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The long-term box office performance of sequel movies

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Abstract With a 26-year-long database of nationally distributed movies, we estimate the prevalence and effectiveness of sequels over time, while controlling for other factors that might influence demand. In particular, we examine whether the effectiveness of a strategy increases over time (possibly due to managerial learning) or decreases (possibly because its effectiveness is competed away or because of consumer satiation). After taking into account both supply side and demand side effects by using simultaneous equations, we find that sequels have a positive effect indirectly (i.e., supply side effect) through a significantly larger number of theaters showing such movies compared to non-sequel movies. In terms of direct effect (i.e., demand side effect), sequels do better than non-sequels in generating more attendance in the first week and in total. Parent movies, the movies from which sequels originate, also do better than non-sequels in terms of total attendance and first-week attendance. Interestingly, sequel movies generate less total attendance than parent movies. On the other hand, sequels generate more revenues upfront than parents. We also find that the impact of sequels on first-week attendance has been increasing over time, but the number of sequels released has not. Our follow-up analysis suggests that one reason can be due to the higher (inflation-adjusted) production budget of a sequel than of the original (i.e., the parent) movie possibly leading to a decreasing gross margin for sequels within a movie franchise.

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1 Introduction

Marketing researchers have examined both the short-term effects of marketing strategies (e.g., Wilkinson et al. 1982) and the long-term effects (e.g., Dekimpe and Hanssens 1995); however, they have rarely examined how the effectiveness of a strategy changes over time. In this paper, we examine this question in the context of the movie industry and, more specifically, movie sequels. As we discuss more fully below, studies of the effect of a sequel on first-week movie performance have typically found that sequels had a significant and positive effect using data from the early 1990s (Ravid and Basuroy 2004; Basuroy et al. 2006) and from the early 2000s (Ho et al. 2009). Even studies, such as Hennig-Thurau et al. (2009), which look at a longer time period (1996–2006) implicitly, assume that the impact of a sequel on performance remains the same over time. In this paper, we relax this assumption and estimate the change in sequel effects over time. The effectiveness of a marketing strategy may, in fact, change over time. Managers may learn how to better develop and deploy a strategy and so become more effective in its use. On the other hand, consumers may tire of a strategy, or the advantage of a strategy may be competed away to some extent as its benefits become common knowledge. As far as we know, no marketing study has examined this issue.

In this paper, we also model and estimate the box office performance of parent movies, the movies from which sequels originate. Basuroy and Chatterjee (2008), for example, examine how, within a sequel franchise, sequel movies perform and find in a sample from the early 1990s that sequels do not perform as well as their parent films. Our study also compares the relative performance of parents and sequels but does so over an extended period of time.

Our primary findings are that parents and sequels, as compared to non-sequels, are shown in a higher number of theaters in the first week and have higher first-week and total attendance, but only sequels have a lower ratio of second-week to first-week attendance (i.e., a lower retention rate of the first week's attendance levels) relative to non-sequels. Moreover, parent movies have higher total (but not first week) attendance than sequel movies, but sequel movies have a higher ratio of first-week to second-week attendance than do parent movies, indicating more "front loading" of the audience for sequels. Interestingly, while the number of movies released each year has increased over time, the number of sequels has remained relatively constant despite their favorable performance (see Figs. 1 and 2).[1] Possible explanations for these results are explored later in the paper.

In terms of estimation, in this paper, we use a newly developed 26-year-long database of movies distributed nationally in the USA to estimate the prevalence

[1] When we ran a regression of the number of sequels made each year as a function of a yearly time trend, we found no significant ($p<0.05$) relationship with time. For non-sequels, the coefficient of time was significant.

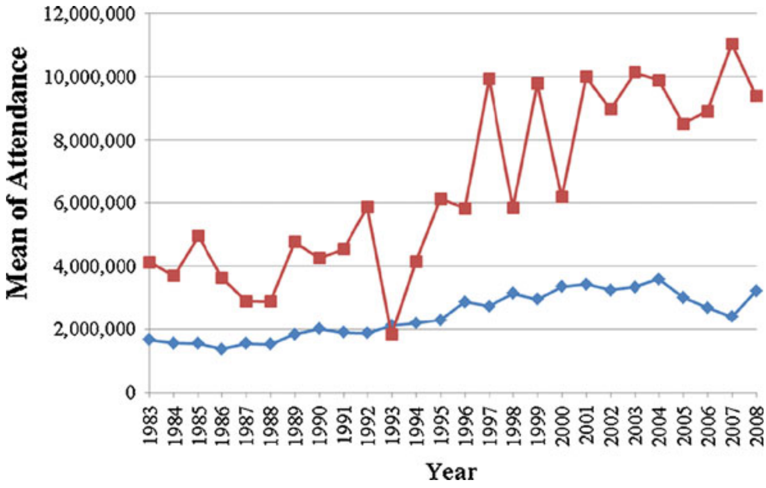

Fig. 1 Mean first week attendance of movies by year

and effectiveness of parents and sequels over time while controlling for other factors that might influence demand. While our study focuses on the performance of sequel movies, we also show how the performance of sequel movies differs from that of parent movies (movies from which sequels originate) and find results consistent with that of Basuroy and Chatterjee (2008).

The remainder of the paper is organized as follows: In the next section, we review literature related to the sequel effect on movie performance. We then set up our empirical research framework, describe the database we employ, and present the results of model estimation and analysis. Finally, we close with a summary of conclusions and a discussion of future research.

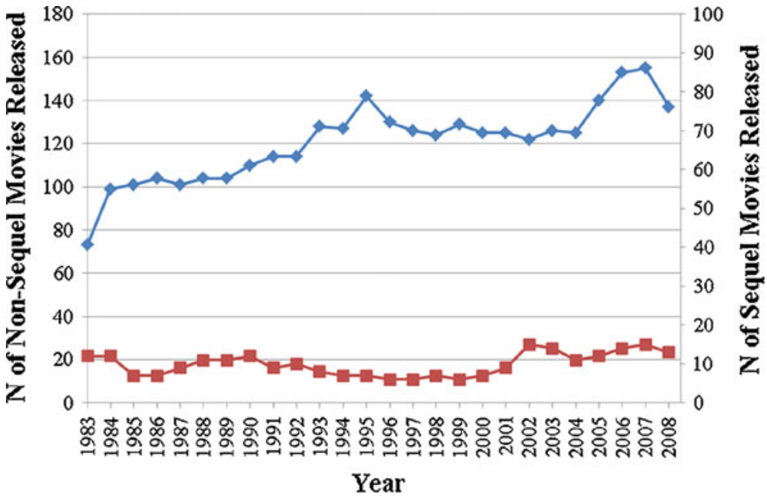

Fig. 2 Number of movies released by year

2 Background

2.1 Effect of sequels on movie box office performance

Extensive, recent reviews of sequels and their effects on audiences and revenues may be found in Sood and Drèze (2006) and Hennig-Thurau et al. (2009), so we only provide a brief review here. Some of the literature conceptualizes sequels as brand extensions and thus suggests that movie goers, who liked the original, would be more likely to see the sequel, thus providing an increase in first-week and total attendance. Hennig-Thurau et al. (2009) suggest that the degree of transfer depends upon how similar the sequel is to the original on such characteristics as genre and MPAA rating. Moreover, while some studies such as Sood and Drèze (2006) have focused on an individual consumer's reactions to such issues as satiation and variety seeking in a decision to see a sequel movie, our focus is on the broader market level effects of sequels.

Table 1[2] summarizes nine selected major empirical studies on movie performance that include a sequel dummy in their models. All but one of the studies listed in Table 1 found a significant and positive effect of sequels on movie performance despite using different estimation methods, outcome measures, and data samples. The estimates of the effect of sequels vary considerably and the previous research has several drawbacks. First, the data used in all previous studies are limited to a short time period, typically 2 to 3 years, with the exception of Hennig-Thurau et al. (2009). Thus, the sequel effects found in these studies are related to a specific short time period, and the results cannot be generalized in a long-term perspective. Second, though Hennig-Thurau et al. examine sequel effects over an extended time period, they implicitly assume that the effect of sequels is constant over time. Our study covers a much longer time period and allows for varying impact over time. Third, the studies in Table 1 focus on revenues and not attendance, and revenue measures can be sensitive to inflation. We use attendance measures, to reflect our interest in how sequels affect the size of the audience. Fourth, some of the earlier studies were limited because of sample selection criteria, lack of explanatory variables and estimation approaches that can lead to biased results. We overcome these disadvantages by preparing a new and extensive database and by employing a system of equations approach (Elberse and Eliashberg 2003; Basuroy et al. 2006 and Ho et al. 2009) that controls for biases in parameter estimation, as discussed below.

2.1.1 Measures of performance

This paper evaluates the parent and sequel effects over time on the box office attendance of movies. We focus on attendance as we are interested in the impact of a sequel on the audience for a movie over time. We believe that this is a first step in evaluating the impact on revenue, both for the movie during its North American release and also for revenues in other markets outside North America and for such

[2] Studies 1–5 in Table 1 used essentially the same sample. However, due to different model specifications and statistical approaches, different results for sequels were reported.

Table 1 Key literatures summary

No	Paper	Data time period	Data selection	Estimation method	Dependent variable	Estimated sequel coefficient	Sequel p value
1	Ravid (1999)	1991–1993	A random sample of over 200 films released between late 1991 and early 1993 and listed in the "Crix Pics" section of *Variety*. Most testing was performed on 175 films, after eliminating all very low budget films	OLS	ln(Domestic box office receipt)	1.144	0.0267
2	Basuroy et al. (2003)	1991–1993	Similar to Ravid (1999)	OLS	1st-week box office revenue	5.223	<0.1
3	Ravid and Basuroy (2004)	1991–1993		OLS	ln(Domestic box office receipt)	0.946	<0.05
4	Basuroy et al. (2006)	1991–1993		3SLS	ln(Revenue in 1st week)	0.22	0.03
5	Basuroy and Chatterjee (2008)	1991–1993		GEE	ln(Weekly revenue)	0.845	<0.01
6	Hennig-Thurau et al. (2009)	1998–2006	101 initial movie sequels released in North America from 1998 to 2006 and a matched subsample of non-sequels drawn from the 1536 non-sequels released during the same time period	3SLS	Ln(Total box office revenue)	0.131	<0.05
7	Ainslie et al. (2005)	Mar 1995–Jun 1998	825 movies released in the United States from 1995 to 1998	Bayesian	Revenue in 1st week	0.038	<0.05
8	Hennig-Thurau et al. (2006)	Aug 1999–May 2001	331 motion pictures released in US theaters and then to video rental stores that appeared at least once in Video Store Magazine's US Top 50 weekly video chart	Latent class regression	ln(Total box office revenue)	−0.91	0.12
9	Ho et al. (2009)	2000–2002	Among the 1,445 movies released in 2000–2002, select: (1) movies released in at least 600 theaters; (2) movies of production budget at least $15 million	GMM-3SLS	ln(1st-week box office revenue)	0.51	<0.05

ancillary products as DVDs and television. We turn to that issue in the discussion section of the paper, as well as discussing issues of profitability.

2.1.2 "Lead and lag" effects in movie demand and distribution

Efforts to build an audience for a movie can have both a direct effect on attendance, as well as an indirect effect, by increasing the number of theaters showing a movie. Elberse and Eliashberg (2003) model movie revenue and number of screens as endogenous variables and estimate a dynamic simultaneous equations model. Basuroy et al. (2006) and Ho et al. (2009) employ similar approaches. These studies support the view that anticipated higher (lower) consumer demand drives movie exhibitors to increase (decrease) the number of screens, while the number of screens, in turn, increases (decreases) attendance in the first week. In subsequent weeks, number of screens lags attendance (see Krider et al. 2005).

3 Model development

3.1 Hypotheses

As discussed above, we follow Elberse and Eliashberg (2003) and others and hypothesize that sequel have a direct effect by directly appealing to people who want to see a sequel to the original (parent) movie and an indirect effect, as more exhibitors show a movie (in anticipation of consumer demand), so that consumers have the movie available at "a theater near you." We do not propose formal hypotheses about the performance of parents as it is quite clear that studios will base sequels on movies that are more successful than the typical movie, ceteris paribus.

We examine the effect on three measures of performance: first-week attendance, total attendance over the run of the movie, and attendance retention from the first week to the second week. We expect the effect of sequels to be the strongest in the first week, as those people who particularly enjoyed the parent movie are most likely to want to see the sequel movie as soon as possible. A sequel can be viewed as a brand extension (Hennig-Thurau et al. 2009). As such, there is a group of people who will see the movie due to the brand effect in addition to the movie's appeal due to its characteristics. This would suggest that overall attendance of the movie would be higher. Our thinking is consistent with the results of the empirical studies summarized in Table 1, but we extend that work by looking at the effect of sequels over a much longer time period and also compare the effect of sequels relative to parents of sequels.

Trade press and academic work suggest that one effect of a sequel is to shift demand forward. In the language of Sawhney and Eliashberg (1996), potential movie goers have a time to decide to see a movie and then a time to act; the effect of a sequel is to shorten the time to decide for a segment of the audience. Controlling for all other factors, this would lead to people going to a sequel earlier than a non-sequel. If demand shifting occurs, then we would expect that attendance would be relatively high in the first week and relatively low in the second week. A weekly attendance retention ratio model is proposed to test whether sequel movies show a faster or a slower drop in weekly box office performance by comparing second-week to first-week attendance. Basuroy and Chatterjee (2008) found that sequels had a faster decay rate than non-sequels when considering the entire length of a movie's run. However, their study is based on a short time period and, given their focus on within franchise dynamics, does not control for the possible endogeneity effects of number of theaters on box office attendance. To remove the effect of length of run on the measured decay rate, we focus on the first 2 weeks of performance.[3] Also, we estimate the effect of both parents and sequels separately, and as a result, we were able to compare them directly in each stages of movie performance.

As noted above, it is reasonable to expect that only highly successful movies will be used to make sequels. And if sequels are brand extension of successful products then sequels should also do better than non-sequels. These arguments lead us to following hypotheses:

H1a: (Indirect path): Sequel movies perform better than non-sequel movies by attracting more movie exhibitors to show them, which induces more demand.
H1b: (Direct path): Sequel movies perform better (in terms of first-week and total attendance) than non-sequel movies by directly attracting more moviegoers.

We test H1a and H1b with data for the first week and with data for the total performance. After testing whether sequels (and parents) perform differently than non-sequels, we then ask whether there are differences between parents and sequels in box office performance. In a thought provoking paper on success rates in different products, services and jobs Lazear (2004) hypothesized that sequels cannot be as successful as their parents because of the phenomenon of regression to the mean. As a result it is difficult to replicate the above average success of a parent in a sequel. This phenomenon is also commonly known as the 'Peter Principle.' Consequently, we propose the following hypothesis:

H1c: (Direct path): Sequel movies directly attract fewer moviegoers than parent movies in terms of first-week and total attendance.

Note that sequel movies do not show the so-called sleeper effect. In our database, only one sequel movie had higher attendance in the second week than the first week, but 11% of non-sequel movies had second-week attendance higher than first-week attendance. Viewing a sequel as a brand extension and thus likely to shift demand forward for moviegoers who decide early that they want to see a movie, we propose the following hypothesis:

H2: The ratio of first-week attendance to second-week attendance is higher for sequel movies than for parents or non-sequel movies.

Following Aaker and Keller (1990), marketing researchers have extensively studied brand extensions, and many trade books and articles have focused on brand equity. Given this focus, we expect that managers have become better able to design and execute brand extension strategies. In the movie industry, sequels are often characterized and studied as brand extensions (e.g., Hennig-Thurau et al. 2009; Sood and Drèze 2006, as discussed above). Newspaper articles (e.g., *The Washington Post*

[3] In our sample, on average, sequels ran for 12 weeks, parents of the sequels ran for 15 weeks, and the rest of the movies ran for 10 weeks.

(May 14, 1989): "Movie Sequels Just Good Business"; *USA Today* (June 27, 2003): "Season of Movie Sequel"; *Variety* (January 25, 2010): "Keeping faith with franchises") report a similar view. Given the increased prevalence of brand extensions in general and the increasing values of major brands, we expect that the impact of sequels will increase over time. Although we recognize the lack of empirical literature to examine this issue, based on the above reasoning, we propose the following hypothesis:

H3a: Sequel movies' advantage over non-sequels in terms of box office performance (e.g., first-week attendance, total attendance) increases over the long term.

Contract terms between movie studios and movie exhibitors generally allow for a higher percentage of box office revenues to go to the movie studio in the first week of a movie's run than in the second and subsequent weeks. So, Hollywood studios would like to shift revenues to the first week. Consequently, as part of the increased sophistication in brand extension strategies as described above, we propose the following hypothesis:

H3b: The ratio of first-week to second-week attendance for sequel movies will increase over the long term.

3.2 Estimation issues

In estimating the effect of sequels on attendance, it is important to note that unobserved or sometime difficult to measure quality can be a potential source of endogeneity. The main sources of endogeneity are the potentially unobserved (i.e., unobserved by the researchers) characteristics influencing the behavior of moviegoers: Moviegoers are more likely to watch a movie that has these unobserved characteristics during its opening week. An example of such unobserved movie characteristics is the level of special effects in a movie. Because this characteristic is unobservable to us and therefore absent from our model, there is a potential for bias in the estimated effects of the endogenous variables. We address the potential endogeneity of our focal variables in two ways. First, we include a comprehensive set of observable movie characteristics in our model (see the discussions in Sections 3.3 and 3.4 below). These observable movie characteristics are usually the cues theater managers and consumers use to infer a new movie's appeal. But this approach still does not control for potential endogeneity of number of theaters in an attendance equation. So, to control for the endogeneity of number of theaters, we use three-stage simultaneous equation system estimation method (3SLS) with unique identifying variables in each equations.

3.3 Control variables

Demand for a movie and the number of theaters willing to show a movie are driven by a number of factors such as movie characteristics, quality of the movie, competitive intensity, and seasonality. Studies vary in specific variables used based on the research objectives of the study and the availability of data. In our case, by studying the impact of sequels over an extended period of time, many variables, which studies focusing on short and recent time periods can employ, are simply not available to us. Nevertheless, our set of variables contains all variables which were

Table 2 Definitions and sources of variables

Variable	Variable description	Source
Weekly attendance	Attendance for movie *j* in the release week from Friday to Thursday	*BoxofficeMojo, IMDB*
Total attendance	Total attendance for movie *j* in all weeks	*BoxofficeMojo, IMDB*
2nd-/1st-week attendance ratio	Ratio of 2nd-week attendance over 1st-week attendance for movie *j*	*BoxofficeMojo, IMDB*
Gross margin	Gross margin of movie *j*, which equals to (total revenue budget)/budget	*BoxofficeMojo, IMDB*
N of theaters	Number of movie theaters engaged for movie *j* in the release week	*BoxofficeMojo, IMDB*
Sequel	A binary variable to indicate if movie *j* is a sequel	*BoxofficeMojo, IMDB*
Parent	A binary variable to indicate if movie *j* is a parent of a sequel	*BoxofficeMojo, IMDB*
T	A year interval variable which captures the trend effect, $T=1$ for base year 1983	*Constructed*
Competition intensity	Total production budgets of all movies released in the same week and one week prior to the release of movie *j*	*BoxofficeMojo, IMDB*
Adjusted budget	Adjusted production budget of movie *j* scaled by average ticket price in the released year	*BoxofficeMojo, IMDB*
Consumer rating	Consumer rating for the movie *j*, ranging from 0 to 10	*IMDB*
Genre	Binary variables to indicate the genre: (1) action, (2) comedy, (3) drama, and (4) others	*BoxofficeMojo, IMDB*
MPAA rating	Binary variables to indicate the MPAA rating: (1) G or PG, (2) PG-13, and (3) R	*BoxofficeMojo, IMDB*
Distributor	Binary variables to indicate if movie *j* is distributed by one of the following distributors: (1) Buena Vista, (2) Fox, (3) Paramount, (4) Sony, (5) Universal, (6) Warner Bros, and (7) others	*BoxofficeMojo, IMDB*
Run time	Length in minutes of movie *j*	*BoxofficeMojo, IMDB*
Holiday	A binary variable to indicate if movie *j* is released in the week of a major US holiday	*Constructed*
Month	Binary variables to indicate the month when the movie *j* released	*Constructed*

found to be statistically significant in the most recent study of sequels, i.e., Hennig-Thurau et al. (2009), Table 2.

The quality of a movie is a critical control variable. Most papers use production budget as an "input" measure of quality. In addition, we include customer ratings of a move as another measure of quality, this time based on an evaluation of the completed movie. Genre (e.g., comedy, drama) may target particular audiences, and MPAA ratings (e.g., G, PG, R) may limit who is willing or allowed to see a movie and can have an important impact on attendance. Following Einav (2007) during certain seasons and holidays, people have more time to see movies, and hence, these variables are included in our model as they are now widely used. The strength of competing movies can also affect attendance. As discussed below, we also include control variables for run time and name of Hollywood studio distributing the movie, as these factors are likely to influence the movie exhibitor's decision to show a movie, but not the individual movie goers' decision to attend a movie.

3.4 Econometric models

To test these hypotheses, we develop the following system of models. We set up a simultaneous equations system relating to the box office attendance (or second-to-first-week ratio of attendance) for movie j (denoted as ATTD_j) and the number of theaters engaged for the opening week of movie j (denoted as THR_j):

$$\mathrm{THR}_j = e^{\beta_1 + \sum_{L=P,S,T} \beta_{1L} L_j + \sum_{Q=P,S} \beta_{1QT} Q_j \ln(T) + \sum_h \beta_{1h} Z_{hj} + \varepsilon_1} \prod_k X_{kj}^{\beta_{1k}} \tag{1}$$

$$\mathrm{ATTD}_j = e^{\beta_2 + \sum_{L=P,S,T} \beta_{2L} L_j + \sum_{Q=P,S} \beta_{2QT} Q_j \ln(T) + \sum_m \beta_{2m} Z_{mj} + \varepsilon_2} \prod_r X_{rj}^{\beta_{2r}} \tag{2}$$

where P, S and T represent parents, sequels and yearly time trend respectively. ε_1 and ε_2 are the errors of the two equations, and the β's are the parameters to be estimated. X_{kj} and Z_{hj} are the kth and hth characteristic potentially influencing theater managers' screening decisions of movie j; the former are a set of continuous variables, and the latter are a set of dummy (binary) variables. Similarly, X_{rj} and Z_{mj} are the continuous and dummy variables potentially affecting moviegoers' decisions. A majority of the variables in X and Z matrices are the same across Eqs. 1 and 2. These common variables are the competitive intensity of movie j, movie j's being of a certain genre, and movie j's MPAA rating.

Some variables are specific to each equation. Similar to the reasoning in Ho et al. (2009), which suggests that these variables are either primarily known by theater managers or most relevant to their decisions, the following three variables are unique to the theater equation (i.e., Eq. 1): total adjusted (for inflation) production budget for movie j, running time of movie j, and distributor/studio of movie j. Three sets of variables are unique to Eq. 2, the box office equation: consumers' ratings of movie j, movie month dummy in which movie j is released, and movie j released during one of the five major US holidays. Consumer ratings are measures of revealed quality and not available when the exhibitor decides to book the movie, and monthly and holiday factors do not affect the total number of screens available, but they do affect the time a moviegoer has to see a movie. To justify the use of 3SLS estimation techniques, we test for the endogeneity of the theater variable in the attendance equation using the Hausman test (Greene 2003) for endogeneity.[4] For each of the three dependent variables in our study, we reject the null that the theater variable is exogenous. As we are using 3SLS to estimate the model, these equation specific unique variables help us to identify the model. As discussed below, the significance of these variables provides evidence that these variables are appropriate instruments to estimate the model.

Models of total attendance and of retention are identical to Eqs. 1 and 2, except that the left-hand side variable in Eq. 2 is modified to capture the dependent variable. Definitions and sources of variables are provided in Table 2.

4 Description of the data

The data collected include all movies shown in the US market between 1983 and 2008. The main sources of data are www.imdb.com and www.boxofficemojo.com.

[4] Detailed Hausman test results are available from the authors.

Consistent with Einav (2007) and Ho et al. (2009), we limited our analysis to nationally released movies and only included movies in our sample that opened in at least 400 theaters. This reduced our sample of 7,824 movies to 3,396. Information on production budgets is not available for many movies, particularly those in the earlier part of our sample; we omitted movies that did not have data on production budgets. While data on consumer evaluations of movies were available for virtually all of the movies in our remaining sample, many movies did not have data on critics' reviews. For movies in which both critics reviews and consumer ratings were available, the two variables were highly correlated at $r=0.76$. Our results are consistent with those of Holbrook and Addis (2007), who found a correlation of $r=0.92$ between expert judgment (critics' ratings) and ordinary evaluation (consumer evaluations). Moreover, when we ran our models on the sample for which critics ratings and consumer ratings were available, there were no differences in the coefficients which were statistically significant at the $p<0.05$ level between these two models. Consequently, to ensure that our sample size was as representative as possible, we use consumer ratings in our analysis. Missing data on other variables led to additional reductions in the sample size for analysis. The final sample includes 1990 movies released between 1983 and 2008. These movies accounted for 25.55% of the total number of movies released between 1983 and 2008, but for 76.32% of opening week attendance. This suggests that our sample well represents the US movie market; sample representativeness is higher in the later years of our study.

Overall sequel movies were shown in more theaters on the opening week than parents and non-sequels (2,696, 2,106, and 2,067 respectively), had higher attendance in the opening week (8.2 million, 6.6 million, and 3.0 million), and a lower retention of audience size from first week to second week (52%, 72%, and 62%); however, parent movies had a higher total attendance (24.1 million) than either sequels (20.5 million) or non-sequels (8.4 million) in our sample . Sequel movies have higher (inflation-adjusted) budgets ($32 million) than patents ($19 million) and non-sequels ($21 million), but obtain approximately the same consumer ratings (6.05 vs. 5.92 on a scale from 0 to 10) as do non-sequels, both of which are lower than the average 6.85 rating of parents. Sequel movies are more likely to be of the Action genre (53%) compared to non-sequels (22%) and parents (47%) and to be released on holiday weekends (16% vs. 10% for both parents and non-sequels) or during May, June, and July (41% for sequels compared to 33% for parents and 23% for non-sequels). While 49% of parent movies are R rated, sequels and non-sequels are slightly less often rated as R (44% vs. 43%).[5]

5 Results and discussion

Table 3 presents the results of estimation for the three models discussed in Section 3. One binary variable of each set of categorical variables (Genre, MPAA rating, Distributor, and Month) is dropped to avoid perfect multicollinearity in the estimation process. In particular, we drop the binary variables indicating (1) that the movie's genre is other than comedy, drama, or action; (2) that it is rated G or PG

[5] Detailed tables of descriptive statistics are available from the authors.

Table 3 Regression analysis of movie performance

Variables	First-week performance model		Total performance model		2nd-week/1st-week performance model	
	Theater equation	Attendance equation	Theater equation	Attendance equation	Theater equation	Attendance equation
ln(*N* of Theaters)		2.017[a]		2.308[a]		0.153[a]
Binary: Parent	0.369[b]	−0.224	0.354[b]	0.138	0.325[b]	−0.021
Binary: Sequel	0.402[a]	−0.060	0.396[a]	0.070	0.387[a]	−0.141[c]
ln(Trend)×Parent	−0.063	0.247[b]	−0.057	0.174	−0.054	0.023
ln(Trend)×Sequel	−0.057	0.146[b]	−0.055	0.069	−0.058	−0.014
ln(Trend)	0.400[a]	−0.660[a]	0.394[a]	−0.938[a]	0.415[a]	−0.241[a]
ln(Competition Intensity)	0.012	−0.047[a]	0.016[c]	−0.046[b]	0.000	0.013[c]
ln(Adjusted Budget)	0.178[a]		0.178[a]		0.177[a]	
ln(Consumer Rating)		0.861[a]		1.503[a]		0.394[a]
Binary: Genre—Comedy	−0.069[a]	0.084[b]	−0.067[a]	0.185[a]	−0.069[a]	0.087[a]
Binary: Genre—Drama	−0.176[a]	0.224[a]	−0.178[a]	0.321[a]	−0.159[a]	0.053[a]
Binary: Genre—Action	−0.010	0.021	−0.009	−0.024	0.004	−0.053[a]
Binary: MPAA-R rated	−0.133[a]	0.159[a]	−0.125[a]	0.002	−0.135[a]	−0.122[a]
Binary: MPAA-PG13 rated	−0.037[c]	0.130[a]	−0.031	0.030	−0.049[b]	−0.121[a]
Binary: Distributor—Buena Vista	0.079[a]		0.084[a]		0.044	
Binary: Distributor—Fox	0.146[a]		0.147[a]		0.119[a]	
Binary: Distributor—Paramount	0.136[a]		0.141[a]		0.100[a]	
Binary: Distributor—Sony	0.130[a]		0.129[a]		0.110[a]	
Binary: Distributor—Universal	0.084[a]		0.078[a]		0.045[c]	
Binary: Distributor—Warner Bros	0.085[a]		0.096[a]		0.089[a]	
ln(Runtime)	−0.072		−0.083[c]		−0.182[a]	
Binary: Holiday		0.165[a]		0.155[b]		−0.089[a]
Binary: Month—Jan		0.194[a]		0.219[c]		0.009
Binary: Month—Feb		0.092		0.128		0.027
Binary: Month—Mar		0.126[b]		0.149[c]		0.008
Binary: Month—Apr		0.017		0.032		0.008
Binary: Month—May		0.286[a]		0.348[a]		0.054[c]
Binary: Month—Jun		0.444[a]		0.438[a]		−0.067[b]
Binary: Month—Jul		0.425[a]		0.411[a]		−0.051[c]
Binary: Month—Aug		0.158[a]		0.164[b]		−0.032
Binary: Month—Oct		0.029		0.074		0.046[c]
Binary: Month—Nov		0.246[a]		0.319[a]		0.025
Binary: Month—Dec		0.241[a]		0.524[a]		0.245[a]
Intercept	6.294[a]	−0.531	6.335[a]	−2.231[a]	6.847[a]	−1.707[a]
Adjusted *R* square	0.5244	0.6372	0.5238	0.5566	0.5369	0.3072

[a] Significant at 1% level

[b] Significant at 5% level

[c] Significant at 10% level

Table 4 Estimated overall effects by models

Model	Equation	Effect of		Estimated effects at the median	Years of insignificant effect (p>0.05)	Years of significant effect (p<0.05)
First-week performance	THR	[1]	P	0.183[a]		1983–2008
		[2]	S	0.234[b]		1983–2008
		[3]	$P-S$	−0.05	1983–2008	
	ATT	[5]	P	0.503[a]	1983–1986	1987–2008
		[6]	S	0.37[a]	1983–1985	1986–2008
		[7]	$P-S$	0.133	1983–2008	
Total performance	THR	[8]	P	0.186[a]		1983–2008
		[9]	S	0.234[a]		1983–2008
		[10]	$P-S$	−0.048	1983–2008	
	ATT	[11]	P	0.65[a]	1983–1985	1986–2008
		[12]	S	0.273[a]	1983–1987	1988–2008
		[13]	$P-S$	0.377[b]	1983–1989	1990–2008
2nd-week/1st-week performance	THR	[14]	P	0.166[a]		1983–2008
		[15]	S	0.216[a]		1983–2008
		[16]	$P-S$	−0.5	1983–2008	
	2nd-week ATT/1st-week ATT	[17]	P	0.046	1983–2008	
		[18]	S	−0.182[a]		1983–2008
		[19]	$P-S$	0.229[a]	1983–1984	1985–2008

P parent, S sequel

[a] Significant at 1% level

[b] Significant at 5% level

by the MPAA; (3) that it is distributed by one of the smaller distributors; and (4) that it was released in September. When interpreting the effects of binary variables, such as whether a movie belongs to the comedy genre, we should note that the estimated parameter associated with MPAA-R captures the effects of MPAA-R relative to the base case, a G-rated or PG-rated movie of another genre movie released in September (by a small distributor, if in the theater equation). In our equations, the sequel dummy captures the fixed sequel effect while the sequel interaction variable captures the dynamic sequel effect. And total effect of sequel is based on the linear combination of these two effects. The parent effect is captured in the same way.

5.1 Hypothesis testing

Note that the effects of parents and sequels in our models can be stated as: $\beta_{in} + \beta_{inT}\ln(T)$, where i=1, 2 and n=S, P. If statistically we find that $\beta_{in} + \beta_{inT}\ln(T) \neq 0$, then we can state that parents and sequels generate different levels of returns from non-sequels at T. Note that we can run the hypotheses tests for each value of T. Table 4 presents the results for hypotheses H1a, H1b and H2. In Table 4, the test results are presented at the median (equal to mean given T is a trend variable) of T, where we also summarize the results for the rest of the values of T.[6]

[6] Detailed test results are available from the authors.

In H1a, we hypothesized that sequel movies perform better by indirectly attracting more movie exhibitors to show the movies, which induces more attendance. In all three models (i.e., first-week performance, total performance, and second-week/first-week performance), the effects are positive and significant (i.e., estimates 0.234 ($p<0.05$) for the first-week attendance model; 0.234 ($p<0.01$) for total performance model, and 0.216 ($p<0.01$) for second-week/first-week attendance model). So H1a is supported for sequels. In addition, parent movies exhibit similar significance levels.

Next, H1b hypothesizes that sequels perform better by directly attracting more moviegoers. For both first-week and total attendance, the effects are positive and significant (i.e., estimates of 0.370 ($p<0.01$) in the first-week model and 0.273 ($p<0.01$) in total performance model). Parent movies achieve similar significance levels.

To test H1c, we test the difference in box office returns between parents and sequels. In terms of total attendance, parents have significantly higher effect than sequels (estimate of 0.377, $p<0.05$), but this is not the case for first-week attendance (estimate of 0.133, $p>0.10$). So, H1c is not supported for first-week attendance but is supported for total attendance.

Next, in the case of H2, we test for the difference in first- to second-week decay rate in attendance between parents and sequels, and sequels and non-sequels. First, we note that parents are not significantly different from non-sequels in terms of decay rate (estimate of 0.046, $p>0.1$). However, sequel decay more rapidly than parents (estimate of 0.229, $p<0.01$) and non-sequels (estimate of −0.182, $p<0.01$; note that the difference in signs is due to the difference in the base case). Overall, sequels are likely moving demand from not just the second week but also from later weeks in the movie's run. Interestingly, first-week attendance, retention, and total attendance per movie are all decreasing significantly over time, so sequels are primarily able to partially offset this trend in the first week but not able to sustain it over the length of a movie's run.

Our third hypotheses (H3a and H3b) examines whether a sequel's influence on demand changes over time. Following standard practice in marketing we are interested in the significance of the interaction terms between the sequel dummy and trend. For first-week attendance, the sequel trend interaction coefficient in the regression estimates (see Table 3) is significant at $p<0.05$. However, there are no significant effects of interactions on total attendance. In other words, first-week attendance for sequels is increasing relative to non-sequels (0.146, $p<0.05$) over time but not in terms of total attendance (0.069, $p>0.10$). So, H3a is supported only in the case of first-week attendance. Similarly, we do not find any significant changes in decay rate (estimate −0.014, $p>0.10$) for sequels over the period of our study. So, H3b is not supported. Similar results hold for parent movies.

6 Conclusions

In comparing sequels and parents to non-sequels, we find that both sequels and parents attract more theaters to show their movie in the first week (an indirect effect) and have higher first-week and total attendance (a direct effect) than non-sequels. However, sequels (but not parents) have a significantly higher ratio of first-week to second-week attendance (i.e., faster decay rate) as compared to non-sequels. These results first confirm that sequels are based on movies which outperform the typical movie. More importantly, over an extended period of time, sequels have outperformed non-sequel movies, increasingly so in terms of first-week, but not total, attendance.

In comparing sequels to parents, we obtain a number of interesting results. First, parents and sequels are statistically equivalent in terms of the number of theaters they attract in the first week and in their first-week attendance. However, parents outperform sequels in terms of total attendance, confirming Lazeare's hypothesis. On the other hand, a positive and significant difference in the second-week/first-week ratio model implies that sequels relative to parents (and also to non-sequels) generate more revenues in the first week than in the second week compared to parents and non-sequels. In other words, sequels do better than parents when it comes to shifting the revenue stream by generating more revenues at the beginning of the run of the movies. This is a form of demand shifting effects, as sequels retain a smaller share of their first-week audience than do parents and non-sequels. As Hollywood studios generally receive a higher proportion of revenues from the first week than from the second and subsequent weeks (Raut et al. 2008), the demand shifting is profitable to the movie studios. For the same reason of revenue sharing rule, parents can be more attractive to theater owners than sequels.

Given these positive effects on attendance, why are movie studios not increasing the number of sequels that they make? In fact in a recent review paper, Eliashberg et al. (2006) argued that based on the attractiveness of sequels, we should observe increasing trends in the number of sequels produced. Our results show that the number of sequels per year has remained stable over the 26-year interval that we study, despite the fact that the number of movies released has grown at an annual rate of 6.68%. One reason can be that sequels are more costly to make. When we ran a regression of the (inflation-adjusted) budget of a sequel as a function of the budget of the original movie (or previous sequel), the coefficient of previous budget equaled 1.15 (significant at $p<0.01$). Sequels may attract more moviegoers than non-sequels, but they may not increase net profit. Our results are consistent with those of Hennig-Thurau et al. (2009). They found that the revenues (including DVD sales and rentals) that studios receive from a sequel are typically higher than what they would receive from an otherwise identical non-sequel. However, if a key component is changed, then the value of a sequel declines. In the case of *Spiderman*, the example presented in Hennig-Thurau et al. (2009), if the star Toby McGuire is not in the sequel, the value of the sequel can in fact be less than that of a non-sequel. Actors, directors, and other key rights holders may be aware of this and may charge fees for sequels that limit their profitability to the studio. Robert Downy Jr., one of the most successful franchise actors in recent years, is reported to have had a significant pay raise for the *Iron Man 2* sequel (*Variety*, January 25, 2010). This also appears to be one reason why Sony decided to re-launch the *Spiderman* franchise with a new cast and director (*Variety*, April 16, 2010). Interestingly, such cost escalation in the fees of big name franchise actors have also made B-list franchises with minimal star power (such as *Fast & Furious*) attractive to studios (*USA Today* (April 1, 2009): "*Fast & Furious* refuels the franchise; sequels low on gas, but they make money"). Unfortunately, due to data limitations on profitability of movies, particularly for the long time span that we analyze here, it was not possible to test this argument rigorously. Not all movie story lines lend themselves to the generation of sequels. In addition, the studios may find that it is difficult to bring together the same production and artistic teams because of scheduling issues, so that it is not feasible to produce a sequel with high continuity value. By contrast, beyond the impact on attendance itself, other factors may push studios to produce sequels. For example, consistent with Hennig-Thurau et al. (2009) and Palia et al. (2008), sequels may have lower variability and risk attached to them. As such, studios would find it useful to include sequels in their portfolio of movies. Also note that current revenue sharing rule in the channel can also limit the number of sequels that can be released due to potential backlash from theater owners as sequels have the ability to lower their share of the revenue stream.

Interestingly, we also show that in all three models, parents and sequels get a significantly higher number of theaters to show the movies relative to non-sequels. If sequels are changing the revenue streams that benefit studios, then why should theater owners' signup in significantly larger numbers than for non-sequel movies. Our result shows that despite the change in the revenue stream, sequels generate more attendance than non-sequels but less than their parents. So, for studio owners, there is a tradeoff. Also, in this marketing channel, due to antitrust regulation, theater owners cannot form bargaining coalition to demand fewer sequels from studios.

We conclude by noting the data limitations of our study. To analyze the effectiveness of a marketing strategy over time, we compiled a database covering a 26-year period. The movie industry is remarkable in that sales, distribution, production costs, and product characteristics information are available for so many individual products. However, reporting for early years is more limited and so the sample for early years is less representative. In addition, revenues on auxiliary products such as DVDs are not available and such important cost items as advertising are not available. While studies such as Hennig-Thurau et al. (2009) have resolved this problem by focusing on shorter time periods, such approaches are not possible to address the impact over time of marketing strategy. Additional data to shed further light on the profit implications of a sequel strategy or other such strategies would be welcome and would lead, we believe, to useful insights.

Also, note that in this paper we focused on the relative performance of parents and sequels. After controlling for quality-driven performance using observable covariates (such as consumer ratings and budget as proxies for quality), in the present models the unobserved quality differences are captured using dummy variables (i.e., fixed effects). These parent and sequel dummies capture the unobserved (by the modelers) quality-driven performance differences among parents, sequels, and non-sequels. Given the subtle and interesting differences in performances among parents, sequels, and non-sequels, in future research we plan to study these differences to identify and quantify the valuation of these unobserved characteristics and quality using a more detailed database.

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