Fast and frequent: Investigating box office revenues of motion picture sequels

Suman Basuroya,1 Subimal Chatterjeeb,*

a College of Business, Florida Atlantic University, Jupiter, Florida 33458, United States
b School of Management, Binghamton University, Binghamton, New York 13902, United States

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Abstract

This paper conceptualizes film sequels as brand extensions of a hedonic product and tests (1) how their box office revenues compare to that of their parent films, and (2) if the time interval between the sequel and the parent, and the number of intervening sequels, affect the revenues earned by the sequels at the box office. Using a random sample of 167 films released between 1991 and 1993, we find that sequels do not match the box office revenues of the parent films. However, they do better than their contemporaneous non-sequels, more so when they are released sooner (rather than later) after their parents, and when more (rather than fewer) intervening sequels come before them. Like other extensions of hedonic products, sequels exhibit satiation to the extent that their weekly box office collections fall faster over time relative to contemporaneous non-sequels. Managerial implications of the results are discussed.

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1. Introduction

The study of motion picture sequels is important, both from a managerial and scholarship perspective. Studio managers view sequels as "a concept with multiple uses that amortize their risks in a product line business" (Wall Street Journal, June 6, 1989; Page 1). For example, studios strategically release sequels during the summer season, the 18-week period when studios typically obtain 40% of their total annual box office. In the summer 2006 season, for example, the studios released four mega sequels: Mission Impossible 3, Dead Man’s Chest (sequel to Pirates of the Caribbean), The Last Stand (from the X-Men franchise) and Superman Returns. In the summer 2007 season, studios have scheduled the release of no less than a dozens sequels, including the third editions of Pirates of the Caribbean, Spider-Man and Shrek, as well as Ocean’s Thirteen, The Bourne Ultimatum, Rush Hour 3, the fourth edition of Die Hard and the fifth edition of Harry Potter. From an academic perspective, some scholars liken sequels to quality signals (Basuroy et al., 2006) and show that sequels signal quality and, acting jointly with advertising, affect box office performance. Other scholars liken sequels to brand extensions of hedonic products (Sood and Dreze, 2006) and show that sequels, unlike traditional brand extensions, may be subject to satiation such that seemingly dissimilar extensions are preferred to seemingly similar extensions.

In this paper, we adopt the perspective that a film sequel is an extension of a hedonic product, and use studio/box office data to address four fundamental issues. First, we examine to what extent sequels (the extensions) are able to match or exceed the box office revenues of the parent film (i.e., the film that starts the franchise). This is an important question for studio managers who count on sequels as a risk reducing strategy in a highly competitive environment (Ravid and Basuroy, 2004). Second, as studios decide to release a sequel, we examine if the time interval between sequels matter, when, for example, the...
sequel is released within 6 months (such as Matrix Reloaded followed by Matrix Revolution) or 6 years (such as Mission Impossible 2 followed by Mission Impossible 3). Would studios rather have the original film fresh in the consumers’ minds as they release the sequel, or rather wait so that consumers not view the sequel as too much of the same thing?

Third, as the parent film or the core brand generates multiple sequels over time, we test if the number of intervening sequels (extensions) affects box office revenues of the target sequel. For example, how does the box office react to the fifth sequel to Star Wars (The Revenge of the Sith)? Does the history hurt the new sequel (e.g., it’s just another Star Wars film), or help it, by serving as a credible signal of quality (e.g., the formula must work, otherwise the studio would not risk repeating this five times).

Fourth, recent research (Sood and Dreze, 2006) suggests that sequels may be prone satiation, in particular if they repeat the same story or genres as the parent film. While our current study does not directly test the satiation model, it nevertheless tests an implication: if sequels invite satiation, then we should observe a quicker decline of the sequel’s box office weekly revenues relative to contemporaneous non-sequels.

The remainder of the paper is organized as follows. In the next section, we develop several testable hypotheses. Then, we describe the data and present the results of our empirical analyses. Finally, we close with a discussion of the theoretical and managerial implications of our findings.

2. Theory

2.1. Strength of the parent brand

Studios make sequels to leverage the success of an initial film into corresponding brand extensions, when, for example, titles such as Star Wars and Lethal Weapon combine plots, actors, and directors into a success formula (e.g., Keller, 1998). Research has shown that a known family brand is often the most important factor for predicting the trial of a new product (Claycamp and Liddy, 1969), because the known brand name is an important risk reducer for consumers (Milewicz and Herbig, 1994). Accordingly, some films can be thought of as “strong brands” promising successful sequels because the consumers “can expect certain things” from the title (Keller, 1998, Page 19).

A fundamental question that we address in this paper is how these extensions or sequels, stemming presumably from strong brands, perform relative to their parents. Economic theory, for example, argues that sequels are destined to fall short of the performance of their parents. Lazear (2004) models a film to have a theme constant component, \( A \), and a transitory (time varying) component, \( \varepsilon \) (e.g., quality of acting, direction, specific story, etc.). He suggests that a film, to be thought worthy of a sequel, must perform extraordinarily well, i.e., over a threshold level, \( A^* \), i.e., \( A + \varepsilon_i > A^* \). However, using a regression to the mean argument, he shows that \( [A + E(\varepsilon_i) \text{ sequel is made}] > [A + E(\varepsilon_i) \text{ sequel is made}], \) i.e., the transitory component averages out over time (Lazear, 2004, Page 146). One implication of his model is that studios cognizant of this effect adjust their thresholds for \( A^* \) such that box office earnings of the parent film are always greater than the box office earnings of the sequel. Accordingly, our first hypothesis is

\[ \text{H1.} \text{ A sequel’s box office revenues will be negatively related to the box office revenues of the parent of the sequel.} \]

2.2. Sequel timing

Should a studio decide to proceed with a sequel, a critical decision for studio managers is timing, i.e., how quickly should the sequel follow the parent. The actual practice seems to be mixed, with some franchises keeping constant time intervals between the sequels (e.g. the X-Men franchise), others delaying the release of sequels (e.g., the Mission Impossible franchise), and others accelerating the release of the sequels (e.g., the Matrix franchise). Of course, studios may not have full control of the timing, when, for example, they have to wait for dates from popular stars (e.g., the release date of Mission Impossible 3 was delayed when Tom Cruise signed on to star and complete Collateral). However, such considerations aside, it makes sense that studios would like to make as salient as possible the favorable associations between the parent film and the sequel. For example, when releasing Mission Impossible 2, the studio might like to associate the sequel with the breath-taking action sequences of the parent film. The accessibility of these associations depends upon their strength in memory (Wyer and Srull, 1986) as well as the retrieval cues provided by the studios in the marketing of the sequel (Lynch and Srull, 1982). Given that memory decays and the strength of the association fades over time, our second hypothesis is

\[ \text{H2.} \text{ A sequel’s box office revenues will be negatively related to the time interval between the release of the sequel and the release of the parent film.} \]

2.3. Franchise length

Over time, a film may spawn multiple sequels and become a franchise. For example, the James Bond franchise, starting with Dr. No in 1963 produced twenty sequels until 2002 (Die Another Day). An interesting question is whether the number of intervening sequels affects the current sequel’s box office performance. Research suggests that the answer might depend upon the quality of the intervening sequels (see for example, Keller and Aaker, 1992). If consumers perceive that the intervening sequels are more or less of the same quality as the parent film, then the number of intervening sequels should not affect their evaluation of the target sequel. However, if consumers perceive that the intervening sequels are of superior (or inferior) quality relative to the parent film, the number of intervening sequels should positively (or negatively) affect the evaluation of the target sequel.

The above line of reasoning suggests that consumers are aware of, and remember, the quality of the intervening sequels, i.e., they might have read the critical reviews, or seen those films. However, what if consumers do not know the quality of the intervening sequels, but the title makes them aware of their
existence (e.g., Halloween 7 suggests that there have been six prior Halloween films)? In this case, the number of intervening sequels might be used as a credible quality signal e.g., a rational studio would not attempt so many remakes unless they have received positive response from the market (Burnkrant and Cousineau, 1975; Cohen and Golden, 1972). Accordingly, our third hypothesis is

H3. A sequel’s box office revenues will be positively related to the number of intervening sequels released prior to the target sequel.

2.4. Sequel satiation

Recent research by Sood and Dreze (2006) suggests that sequels may be prone to satiation effects, if, for example, consumers think that the sequel is a repeat of the same storyline or plot of the parent film. The underlying argument is that films are hedonic in nature (Hirschman and Holbrook, 1982) where consumers typically prefer a variety of experiences. One way to inject variety is by introducing new plots, for example, by inserting a romance component to an otherwise action adventure genre. While our investigation does not directly address the effects of enriching genres, we test for an implication of the satiation model. If sequels are subject to satiation and consumers quickly tire of them, we should observe that sequels do worse than their contemporaneous non-sequels, and their weekly box office collections drop faster relative to their contemporaneous non-sequels. Accordingly, our fourth hypothesis is

H4 (a). A sequel’s box office revenues will be negatively related to the box office revenues of its contemporaneous non-sequels.

H4 (b). A sequel’s weekly box office revenues will drop faster than the weekly box office revenues of its contemporaneous non-sequels.

3. Empirical analysis

3.1. Variables

The dependent variable in our study is a film’s weekly box office revenues (e.g., Eliashberg and Shugan, 1997). The independent variables, or predictors, include explanatory variables that relate to all films, explanatory variables that relate only to the sequels, and control variables or covariates that relate to all films. For all films, we use a dummy variable SEQUEL (which takes a value of 1 if the film is a sequel, and 0 if it is not), a WEEK variable (denoted as 1, 2, 3, etc, capturing the week after release), and a SEQUEL * WEEK interaction to capture how rapidly weekly box office revenues drop for sequels and non-sequels.

For sequels, we use three variables: (1) REVPARENT or the revenue of the parent film of the franchise; (2) GAPSEQ or the time gap between the parent film and the target sequel; (3) NUMSEQ or the number of intervening sequels released prior to the release of the target sequel.

There are six control variables in our study. They are (1) the MPAA (Motion Picture Association of America) ratings for the films; (2) the nature and number of critical reviews received by the film; (3) star power, denoted by any cast member having won an Oscar before the release of the target film; (4) the number of screens running the film on any particular week; (5) the cost of making the film; (6) the time of release of the film to adjust for seasonality effect.

In the next section, we describe how we operationalize these variables.

3.2. Data

We select a random sample of films from a sampling universe of all the films listed in the “Crix Pics” section of the Variety magazine between late 1991 and early 1993. The final sample contains 167 films, and comes from Ravid (1999). Table 1 shows the relevant descriptive statistics.

3.2.1. Variables for sequels and time

To distinguish between sequels and non-sequels, we create a dummy variable, SEQUEL, which takes a value of 1 for sequels and 0 for non-sequels. Sequels represent 11 films or 6.58% of our sample set of 167 films. The proportion of sequels in our sample is consistent with past research (see Table 3 of Dominick, 1987, p. 146), as well as with the actual proportion of sequels in recent years. For instance, a check of the films released in 2000 by MPAA indicates that about 6% of the films were sequels.

Table 1

<table>
<thead>
<tr>
<th>Variables</th>
<th>Sample value/mean (std. deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of films</td>
<td>167</td>
</tr>
<tr>
<td>Average number of weeks at the box office</td>
<td>10.4</td>
</tr>
<tr>
<td>Total number of observations</td>
<td>1732</td>
</tr>
<tr>
<td>Percentage of films rated G: (Dummy Variable, G)</td>
<td>3.4%</td>
</tr>
<tr>
<td>Percentage of films rated PG: (Dummy Variable, PG)</td>
<td>14.3%</td>
</tr>
<tr>
<td>Percentage of films rated PG13: (Dummy Variable, PG13)</td>
<td>25.1%</td>
</tr>
<tr>
<td>Percentage of films that are sequels: (Dummy Variable, SEQUEL)</td>
<td>6.5%</td>
</tr>
<tr>
<td>Box office revenue of parent film, in CPI adjusted $ million (REVPARENT)</td>
<td>6.08 (34.17)</td>
</tr>
<tr>
<td>Number of sequels in the franchise (NUMSEQUEL)</td>
<td>0.11 (0.51)</td>
</tr>
<tr>
<td>Time interval between parent and sequel, in years (GAPSEQUEL)</td>
<td>0.37 (1.75)</td>
</tr>
<tr>
<td>Percentage of films with Oscar winning directors/actors (AWARD)</td>
<td>14.8%</td>
</tr>
<tr>
<td>Total number of reviews (TOTREVIEW)</td>
<td>34.22 (17.45)</td>
</tr>
<tr>
<td>Percentage of “pro” reviews (PRORATIO)</td>
<td>43% (0.24)</td>
</tr>
<tr>
<td>Percentage of “con” reviews</td>
<td>31% (0.22)</td>
</tr>
<tr>
<td>Percentage of “mixed” reviews</td>
<td>26% (0.11)</td>
</tr>
<tr>
<td>Number of screens on the opening week</td>
<td>749 (841)</td>
</tr>
<tr>
<td>Production budget, in $ million (BUDGET)</td>
<td>15.68 (13.90)</td>
</tr>
<tr>
<td>Seasonality index, (SEASON)</td>
<td>0.63 (0.16)</td>
</tr>
<tr>
<td>Domestic box office revenue, in $ million</td>
<td>22.09 (32.80)</td>
</tr>
</tbody>
</table>
Since we observe the box office revenues of each film across several weeks, we create a variable, WEEK, denoted by numbers such as 1, 2, 3, etc., capturing the week after release of the film. The two variables, SEQUEL and WEEKS are relevant to the tests of H4 (a) and H4 (b).

For sequel specific variables (to test H1, H2, and H3), we create three variables. First, the variable, REV_PARENT, measures the strength of the original (parent) film in terms of its CPI adjusted gross revenue, in million dollars. The CPI adjustment is necessary to take into account the long gaps that we often encountered between the parent film and the sequel. Second, the variable, GAP_SEQ, measures the time elapsed (in years) between the release of the parent film and the target sequel. Third, the variable, NUM_SEQ, is a count of the number of intervening sequels produced between the target sequel and the parent. Note that these three variables are sequel specific, i.e., they take a value of 0 for non-sequels.

### 3.2.2. Control variables

As indicated in the last section, we also create several control variables from our dataset to serve as covariates in our study.

First, we classify all films into five mutually exclusive groups: G, PG, PG13, R and NR (“Not Rated”) based upon the MPAA (Motion Picture Association of America) ratings, given that ratings affect box office revenues (De Vany and Walls, 1999; Eliashberg and Shugan, 1997). Given that the distribution of box office revenues in our sample is positively skewed (e.g., *Batman Returns* with $163 million at the box office; *Lethal Weapon 3* with $145 million at the box office, representing two of our higher-end films), we use the log of the weekly box office domestic revenues, WEEK_REV, in million $, as our dependent variable. The log transformation enables us to pull outlying data from a positively skewed distribution closer to the bulk of the data in a quest to have the variable be normally distributed.

### 3.2.3. Dependent variable

For each film, we collect data on domestic box office revenues for each week for up to the fifteenth week (if it ran that long) from various issues of the *Variety* magazine. Our fifteen-week time period for analysis is significantly longer than similar recent studies (e.g., eight weeks of data used by Basuroy et al., 2003; Eliashberg and Shugan, 1997). Given that the distribution of box office revenues in our sample is positively skewed (e.g., *Batman Returns* with $163 million at the box office; *Lethal Weapon 3* with $145 million at the box office, representing two of our higher-end films), we use the log of the weekly box office domestic revenues, WEEK_REV, in million $, as our dependent variable. The log transformation enables us to pull outlying data from a positively skewed distribution closer to the bulk of the data in a quest to have the variable be normally distributed.

### 3.3. Analysis and results

#### 3.3.1. Panel regression

Since our observations for each film are longitudinal (spread across weeks), we use the Generalized Estimating Equations (GEE) method to test our hypotheses. We briefly describe the procedure below and point readers to other references for a more extensive treatment (Diggle et al., 1995; Haubl and Trifts, 2000; Liang and Zeger, 1986).

In the GEE framework, we assume the marginal regression model

\[
g(E[Y_{ij}]) = X' \beta
\]

where \(Y_{ij}\) is the box office revenue of film ‘i’ at week ‘j’, \(X_{ij}\) is a \(p \times 1\) vector of our study variables described in the preceding sections, \(\beta\) is a \(p \times 1\) vector of the regression parameters of interest and \(g(\cdot)\) is the link function. The marginal model gives an average response for observations sharing the same \(X\)’s as a function of the \(X\)’s. The GEE procedure assumes that observations on different films are independent but it allows for associations between outcomes observed on the same film. The link function, \(g(\cdot)\), which may be any monotonic differentiable function, allows nonlinear relationships between predictor and outcome variables. For example, for normally distributed measured data, the link function might be \(g(a) = a\) (the identity link), for count data, the link function might be \(g(a) = \log(a)\) (the log link).

In addition to the marginal response model, the GEE framework models a “working” covariance matrix structure of the correlated observations on a given film \(Y_i\) as

\[
V_i(x) = \phi A_i^{-1/2} R(x) A_i^{-1/2}
\]

where \(\phi\) is a scale parameter, \(A_i\) is a diagonal matrix of variance function \(V(E(Y_i))\), and \(R(x)\) is the working correlation matrix.
of \(Y_i\) indexed by a vector of parameters \(\alpha\). For example, if we assume normally distributed responses of weekly revenues, \(A_i=I_i\) and \(V(\alpha)=\phi R(\alpha)\).

The GEE estimate of \(\beta\) is the solution of

\[
\sum_{i=1}^{N} D_i'[V(\hat{\alpha})]^{-1}(Y_i - E(Y_i)) = 0
\]

where \(\hat{\alpha}\) is a consistent estimate of \(\alpha\) and \(D_i = \partial(E(Y_i))/\partial\beta\).

For the normal case, \(E(Y_i)=X_i\beta, D_i=X_i, V(\hat{\alpha})=R(\hat{\alpha})\) and the GEE estimate of \(\beta\) is

\[
\hat{\beta} = \left( \sum_{i=1}^{N} X'_i[R(\hat{\alpha})]^{-1} X_i \right)^{-1} \left( \sum_{i=1}^{N} X'_i[R(\hat{\alpha})]^{-1} Y_i \right)
\]

Briefly, GEE works by first carrying out a naïve regression analysis, assuming that the weekly box office revenues are independent, calculating residuals from the naïve model, and estimating a working correlation matrix from these residuals, and refitting the regression coefficients correcting for the correlation (the latter being treated as a covariate) using an iterative process.

### 3.3.2. Model assumptions

Our data set contains 167 films (each film forms the group or cluster) with observations ranging from 1 to 15 weeks of box office revenues for each film (an average of 10.4 weeks) for a total of 1732 observations. We use an identity link function (typically used when assuming that the dependent variable is normally distributed) and specify an “exchangeable” correlation structure for the weekly box office revenues within each film. The exchangeable structure assumes a constant correlation of box office revenues between any two weeks (unlike, for example, an autoregressive structure which assumes decreasing correlations for later periods).

Although the GEE technique under our assumptions (exchangeable working correlation matrix, measured data, identity link function) is equivalent to a random effects model with a random intercept for each film (see Horton and Lipsitz, 1999), there are at least two important differences between random effects modeling and GEE (Rabe-Hesketh and Everitt, 2006). First, whereas in random effects models, the coefficients represent conditional or subject-specific effects given the values of the random effects, the GEE regression coefficients represent marginal or population averaged effects. Second and more importantly, GEE is often preferred in terms of modeling technology because, in contrast to random effects approach, the parameter estimates are consistent even if the “working” covariance matrix of \(Y_i\) is not correctly specified (Rabe-Hesketh and Everitt, 2006) as long as the marginal regression model is correct.

### 3.3.3. Results

Table 2 reports the estimation result for the regression model. We performed the estimations using Stata (release 9.0).

Among the variables specific to sequels, the predictor REVPARENT has a significant and negative coefficient (\(\hat{\beta}_{\text{REVPARENT}}=-0.003, p<0.01\)), supporting H1 (a sequel’s box office revenues is negatively related to the box office revenues of the parent of the sequel). The predictor GAPSEQUEL has a significant and negative coefficient (\(\hat{\beta}_{\text{GAPSEQ}}=-0.10, p<0.00\), supporting H2 (a sequel’s box office revenues is negatively related to the time interval between the release of the sequel and the release of the parent film). The predictor NUMSEQUEL has a significant and positive coefficient (\(\hat{\beta}_{\text{NUMSEQ}}=+0.45, p<0.00\), supporting H3 (a sequel’s box office revenues is positively related to the number of intervening sequels released prior to the target sequel).

Comparing sequels to their contemporaneous non-sequels, the predictor SEQUEL has a significant and positive coefficient (\(\hat{\beta}_{\text{SEQUEL}}=+0.84, p<0.01\), suggesting that sequels attract more box office revenues than their contemporaneous non-sequels. The WEEK*SEQUEL interaction, however, has a significant and negative coefficient (\(\hat{\beta}_{\text{WEEK*SEQUEL}}=-0.04, p<0.01\), suggesting that the weekly revenues drop faster for sequels relative to their contemporaneous non-sequels. Thus, our fourth hypothesis, receives mixed support. On one hand, inconsistent with the saturation model, week by week, sequels appear to outperform non-sequels at the box office. On the other hand, and consistent with the saturation model, sequels show a faster drop in weekly revenues relative to contemporaneous non-sequels. One can surmise that sequels attract a dispropor- tionate number of curious consumers in the opening week relative to non-sequels, but are not able to sustain this initial draw.

Of the control variables, we find that all the MPAA ratings (coded as dummy variables with respect to non-rated films) are significant predictors of box office revenues. The number of screens (SCREENS) plays a strong positive role on the weekly box office revenue. The quadratic term (SCREENS\(^2\)) is negative and significant, and shows that saturation sets in as a film is widely released. The WEEK variable is negative and

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (semi-robust std. error)</th>
<th>z-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>REVPARENT</td>
<td>-0.003 (0.001)</td>
<td>-2.84*</td>
</tr>
<tr>
<td>GAPSEQUEL</td>
<td>-0.097 (0.026)</td>
<td>-3.77**</td>
</tr>
<tr>
<td>NUMSEQUEL</td>
<td>+0.446 (0.113)</td>
<td>3.93**</td>
</tr>
<tr>
<td>SEQUEL</td>
<td>-0.845 (0.254)</td>
<td>3.32*</td>
</tr>
<tr>
<td>SEQUEL*WEEK</td>
<td>-0.045 (0.001)</td>
<td>-2.67*</td>
</tr>
<tr>
<td>G</td>
<td>+1.163 (0.331)</td>
<td>3.51**</td>
</tr>
<tr>
<td>PG</td>
<td>+1.055 (0.326)</td>
<td>3.23**</td>
</tr>
<tr>
<td>PG13</td>
<td>+0.950 (0.297)</td>
<td>3.19**</td>
</tr>
<tr>
<td>R</td>
<td>+0.903 (0.281)</td>
<td>3.22**</td>
</tr>
<tr>
<td>AWARD</td>
<td>+0.088 (0.135)</td>
<td>0.65</td>
</tr>
<tr>
<td>BUDGET</td>
<td>+0.011 (0.004)</td>
<td>2.51*</td>
</tr>
<tr>
<td>PRORATIO</td>
<td>+0.056 (0.266)</td>
<td>0.21</td>
</tr>
<tr>
<td>TOTREVIEWS</td>
<td>+0.020 (0.004)</td>
<td>4.67**</td>
</tr>
<tr>
<td>SEASON</td>
<td>+0.515 (0.335)</td>
<td>1.54</td>
</tr>
<tr>
<td>SCREEN</td>
<td>+0.003 (0.000)</td>
<td>15.45**</td>
</tr>
<tr>
<td>SCREEN(^2)</td>
<td>-0.000 (0.000)</td>
<td>-7.19**</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>-4.17 (0.325)</td>
<td>-12.84**</td>
</tr>
</tbody>
</table>

**Significant at p<0.001.

*Significant at p<0.01.
significant and suggests that weekly revenues drop over time. The BUDGET variable is positive and significant, and so is the total number of reviews, TOTREVS indicating that they positively affect weekly box office revenues.

4. Discussion

Film sequels have been looked upon as brand extensions in the recent marketing literature (Sood and Dreze, 2006). In this research, we consider several fundamental brand extension issues, as applied to sequels, and test them using a random sample of films released between 1991 and 1993 containing sequels as well as non-sequels.

Our first result shows that sequels perform worse than the parent film in terms of box office revenues and in that respect, appears to mimic the regression to the mean argument (Lazear, 2004). Our second result shows that sequels that quickly follow their parents do better than sequels with longer time gaps. Indeed, some franchises seem to follow this practice: New Line Studios released the Lord of the Rings trilogy in almost clocklike precision: Fellowship of the Ring in December 2001, The Two Towers in December 2002, and The Return of the King in December 2003. Our third result demonstrates that, across sequels, the franchise length (number of intervening extensions of a brand) has a positive impact on the current extension, presumably because larger numbers create more buzz and generate greater anticipation for the current extension. Our fourth, and final, result is consistent with a satiation model showing that weekly box office revenues drop faster for sequels relative to their contemporaneous non-sequel competitors.

There are a number of key managerial implications of our findings. First, studios should be careful while embarking on the production of sequels because they may not perform as well as the parent film. As production costs escalate for all films and especially for sequels, studios need to be careful in managing the production budget of the sequels. Second, although there has been some research on the timing of release of films (Krider and Weinberg, 1998), research has not explored the timing of release of sequels. Our results show that a shorter time gap for releasing sequel is better than a longer time gap given that the buzz and anticipation perhaps dissipate in consumers’ memory with longer wait. Third, in recent times we have witnessed a tendency to turn some films into franchises— Matrix, the Lord of the Rings, etc.—and our results show that a larger number of intervening films help the current extension/sequel and build the overall franchise. Once again, the buzz and anticipation created by the prior films help the current extension succeed.

We conclude by addressing a limitation of our study. The number of sequels in our first data set is relatively small, 11 to be precise, and 6.5% of the total films in our sample. Although recent empirical findings concerning sequels have drawn on similar small samples of sequels (see Basuroy et al., 2006), future work should examine these results with a much larger data set spanning many more years (say 10 years). We do not expect the percentage of sequels to change, but there will be more of them in such a dataset.

References


