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# Can good marketing carry a bad product? Evidence from the motion picture industry

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**Abstract** We examine the relative roles of marketing actions and product quality in determining commercial success. Using the motion picture context, in which product quality is difficult for consumers to anticipate and information on product success is available for different points in time, we model the effects of studio actions and movie quality on a movie's sales during different phases of its theatrical run. For a sample of 331 recent motion pictures, structural equation modeling demonstrates that studio actions primarily influence early box office results, whereas movie quality influences both short- and long-term theatrical outcomes. The core results are robust across moderating conditions. We identify two data segments with follow-up latent class regressions and explore the degree of studio actions needed to "save" movies of varying quality. We finally offer some implications for research and management.

**Keywords** Motion pictures · Product quality · Marketing actions · Structural equations modeling · Latent class regressions

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"Build a better mousetrap and the world will beat a path to your door."

Although this ubiquitous saying has some appeal, producing a quality product simply is not a sufficient condition for success; marketing activities also are needed to inform and influence customers. However, some consumer advocates argue that marketers misuse this influence in messages that manipulate consumers by creating demand for unnecessary or harmful products or provide misleading information that dupes consumers into buying products of poor quality (Kotler and Keller, 2006). The latter part of this concern relates to information asymmetry (Akerlof, 1970), which occurs when consumers are at an information deficit relative to producers (Basuroy et al., 2006). The relative importance of quality versus marketing for success is not completely clear, especially when quality signals are hard to verify prior to purchase (Kirmani and Rao, 2000), but this topic has significant implications for both public policy and managers. In this study, we therefore explore a simple question: Can marketing activities cause a product of poor quality to succeed?

To address this question, we examine the motion picture industry, for which significant secondary data are available about product attributes, marketing activities, product quality, and financial outcomes. Various studies recently have examined motion picture success (e.g., Basuroy et al., 2003; Elberse and Eliashberg, 2003; Lehmann and Weinberg, 2000), often by investigating how specific "success drivers" (e.g., stars, reviews) relate to economic outcomes. However, the complex relationships among these individual factors make predictions about an individual film's success extremely demanding. To focus attention on our central research question, we step back from the level of individual drivers and consider specific factors as indicators of two higher-order constructs: *movie quality* (i.e., the movie's degree of technical and/or creative excellence) and *studio actions* (i.e., the efforts taken by a movie studio to produce, promote, and distribute an appealing product). This approach enables us to disentangle the impact of these two possibly independent factors. We also disaggregate studio actions in post hoc analyses to provide more precise insights.

Furthermore, by distinguishing between opening weekend box office (OWBO) and long-term box office (LTBO) revenues earned by a movie as distinct success variables, we hypothesize that studio actions can significantly influence a movie's opening weekend success, but the quality of the movie will have a greater impact thereafter (see Figure 1). To test our hypotheses, we create a structural equation model that uses data from 331 recent motion pictures and employ a post hoc latent-class regression that reveals (response) heterogeneity in the data. We model box office revenues as a nonlinear function of quality and studio actions and conduct a sensitivity analysis to explore the level of marketing actions required to improve the outcomes of low- and high-quality movies. Finally, we offer some implications of our findings for motion picture–related research and management.

## 1. Key concepts: Studio actions and movie quality

### 1.1. Studio actions

In recent years, many studies have tested the impact of individual elements of a movie studio's marketing mix and production efforts, such as the movie's advertising

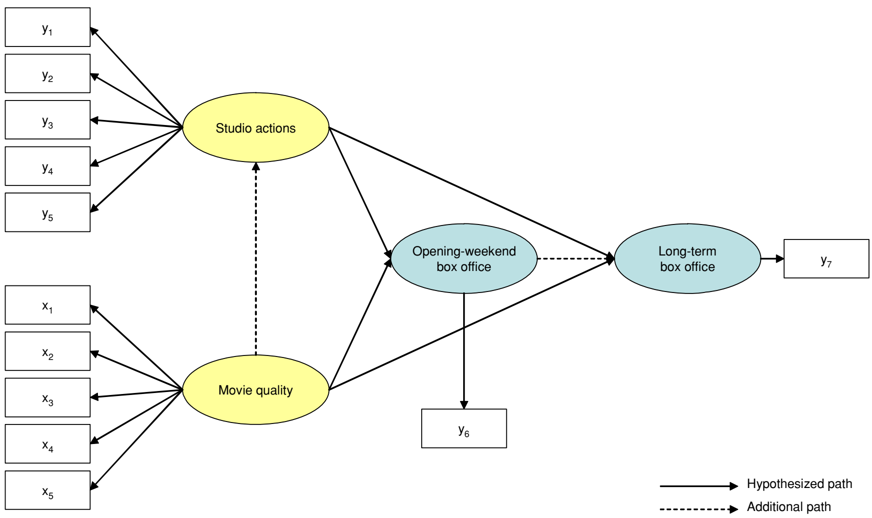


**Fig. 1** Conceptual model of studio actions, movie quality, and success.

(Lehmann and Weinberg, 2000) and production budget (or "negative costs"), the participation of stars and other high-profile personnel (Basuroy et al., 2006), and the number of screens on which a new movie is released theatrically (Elberse and Eliashberg, 2003). Combining individual elements into a higher-order construct offers two benefits. First, it enables us to examine the general impact of studio actions on performance outcomes in a parsimonious manner while deferring to many extant studies that examine relationships among individual studio actions and performance. Second, it recognizes that an underlying latent factor (i.e., studio executives' expectations/confidence regarding a film) likely drives the set of studio actions. We employ five variables that capture production, advertising, and distribution efforts, each of which reflects the underlying expectations/confidence held by the studio (Jarvis et al., 2003). A formative interpretation (Diamantopoulos and Winkelhofer, 2001), in contrast, would require the studio's production, advertising, and distribution efforts to function as independent elements.

## 1.2. Movie quality

Movies can range from "good" to "bad." Although standards might differ among the producers, consumers, and professional reviewers of movies, various studies have shown that the quality judgments of different groups are related, though the exact nature of the relationship is not clear (Holbrook, 1999). Eliashberg and Shugan (1997) find that reviewers can predict but not influence audience behavior, whereas Basuroy et al. (2003) suggest that reviewers both predict and influence consumer perceptions. Holbrook (2005) demonstrates that consumers appear to use the same norms as professional reviewers to recognize a film's quality, though they may enjoy films that experts would regard as bad.

Because both employ the same norms (Holbrook, 2005), we use critics' and consumers' perceptions of movie quality as reflective indicators of a higher-order quality construct. This approach aligns with an objectivist view (Schindler et al., 1989) that suggests that aesthetic quality determines each indicator (critic- and audience-perceived quality), such that the indicators reflect quality (Jarvis et al., 2003). The technical and creative excellence embodied in the final product, as well as the overall "fit" of the movie's elements, affect quality.

## 2. The roles of studio actions and movie quality for financial outcomes

In this section, we discuss the impacts of studio actions and quality on success during two sequential phases of a film's box office run.

### 2.1. Studio actions, movie quality, and OWBO

The quality of a movie is difficult for consumers to assess before its release because of its intangible and experiential nature. The information economics perspective indicates the clear dominance of experience qualities ("no one knows they like a movie until they see it," De Vany and Walls, 1999, p. 288). However, because consumers strive to reduce buying risk before spending money for their theater visit, they rely on information available before the movie's release. At this point, relevant information sources are usually limited to the studio's prerelease advertising and reviews by critics, because word of mouth from other consumers is not yet available.

Due to the limited amount of neutral quality-related information, we expect consumers to be strongly influenced by studio actions for a film's opening weekend. Studio actions generate awareness and can be interpreted by consumers as a signal that the studio has confidence in its film's quality, which thereby reduces consumers' risk perceptions (Kirmani and Rao, 2000). In short, to be a credible signal, consumers must perceive that the studio would not incur upfront costs (e.g., of aggressive promotions) unless the product was of high enough quality that its investments could be recouped (Basuroy et al., 2006). Regarding quality, though consumers do not yet have the experience to judge the film's quality, some quality information may be reflected in critics' reviews. Studies suggest that reviews correlate with movie success; therefore, we expect quality to influence OWBO (Basuroy et al., 2003). However, because moviegoers might not read reviews or believe that their own film preferences align with those of reviewers (Eliashberg and Shugan, 1997), quality's impact will be less than that of studio actions in this phase.

$H_1$: Both (a) studio actions and (b) movie quality will have a positive impact on OWBO, with (c) studio actions having a stronger impact than movie quality.

### 2.2. Studio actions, movie quality, and LTBO

After the opening weekend, additional quality-related information becomes available. Specifically, consumers can rely on the quality judgments of friends and other acquaintances who have watched the movie. However, to maximize a movie's OWBO, studio actions tend to focus on the weeks just prior to a movie's release. Ho et al. (2004) report that promotional expenditures peak during the week of (or weeks prior to) release for the 390 movies in their sample. Less promotional effort is spent during the weeks thereafter (Elberse and Eliashberg, 2003). Therefore, though we expect both studio actions and quality to continue to influence box office outcomes, the quality of the movie will have a stronger impact than studio actions on LTBO.

$H_2$: Both (a) studio actions and (b) movie quality will have a positive impact on LTBO, with (c) movie quality having a stronger impact than studio actions.

### 2.3. Additional paths

Finally, we control for interrelationships among the success variables and between the latent constructs. The success of a movie in one channel may influence its success in subsequent channels through media coverage, consumer bandwagon effects, and the allocation of additional screens to the market (i.e., "success-breeds-success" effect; Elberse and Eliashberg, 2003). Initial box office success provides a hard-to-falsify signal of consumer acceptance (Kirmani and Rao, 2000), so though we do not offer a formal hypothesis, we expect OWBO to affect LTBO. Moreover, we have argued that studio actions reflect the expectations/confidence about a film by studio executives, so a film's quality also should influence studio actions.

## 3. An empirical test of the studio actions–movie quality model

### 3.1. Sample and operationalization of variables

We identified a sample of 331 motion pictures released at North American box offices and then to video rental stores that appeared at least once in *Video Store Magazine*'s *US Top 50* weekly video charts between August 1999 and May 2001. This criterion helped identify a sample of films with adequate distribution to be potentially salient to audiences. In 1999–2001, 21,462 films (excluding made-for-TV, direct-to-video, and television series) were produced, according to IMDb.com; of these, IMDb.com lists business information for 4,068, and 2,008 were rated by the Motion Picture Association of America (MPAA). Most of these movies have little or no ambition in terms of wide commercial success and receive almost no public attention or distribution effort. In contrast, nearly all films with modest to wide release, regardless of their box office or final rental success, reach the weekly Top 50 video chart at least once. Thus, the Top 50 requirement retains films with varying outcomes and does not introduce a success bias but reduces the heterogeneity of our sample. We designate OWBO as the dollar amount of box office receipts generated by a film during its nationwide opening weekend and LTBO as the total receipts generated by a movie during its theatrical run minus the opening weekend amount. We gather both measures from IMDb.com based on Nielsen calculations.

We measure the studio actions variable with five reflective items: personal attractiveness, cultural familiarity, advertising expenditures, number of screens, and production budget. *Personal attractiveness* is operationalized as a weighted composite measure that takes into account the participation of stars and high-profile directors and producers.[1] For each star, director, and producer, we drew data from IMDb.com and calculated the mean box office receipts for that person's three most recent movies.[2] When the movie's poster listed multiple actor names, we calculated an overall star power index by weighting the mean box office value of the first listee by 1, that of the second by .5, the third by .25, and the fourth by .125, then summed the products to account for the nonlinear effect of multiple stars appearing in a movie on the box office results. For *cultural familiarity*, we use a 0–1 scale, in which we assigned one point to the movie if it was a sequel, remake, or adaptation of a novel or television series. We take actual *advertising expenditures* from the 1998, 1999, 2000, and 2001 volumes of the annual *Ad $ Summary* (published by Competitive Media Reporting). For the *number of screens* on which each film opened, we consulted the Screenline database, and we collected *production budget* information from various sources, including IMDb.com and Screenline.

To measure movie quality, we use both expert and customer items, consistent with Holbrook's (2005) finding that consumer and expert quality judgments appear to be created with the same norms. Specifically, five measures operationalize movie quality in a reflective way: the average ratings of up to 40 leading U.S. film critics, as represented by the Metascore index (calculated and published by metacritic.com); opening weekend polls of moviegoers conducted and made available by Cinemascore.com; the weighted movies' rating by IMDb.com members, as published on IMDb.com; the rating listed in the Martin and Porter movie guide (Martin and Porter, 2001); and the rating by the Maltin movie guide (Maltin, 2002). For the movie guides, we transform the ratings (0–5 stars, Martin/Porter; 0–4 stars, Maltin) into a 1–5 scale, with higher scores reflecting better quality.

## 3.2. Exploratory data analysis

In Table 1, we list the descriptive statistics and correlations. We find good reliability for both studio actions ($\alpha = .72$) and movie quality ($\alpha = .82$), and the maximum-likelihood confirmatory factor analysis (LISREL 8.5) shows acceptable global fit (comparative fit index [CFI] = .93, goodness-of-fit index [GFI] = .92, normed fit index [NFI] = .91, root mean square error of approximation [RMSEA] = .09, root mean square residual [RMR] = .08). The average variance extracted is .45 for studio actions and .51 for quality. Moreover, the coefficients of determination are .40 or higher, with the exception of those for personnel attractiveness (.33) and cultural familiarity (.23). To capture the domain of the studio actions and quality, we retain all these items in the analysis.

## 3.3. Results of structural equation modeling

To test the hypotheses, we applied structural equation modeling using the maximum likelihood algorithm of LISREL 8.5. The model fit is good, with CFI = .95, GFI = .92,

[1] Because it is logical to assume that a studio or distributor will promote its most influential assets, we use only those actors listed on the film's theatrical poster (available at moviegoods.com).

[2] In the case of movie stars, we considered only those movies in which the star played a major role (i.e., received first, second, or third billing).

**Table 1** Correlation matrix and descriptive statistics

| | Mean | s | CD# | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Personnel attractiveness | 55.27 | 59.09 | .096 | .389** | .153** | .299** | .249** | −.025 | .001 | .042 | .117* | .031 | .237** | .233** | .294** |
| 2. Budget | 30.86 | 28.97 | .718 | 1 | .218** | .660** | .679** | −.008 | .002 | .212** | .133* | .028 | .705** | .613** | .550** |
| 3. Cultural familiarity | .39 | .49 | .039 | | 1 | .083 | .174** | −.064 | .026 | .015 | .050 | .003 | .197** | .126* | .079 |
| 4. Advertising expenditures | 10.58 | 89.20 | .615 | | | 1 | .732** | .078 | .039 | .304** | .123* | .056 | .643** | .603** | .672** |
| 5. Number of screens | 1575.60 | 1094.40 | .855 | | | | 1 | −.229** | −.256** | .185** | −.083 | −.174** | .715** | .543** | .704** |
| 6. IMDb rating | 6.19 | 1.19 | .864 | | | | | 1 | .832** | .458** | .628** | .704** | .014 | .214** | .125* |
| 7. Metascore review value | 4.86 | 2.15 | .795 | | | | | | 1 | .402** | .586** | .702** | .057 | .197** | .050 |
| 8. Cinemascore value | 3.84 | .91 | .231 | | | | | | | 1 | .349** | .423** | .293** | .410** | .268** |
| 9. Martin and Porter movie guide | 2.95 | .98 | .464 | | | | | | | | 1 | .556** | .098 | .293** | .157** |
| 10. Maltin movie guide | 2.34 | .63 | .597 | | | | | | | | | 1 | .051 | .220** | .069** |
| 11. Opening weekend box office | 9.48 | 11.63 | 1.000 | | | | | | | | | | 1 | .830** | .675** |
| 12. Long-term box office | 27.80 | 40.94 | 1.000 | | | | | | | | | | | 1 | .648** |
| 13. Video rental revenues | 26.80 | 21.21 | – | | | | | | | | | | | | 1 |

*Correlation is significant at $p < .05$.

**Correlation is significant at $p < .01$.

*Notes:* CD is the coefficient of determination of the variable in the full structural equation model.

**Table 2** Direct and total effects of structural model elements

| Effects of | On | LISREL estimates | $t$-Values | Total effects ($t$-values) |
|---|---|---|---|---|
| Studio actions | Opening weekend box office | .813 | 17.641 | .813 (17.641) |
| | Long-term box office | .030 | .569 | .671 (13.454) |
| Movie quality | Opening weekend box office | .150 | 4.046 | .150 (4.046) |
| | Long-term box office | .238 | 7.129 | .386 (8.281) |
| | Studio actions | −.138 | −2.318 | −.138 (−2.318) |
| Opening weekend box office | Long-term box office | .788 | 15.776 | .788 (15.776) |

NFI = .94, RMSEA = .09, RMR = .09, and $\chi^2 = 171.52$ (45 df). The variables in the model explain much of the variance of the different kinds of motion picture success, with $R^2$ values of .650 for OWBO and .734 for LTBO.

We use two different criteria to test our hypotheses: For the hypothesized direct relationships, we refer to the significance of the respective path coefficient, whereas for those hypotheses in which we postulate that the impacts of studio actions and movie quality on success will differ in strength, we apply a $\chi^2$ difference test (Bollen, 1989). Specifically, this type of hypothesis is supported if the order of the standardized path coefficients is as predicted and the $\chi^2$ statistic is significantly lower for a model in which the paths are allowed to vary freely compared with that for a model in which both paths are constrained to be equal (Jöreskog and Sörbom, 1993).

When applying these procedures, we find support for most of our expectations. The results in Table 2 show that both studio actions and movie quality have a significant positive impact on a movie's OWBO, in support of H1a and H1b, and that the impact of studio actions is 5.6 times greater than that of quality with the difference being significant ($\Delta\chi^2 = 108.56$, $p < .001$), in support of H1c. Furthermore, we expected both studio actions and quality to influence LTBO (H2a and H2b) and the impact of quality to be higher (H2c). We find support for H2c; the impact of quality is four times greater than that of studio actions on LTBO, and the difference is significant ($\Delta\chi^2 = 13.44$, $p < .001$). However, H2 is only partially supported, in that the impact of quality is significant (H2b) but that of studio actions is not (H2a). The data also provide evidence for a significant success-breeds-success effect of OWBO on LTBO. Surprisingly, quality was weakly but negatively related to studio actions. Although we did not theorize this path in our framework, the weak correlation suggests that studios do not base their marketing spending on the final product's quality but rather on the "product concept" (i.e., the potential appeal that the movie's combination of stars, story, and so forth *could* have). The negative direction of the relationship suggests that for a film that is unlikely to generate positive word of mouth, studios expend additional promotional resources in an attempt to maximize opening weekend grosses.

We also ran tests for the potential moderating impacts of genre (Ho et al., 2004), timing of release (Krider and Weinberg, 1998), and MPAA rating (Ho et al., 2004). Through multigroup structural equation modeling (Jöreskog, 1971), we find no significant moderation of any model paths (Table 3).

**Table 3** Results of moderator analyses for rating, timing of release, and genre

| | Certification | | | | Timing of release | | | | Genre | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Standardized path coefficient: R-rated movies | Standardized path coefficient: Other ratings | $\chi^2$ Model when path is released | Difference significant? | Standardized path coefficient: Winter release | Standardized path coefficient: Summer release | $\chi^2$ Model when path is released | Difference significant? | Standardized path coefficient path coef ficient: Dramas | Standardized path coefficient: Other genres | $\chi^2$ Model when path is released | Difference significant? |
| $\chi^2$ all paths equal model | 409.27 (168 d.f.) | | | | 284.33 (168 d.f.) | | | | 413.29 (168 d.f.) | | | |
| Studio action → OWBO | .85 | .81 | 409.08 | n.s. | .78 | .81 | 284.06 | n.s. | .86 | .81 | 412.08 | n.s. |
| Studio action → LTBO | .01 | .05 | 408.96 | n.s. | .06 | .01 | 284.12 | n.s. | −.07 | −.05 | 413.29 | n.s. |
| Quality → OWBO | .12 | .17 | 409.09 | n.s. | .15 | .14 | 284.33 | n.s. | .14 | .17 | 413.09 | n.s. |
| Quality → LTBO | .24 | .25 | 409.27 | n.s. | .26 | .24 | 284.33 | n.s. | .22 | .21 | 413.29 | n.s. |
| OWBO → LTBO | .75 | .77 | 409.27 | n.s. | .76 | .74 | 284.27 | n.s. | .79 | .80 | 413.29 | n.s. |

*Note:* Critical $\chi^2$ difference scores: $p < .001 = 10.83$; $p < .01 = 6.63$; $p < .05 = 3.84$.

## 4. Alternate approach: Latent class regression

With this study, we ask whether good marketing (studio actions) can save a bad (poor quality) product. Although our structural equation analysis reveals that studio actions affect short-term success and that quality is more influential in the long run, we also explore the degree to which studio actions can compensate for quality. Thus, we analyze box office revenues using a latent class regression (Wedel and Kamakura, 2000), for which we sum OWBO and LTBO into total box office revenues. The regression approach offers several benefits; we can explore unobserved heterogeneity and perform a sensitivity analysis to assess the level of studio actions required to compensate for a given level of quality, thereby modeling box office revenues as a nonlinear function of quality and studio actions.

### 4.1. Data, variables, and model

Using the previously described data, we perform a cross-sectional analysis to explain total box office revenues (R). To account for both promotion and distribution aspects, we measure studio actions by two variables: advertising expenditures (A) and the number of screens on which the film opened (S). We treat quality as an equally weighted average measure (denoted by Q, ranging from 0 to 10, with 0 being the worst) comprising ratings and reviews provided by critics (metacritic.com, Martin and Porter movie guide, Maltin movie guide) and general viewers (Cinemascore.com and IMDb.com ratings). To describe any latent segments, we also use covariate dummies, including year $\delta_1$ ($1 = 1999$, $2 = 2000$, $3 = 2001$), rating $\delta_2$ ($1 =$ R-rated, $0 =$ other), summer release $\delta_3$ ($1 =$ summer release, $0 =$ other), and sequel $\delta_4$ ($1 =$ sequel, $0 =$ not). After removing data rows with missing data points, we obtained a sample of 255 for the regression. Following Basuroy et al. (2006) and Elberse and Eliashberg (2003), we specified the following multiplicative formulation:

$$R_i = e^{\beta_0} S_i^{\beta_1} Q_i^{\beta_2} A_i^{\beta_3} e^{\beta_4 \delta_i} e^{\epsilon_i} \quad (1)$$

where the subscript i denotes the *i*th movie, $\delta$ is a $(4 \times 1)$ vector $\{\delta_1, \delta_2, \delta_3, \delta_4\}$ of the dummy variables described, and $\varepsilon_i$ represents the error term that is assumed to be normally and identically distributed [NID $(0, \sigma^2)$].

### 4.2. Estimation results and discussion

We estimated a log-linearized version of Equation (1) without the dummy variables using a latent class regression model. Next, we estimated a one-segment model and added more segments one at a time. To assess the relative contribution of each additional segment, we observed the Bayesian information criterion (BIC), which is useful because its parameter/sample size ratio is small (less than 5%), and selected the model with the lowest BIC. Our estimations yield a BIC of 687.87 for the one-segment, 680.43 for the two-segment, and 682.82 and 711.38 for the three- and four-segment models, respectively. Because the two-segment case offers the lowest BIC, we chose it to be the final estimated model.

We provide the estimation results in Table 4. According to the high variance explained ($R^2 = .862$), the two-segment model appears to fit the data adequately, and all the slope coefficients have correct signs. The box office revenues in both segments are most responsive to quality (.89 and 1.67, respectively), demonstrating that for our sample, quality is the better driver of revenues. As the Wald tests and *p*-values in Table 4 indicate, the best distinguishing features between segments, in terms of covariates, appear to be ratings (which may reflect a restrictive effect for R-rated movies or a conscious decision by studio executives to target a specific market) and sequels (though only marginally). Films in Segment 1, to which sequels are likely to belong, are responsive to advertising but not very responsive to distribution (coefficients of .78 versus .15). In contrast, films in Segment 2, in which R-rated and summer release films are likely to reside, are more responsive to distribution than to advertising (coefficients of 1.18 and .02).

The z-values of the coefficients indicate that all the estimates are significant except for advertising in Segment 2, which does not represent a problem because of the lack of sensitivity of revenues to advertising in this segment. The Wald (equal across segments, '=') test, which we performed to determine if the coefficient values were the same across segments, is rejected in all cases, which suggests that the sensitivities observed are segment specific. Overall, the results are consistent with our structural model findings; in the long run, quality is the best driver of box office revenues. However, using the latent class regression approach, we find that certain studio actions are more influential for specific categories of films. Obtaining more covariates could provide a richer classification; though covariates simply serve the function of scaling predictions on data, the more covariates included in a latent class approach, the richer the classification becomes.

### 4.3. Sensitivity analysis

To assess the impact of quality on revenues, we performed a sensitivity analysis. Specifically, we chose a movie of average quality according to the data (screens = 1,832, advertising = \$10.25 million, quality = 5) and used the coefficients obtained in Table 1 to predict its revenues. That is, we set a goal of a 10% increase in revenues and predicted the percentage change, *ceterus paribus,* in the appropriate studio action variable (advertising if the film belongs to Segment 1, number of screens if it belongs to Segment 2) for varying levels of quality (i.e., 3–8). In Figure 2, we illustrate the percentage change required in the studio action variable as quality increases. For example, if the movie is of poor quality (3), up to a 68% increase in advertising is required to generate a 10% increase in revenue if the movie resides in Segment 1. If the quality rating were a 4, then the percentage increase in advertising required drops to 34.1%, while if the quality rating was much higher (7), advertising expenditures could be *decreased* by 18.5%.

## 5. Discussion and implications

We report the impact of two higher-order constructs on the financial success of motion pictures during different phases of the movies' box office run. Studio actions

**Table 4** Estimation results of latent-class regressions

| | Segment mean | | | | Segment mean | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | $z$-value | Segment mean of IV's | Coefficient | SE | $z$-value | Segment mean of IV's | Wald (=) | $p$-value |
| Intercept | −6.83 | .65 | −10.20 | | −8.40 | .60 | −13.95 | | 2.57 | .11 |
| Ln(Screens) | .15 | .08 | 1.78 | 6.17 | 1.18 | .06 | 19.96 | 7.22 | 100.36 | <.01 |
| Ln(Quality) | .89 | .33 | 2.71 | 1.68 | 1.67 | .25 | 6.70 | 1.63 | 2.71 | .1 |
| Ln(Advertising) | .78 | .11 | 6.83 | 8.43 | .02 | .03 | .90 | 8.68 | 40.56 | <.01 |
| Year dummy | −.26 | .28 | −.95 | | .26 | .28 | .95 | | .91 | .34 |
| Rating dummy | .54 | .31 | 1.79 | | −.54 | .31 | −1.79 | | 3.2 | .07 |
| Summer dummy | .43 | .31 | 1.42 | | −.43 | .31 | −1.42 | | 2.02 | .16 |
| Sequel dummy | −.91 | .59 | −1.54 | | .91 | .59 | 1.54 | | 2.38 | .12 |
| | Segment 1 Model $R^2 = .794$ | | | | Segment 2 Model $R^2 = .876$ | | | | | |

Overall Model $R^2 = .862$

Segment 1 membership = 52%, (Ln(Revenue) mean = 2.34)

Segment 2 membership = 48%, (Ln(Revenue) mean = 2.57)

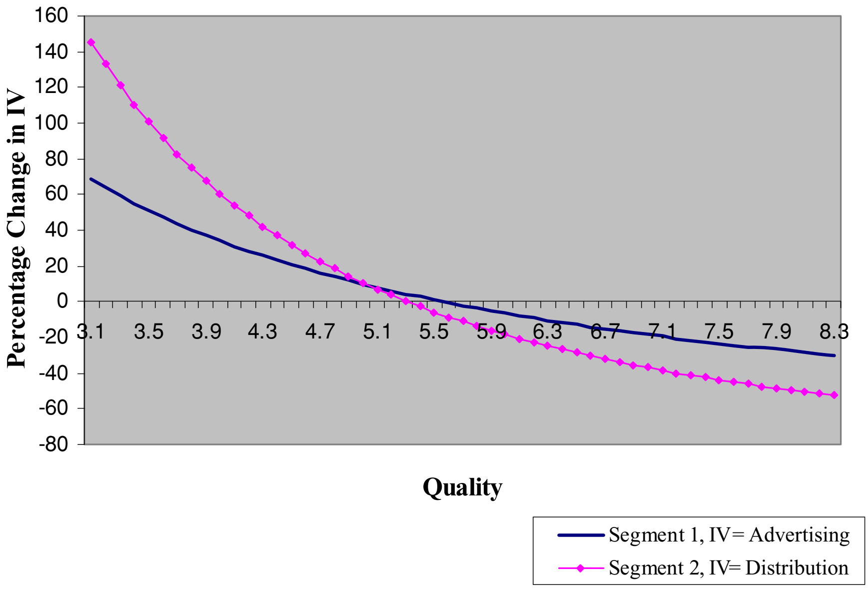


**Fig. 2** Percentage increase in independent variable to gain a 10% increase in revenue.

(promotion and distribution efforts) and the movie's quality (as perceived by audiences and professional critics) together explain between 65 and 73% of the revenues earned by films during different distribution windows. Post hoc latent class regressions also identify two segments for which 79% and 86% of total box office revenues can be explained by the model variables.

The two factors affect movie success differently across both the box office distribution phases and segments. Across distribution phases, studio actions can generate short-term success, but quality is the primary long-run success driver. Specifically, the OWBO is strongly affected by studio activities but the impact of quality is limited. However, when more neutral information becomes available from other sources, quality grows more important for box office success, whereas studio actions cease to have a direct effect. Studio actions retain an indirect effect on LTBO, meditated through OWBO. Apparently, it is no longer the studio actions themselves that influence audience behavior but the opening weekend success that gets interpreted by potential audiences as a signal of the movie's attractiveness. The long-term success of a studio's actions therefore strongly depends on whether those measures are effective in the first place. In other words, if studio actions do not manage to bring people into theaters when a movie opens, they will not have any kind of effect thereafter.

With regard to the impact of success factors across segments, we find similar results from our latent class regression; in both segments, quality has a higher impact on total box office revenues than do studio actions. Beyond quality, however, in Segment 1, revenues are more sensitive to advertising than to distribution intensity. In contrast, distribution has a higher impact on revenues than does advertising in Segment 2. Further research with other covariates could provide richer descriptions of the segments.

Turning to the question that began our inquiry, our results suggest that quality is the main driver of a film's LTBO success. For a film of poor quality, studio actions must be increased greatly (e.g., a 68% increase in advertising intensity for Segment 1; a 145% increase in distribution for Segment 2) just to achieve a modest gain (10%) in box office revenues. According to the averages from our sample, to increase the revenues of a film in Segment 1 by \$3.73 million, a boost in advertising spending of \$7.19 million would be required, clearly a losing proposition. Combined with our structural equation results, it appears that only in the short-run (opening weekend) can studio actions save a "bad" movie.

However, the domestic box office is only the first window in a sequential chain of distribution that includes video/DVD rentals and sales, television rights, overseas receipts, and merchandising earnings (Lehmann and Weinberg, 2000). Additional work should explore the impact of studio actions before a theatrical release (e.g., Ho et al., 2004) and before its release into a secondary channel in which consumer decision processes likely differ (Weinberg, 2005). For example, though we do not focus on the rental channel, post hoc analyses of rental revenues for the films in our sample suggest that, surprisingly, studio actions prior to theater release might play a more important role than quality for determining rental success.[3] Perhaps the lower cost of rentals alters consumers' movie decision processes so that peripheral cues (e.g., heavy promotion) and/or simple entertainment are more influential than substantive information or literary quality.

Further research could also explore alternative ways to assess quality and its interrelationship with studio actions. For example, researchers might develop a "gap" measure to isolate whether studios over- or underspend on their actions for a given level of film quality. Our finding that quality relates weakly but negatively to studio actions implies that studios currently might slightly overspend on movies of poor quality to maximize OWBO revenues. Because our findings indicate that the effect of such industry behavior might differ between movie segments, additional studies should shed more light on this interrelationship.

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[3] Rental revenues were the dollar amount estimates of a video's cumulative North American rental earnings, as reported by *Video Store Magazine*

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