3b. We include prelaunch advertising expenditures in Equation 3b because prelaunch advertising may have carryover effects. We compare the coefficients of quality γ_1 and δ_1 to examine whether the effect of quality changes when we add advertising expenditures as another quality measure.

Among the independent variables, the number of screens may be endogenous; expected revenues in a specific week can determine the number of screens in the same week (Elberse and Eliashberg 2003). Endogeneity due to simultaneity might be addressed by adding a screen equation (e.g., Basuroy, Desai, and Talukdar 2006; Elberse and Eliashberg 2003). However, unlike these papers, modeling screen decisions is not the focal goal of this study. To handle the potential simultaneity between revenues and the number of screens, we lagged the number of screens in each week.

While lagging the screen variable can account for the endogeneity due to simultaneity, additional concern remains. Both the lagged number of screens and professional reviews can still be endogeneous due to unobserved heterogeneity. To deal with this potential endogeneity, we adopted a panel data estimation technique. Although first-difference and fixed effects models eliminate the fixed effects and thus offer potential solutions for endogeneity, none of those models can estimate the coefficients of time-invariant variables, which would prevent estimates of our focal professional review variable. Therefore, we opted instead for a Hausman-Taylor (1981) estimate (Boulding and Christen 2003). This estimator uses a random effects generalized least squares (GLS) transformation; it thus retains time-invariant variables including movie-specific unobserved factors. To deal with endogeneity, the estimator relies on an instrumental variable approach. For time-varying endogenous variables, the within transformations of those variables ($X_{mt} - \overline{X}_m$) are used as the instruments, which are uncorrelated with unobserved heterogeneity. For time-invariant endogenous variables, the instruments are the average values of the time-varying exogenous variables over time. The number of time-varying exogenous regressors is greater than the number of time-invariant endogenous regressors, so our model can be identified.

3.2. Data

The movie industry is an ideal setting to examine the roles of prelaunch and postlaunch advertising for several reasons. First, advertising is critical in the motion picture industry. Movie studios spent $3.35 billion on advertising during 2012 (Kantar Media). The MPAA advertising-to-sales ratio of 16%–17% exceeds those of the most highly advertised companies, such as Procter & Gamble, Coca-Cola, and Nike, and is one of the highest across all U.S. industries (Vogel 2007). Second, the distinction between prelaunch and postlaunch advertising is important for the movie industry (Elberse and Anand 2007); most firms spend substantially on advertising during the prelaunch period to create good opening demand. Third, reasonable quality measures of movies exist, in the form of widely available movie ratings by professional critics.

We collected data on 1,123 movies released during 2003–2011 from Boxofficemojo (www.boxofficemojo.com, hereafter “Mojo”). These movies represent more than 90% of domestic gross revenues each year. After dropping unusable movies, such as those without production budgets and advertising information or limited releases, we retained a sample of 1,078 movies. Table 1 summarizes the variables, measures, and data sources; Table 2 presents the descriptive statistics. We adjusted the variables for inflation where appropriate.

TABLE 1

TABLE 2

Professional reviews provide measures of objective product quality, which differ from consumers’ subjective quality perceptions. Prior studies show that a measure of quality obtained from third-party reviews affects firm value and can serve as a reliable indicator of quality (Chen, Liu, and Zhang 2012; Tellis and Johnson 2007). In addition, experts are less subject to behavioral tendencies and advertising influences than the general public (List 2003; Maheswaran 1994). Because of this creditability, professional reviews represent a valuable source of information for assessing product quality (Chen and Xie 2005; Reddy, Swaminathan, and Motley 1998), so we used professional reviews as the objective measure of product quality.

3.3. Preliminary analysis

Figure 1 depicts the relationships of professional reviews, as a quality measure (X-axis), with prelaunch and postlaunch advertising expenditures (Y-axis). When professional reviews increase, postlaunch advertising expenditures increase, indicating their positive relationship.

<Figure 1>

In contrast, the relationship between professional reviews and prelaunch advertising expenditures is more complicated. Prelaunch advertising expenditures do not differ much for low (40–60) to medium (70–80) quality. However, when product quality is very low (0–20), prelaunch advertising amounts are also significantly low. In contrast, studios spend vast amounts on prelaunch advertising for movies whose professional review ratings exceed 90. That is, prelaunch advertising offers a reliable quality indicator for the highest quality movies. Across all quality levels, Figure 1 offers preliminary evidence that postlaunch advertising is a strong indicator of quality, but prelaunch advertising is not totally reliable as a quality indicator.

3.4. Results

According to the estimation results, postlaunch advertising is associated with professional reviews, but prelaunch advertising is not. In addition, the effect of quality on revenue changes when we include the postlaunch advertising amount in the model. The consistent results across different models confirm that postlaunch advertising is a more reliable quality indicator than prelaunch advertising. We briefly discuss the effects of the other variables as well.

3.4.1. Results of advertising–quality model

In Table 2, which presents the results of the advertising–quality models, professional reviews, as our measure of quality, are not associated with prelaunch advertising expenditures ($a_1 = 0.002$, not significant at the 5% level), but they relate positively to postlaunch advertising ($b_1 = 0.017$). If movie quality is higher, studios spend more on postlaunch advertising but not on prelaunch advertising. Thus, consumers exposed to highly advertised movies during the postlaunch period may anticipate that these movies offer high quality. We observe the positive effect of quality on postlaunch advertising, even after controlling for the other potential determinants, such as the positive effect of first week revenues ($b_2 = 0.019$). Regarding the other variables, we find that production budget, star, season, and major studios have positive impacts on advertising amounts, whereas competition and sequels have negative impacts. All variables exhibit the expected signs.

TABLE 2

3.4.2. Results of revenue–quality model

In Table 3, we distinguish the results of the revenue–quality models without and with advertising for the first and subsequent weeks. In the first-week revenue equations, the coefficient of professional reviews without advertising is $\alpha_1 = 0.008$, and the coefficient with prelaunch advertising is $\beta_1 = 0.007$. The difference between the coefficients is not significant (95% confidence intervals overlap[2]). Therefore, when we added prelaunch advertising, the effect of professional reviews did not change, so the effect of prelaunch advertising differed from that of professional reviews. That is, prelaunch advertising did not serve as a quality indicator.

TABLE 3

However, the coefficients of professional reviews in the subsequent weeks' revenue equations revealed a different pattern. The coefficient of professional reviews without advertising was $\gamma_1 = 0.022$ while the coefficient with postlaunch advertising was $\delta_1 = 0.016$. The difference between two coefficients was significant (95% confidence intervals did not overlap: $\gamma_1 \in [0.020, 0.025]$ and $\delta_1 \in [0.015, 0.019]$). The effect of professional reviews changed when we included postlaunch advertising, because postlaunch advertising accounted for some portion of the effect of professional reviews. These results imply that postlaunch advertising relates closely to quality.

Regarding the effects of advertising, prelaunch advertising had a positive impact on first-week ($\beta_2 = 0.013$) and subsequent weeks' ($\delta_2 = 0.0017$) revenue. Even though prelaunch advertising was not a reliable indicator of quality, it exerted a positive effect on revenues. In addition, postlaunch advertising showed a positive impact on subsequent weeks' revenue ($\delta_3 = 0.095$). Regarding the effects of the control variables, revenues from previous weeks, sequels, and number of screens had positive impacts on revenues. Production budget, director, competition, seasonality, and major studio dummies had no such impact after controlling for the effect of revenues from previous weeks, which may already reflect the effects of these variables.

In conclusion, both prelaunch and postlaunch advertising spending affected revenues, but only postlaunch advertising indicated movie quality.

4. Discussion

In this study, we sought to examine whether the quantity of advertising indicates product quality in prelaunch and postlaunch periods. Using data from the movie industry, where the distinction between prelaunch and postlaunch advertising is important and quality information is widely available, we uncovered different roles of advertising in the prelaunch and postlaunch periods. The prelaunch advertising amount did not relate to product quality, but the postlaunch advertising amount related positively to quality. Despite the nonsignificant link between prelaunch advertising and product quality, prelaunch advertising can be effective for increasing demand.

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[2] Because we use the same sample for the different regression models, it is not possible to apply the typical equality test of two regression coefficients, which is based on independent samples. Instead, we check the significance of the difference between the two coefficients by comparing their confidence intervals. If two intervals overlap, there is no statistical difference between the two coefficients.

Prior literature suggests that advertising offers a reliable indicator of quality only if firms with high quality products find it profitable to invest in advertising while firms with low quality products do not (Kihlstrom and Riordan 1984). In other words, it requires a separating equilibrium between high quality and low quality firms. Our findings identify such a separating equilibrium in the postlaunch period, when it would not be profitable for a low quality movie to advertise heavily, because its quality has been revealed. Thus, low quality firms have few incentives to mimic the advertising expenditures adopted by high quality firms, and consumers can correctly infer product quality from higher levels of postlaunch advertising.

In contrast, a separating equilibrium does not appear to exist in the prelaunch period, likely due to several institutional features of the movie industry. First, first-week revenues are critical as a means to recoup investments quickly. Because movie quality is unobservable in the prelaunch period, firms have incentives to overstate product quality and stimulate initial demand, regardless of the quality of the movies. Second, studios typically earn a lion’s share of their revenues in early weeks, when the effects of prelaunch advertising are likely strongest. Taking advantage of this feature should lead to overestimates of the optimal levels of prelaunch advertising. Third, even if consumers are disappointed with a movie, they rarely criticize the studios, so the long-term negative impacts are relatively minor, and studios are less cautious about promoting low-quality movies.

Our findings provide several managerial implications. Firms should consider the different roles of advertising during prelaunch and postlaunch periods and allocate their budgets accordingly. For a high quality product, more advertising expenditures can be dedicated to the postlaunch period, to increase postlaunch demand by helping consumers infer quality. This strategy echoes an observation by Rennhoff and Wilbur (2011) that postlaunch advertising generates substantial returns for many movies. In addition, firms can use prelaunch advertising to achieve other purposes, such as increasing product awareness or providing other direct information. As our results show, prelaunch advertising is effective for increasing revenues, even when its role is not to indicate quality.

We encourage additional research in several areas. First, researchers can determine the exact role of prelaunch advertising, using experimental or survey data combined with secondary data. Second, it would be interesting to discover whether we could find similar results in other industries, such as books, music, gaming, or consumer electronics. As product life cycles continue to become shorter, a large portion of revenue in these industries gets realized shortly after product launch. A few institutional features of the movie industry might influence our findings, as we noted; it is worth examining the generalizability of our findings to other industry settings.

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Table 1 Variables, Measures, and Data Sources

Variable	Description (Measure)	Source	Mean	SD
REV	Total box office revenue ($)	Mojo	78.64	82.09
FIRSTWKREV	Box office revenue in the first week ($)	Mojo	24.33	23.64
OTHERWKREV	Box office revenue in subsequent weeks ($)	Mojo	54.31	61.41
AD	Total advertising expenditure ($)	Kantar Media	26.37	11.91
PREAD	Total advertising expenditure before release ($)	Kantar Media	20.92	8.55
POSTAD	Total advertising expenditure after release ($)	Kantar Media	5.45	5.50
QUALITY	Professional reviews (0–100 scale)	Metacritic	49.13	16.01
BUDGET	Production budget ($)	Mojo	61.67	52.70
DIRECTOR	Total box office revenue of the movies directed by the director five years prior to the release of the movie ($)	Mojo	86.36	150.95
STAR	Total box office revenue of the movies in which the actors were starring cast members five years prior to the release of the movie ($)	Mojo	1011.22	1073.72
SEQUEL	Dummy variable: 1 if a movie is a sequel, 0 otherwise	Mojo	0.13	0.33
COMPETITION	Total production budget of all movies weighted by time since release ($)	Mojo	468.27	126.93
SEASON	Average weekly revenue share from top 30 movies each week during 2003–2008 (%)	Mojo	1.89	0.46
SCRN	Number of screens per week	Mojo	961.89	1134.57
MAJOR	Dummy variable for major studios	Mojo	0.82	0.38
GENRE	Dummy variables for 15 genres	Mojo		
MPAA	Dummy variables for MPAA ratings (G, PG, PG13, R)	Mojo		

Notes: N = 1,078. Revenue, advertising, production budget, director, star, and competition are in millions of dollars. Competition, seasonality, and number of screens are the average values over the screening periods.

Table 2 Advertising–Quality Models

Variable	ln(PreAD)		ln(PostAD)	
	Coeff.	S.E.	Coeff.	S.E.
Intercept	**2.341**	0.121	-0.332	0.344
QUALITY	0.002	0.001	**0.017**	0.003
FIRSTWKREV			**0.019**	0.002
BUDGET	**0.003**	0.0005	**0.004**	0.001
DIRECTOR	0.0001	0.0001	-0.0001	0.0003
STAR	**0.00004**	0.00002	-0.00002	0.00005
COMPETITION	0.0001	0.0001	**-0.001**	0.001
SEASON	0.053	0.040	**0.325**	0.155
SEQUEL	-0.046	0.054	**-0.272**	0.132
MAJOR	**0.217**	0.046	**0.205**	0.104
System Weighted R^2	0.240			

Notes: N = 1,078. Professional reviews serve as the quality indicator. Coefficients in bold are significant at the 5% level. Advertising, production budget, director, star, and competition are in millions of dollars. Competition and seasonality are the opening week values in the prelaunch advertising equation and the average values over subsequent weeks in the postlaunch advertising equation. The coefficients of 14 genres, 3 MPAA rating dummies, and year dummies are not reported.

Table 3 Revenue–Quality Models

A. First week: ln(FIRSTWKREV)

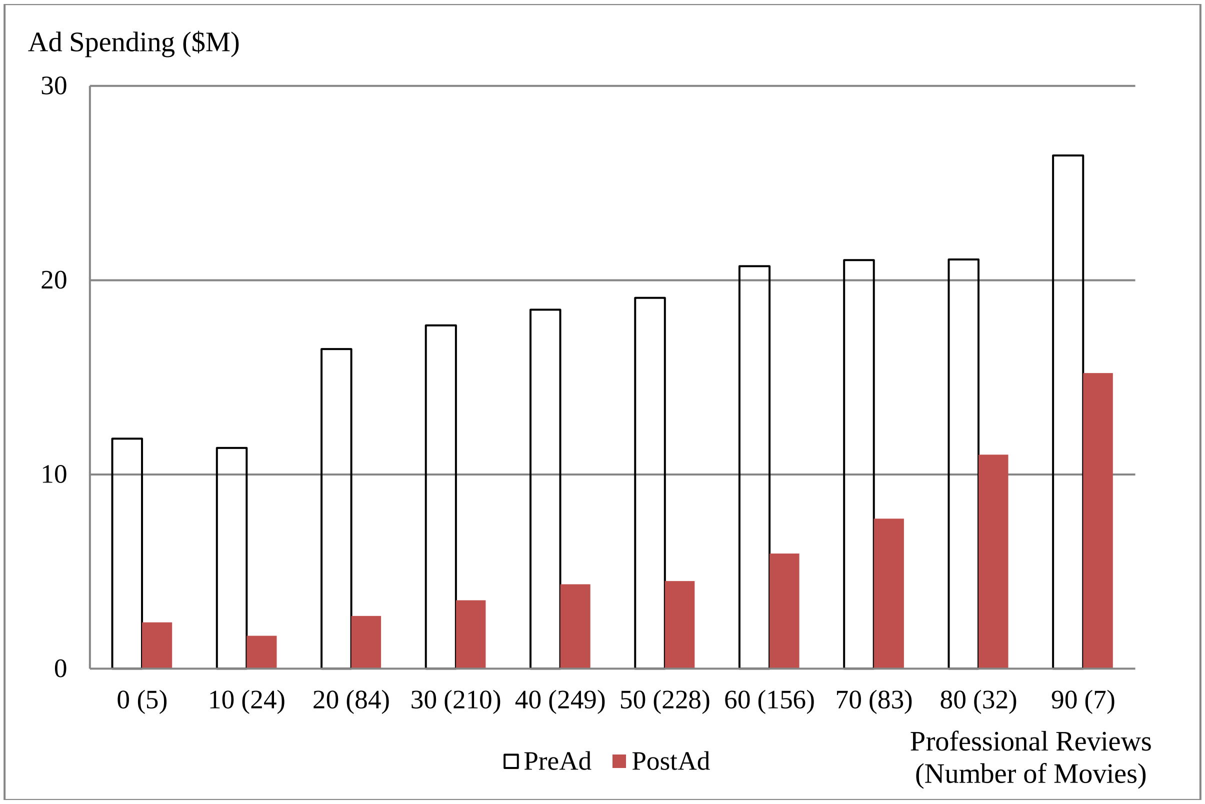
Variable	Without Advertising		With Advertising	
	Coeff.	S.E.	Coeff.	S.E.
INTERCEPT	**0.859**	0.109	**0.750**	0.110
QUALITY	**0.008**	0.001	**0.007**	0.001
PREAD			**0.013**	0.002
BUDGET	**0.004**	0.0004	**0.003**	0.0004
DIRECTOR	**0.0003**	0.0001	**0.0003**	0.0001
STAR	0.00003	0.00002	0.00002	0.00002
COMPETITION	-0.00001	0.0001	-0.00004	0.0001
SEASON	0.045	0.027	0.041	0.027
SEQUEL	**0.459**	0.045	**0.493**	0.045
SCRN	**0.0004**	0.00002	**0.0004**	0.0003
MAJOR	**0.098**	0.037	0.049	0.038

B. Other weeks: ln(OTHERWKREV)

Variable	Without Advertising		With Advertising	
	Coeff.	S.E.	Coeff.	S.E.
INTERCEPT	**-0.201**	0.094	0.09289	0.083
Lag REVENUE	**0.860**	0.005	**0.862**	0.005
QUALITY	**0.022**	0.001	**0.016**	0.001
PREAD			**0.0017**	0.0008
POSTAD			**0.095**	0.006
BUDGET	-0.0001	0.0002	-0.00005	0.0001
DIRECTOR	-0.00005	0.00005	-0.00004	0.00004
STAR	**-0.00003**	0.00001	**-0.00002**	0.00001
COMPETITION	-0.00007	0.00004	-0.00007	0.00004
SEASON	**0.026**	0.011	0.013	0.010
SEQUEL	**0.043**	0.019	**0.042**	0.017
SCRN	**0.139**	0.010	**0.085**	0.010
MAJOR	0.012	0.018	0.017	0.016

Notes: N = 1,078. Professional reviews serve as the quality indicator. Coefficients in bold are significant at the 5% level. *Lag REVENUE* is lagged revenues by one period (week). Revenue, advertising, production budget, director, star, and competition are in millions of dollars. The coefficients of 14 genres, 3 MPAA rating dummies, and year dummies are not reported.

Figure 1 Prelaunch and Postlaunch Advertising by Quality



The X-axis represents professional reviews split into deciles, along with the number of movies in parentheses. The Y-axis represents the prelaunch and postlaunch advertising expenditures in millions of dollars.