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Turning the silver screen to gold: An analysis of opening weekend box office success

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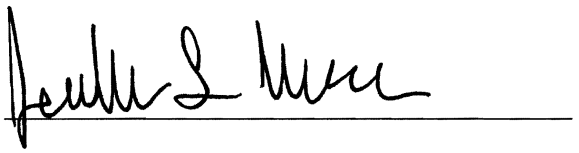

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Turning the Silver Screen to Gold:

An Analysis of Opening Weekend Box Office Success

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BY

Jennifer Muser

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Turning the Silver Screen to Gold

An Analysis of Opening Weekend Box Office Success

Jennifer Muser

Contents

Abstract

Success at the box office can be difficult to predict. While one combination of stars, budget, or praise produces a blockbuster, the slightest tweaking in a sequel can produce a bomb. The objective of this research is to model the opening weekend box office revenue per screen based on a set of variables parsed from the Internet Movie Database and using a critical review index variable retrieved from RottenTomatoes.com. First, the author estimates opening weekend revenue per screen from a sample of 1116 movies as a function of the movies' characteristics, such as genre, MPAA rating, critical rating, and budget. Then the author takes a random sample of the data set and models opening weekend revenue per screen with several additional variables. Results from the full sample indicate production budget, Rotten Tomatoes Critic Rating, and a prestigious director significantly increase opening weekend box office revenue per screen. Results from the random sample indicate that films that were sequels or prequels or that incorporated a significant advance in special effects also had higher opening weekend revenues per screen on average. Surprisingly results from the random sample also showed that films which included adult content or which were distributed by one of the big six distributors did not have significantly different opening weekend revenue per screen than those that did not.

Introduction

While many industries experienced difficult times during the recent recession, the domestic box office remained relatively stable. Tickets sold in the U.S. and Canada decreased from 1.4 billion in 2007 to 1.34 billion in 2008; however, in 2009, ticket sales rebounded to 1.42 billion, according to the Motion Picture Association of America (MPAA, 2010), and from 2007 to 2008 and 2008 to 2009 real gross revenue increased (see Figure 1 on p. 7). Additionally, although distributors released approximately 630 movies in 2008, roughly 40 percent of the $9.8 billion total box office revenue came from the 20 top grossing movies of 2008 (MPAA, 2009). In 2009, distributors released approximately 550 movies and the top 20 grossing movies again accounted for roughly 40 percent of the total U.S. and Canadian box office (MPAA, 2010). With the top grossing movies pulling in much of the industry total, studios, producers, and directors should have a stake in research that attempts to glean information about why consumers choose to see some movies over others. Any additional information could perhaps help to create movies that will more than cover their production costs and could possibly even help create a movie that will make a future years' top twenty.

For example, the 1997 movie *Titanic* alone brought in two percent of the total domestic box office revenues during the 1997 calendar year (the-numbers.com). The impressive fact is that Paramount Pictures and 20th Century Fox released the film on December 19 that year. In just 17 days (due to the way the-numbers.com calculates a box office calendar year), the film grossed $157 million. The movie, with its $200 million budget, was the most expensive ever created at that time, and yet it still brought in three

times its production budget in gross revenue. Titanic was a 'blockbuster' but the studios needed it to be wildly successful just to cover its costs.

An unexpected 'sleeper' blockbuster was the 1990 movie *Home Alone* (the-numbers.com). The term 'sleeper' refers to films that have modest success in their opening weekend and build dramatically due to word-of mouth effects over their 'life' in theaters before tailing off and being replaced. *Home Alone* was created on a shoestring budget of $18 million and yet brought in a total box office gross of over $285 million, vaulting Macaulay Culkin into childhood stardom and proving that even lower budget 'indie' type movies have blockbuster potential when the audience finds something they enjoy.

As mentioned, studios produce hundreds of movies each year and yet the top 50 films (or even top 25) split most of the revenues, so clearly many movies each year are going to fail, or flop as they say in the industry. With this kind of risk riding on individual movies, it is no wonder that many scholars have researched revenues, the power of stars, and the impact of Oscars, just to name a few topics. Although research examining certain aspects of the movie industry is abundant, research which focuses on the opening weekend for movies is not abundant. Concerning the dataset considered in this work, an average movie accrues 34 percent of its gross total revenue in the opening weekend alone. This paper will continue to build on past work to construct a more complete model of opening weekend domestic revenue per screen.

Brief History and Development of the Movie Industry

Cinematic history in the United States can be broken into four main periods: silent film, studio era, the director era, and the contemporary period. From the time silent film developed in New York in the early 1900s, entrepreneurs realized the potential for film and began forming studios. Since the fickle weather in New York made for inconveniences in filming, many studios headed west where mild weather allowed for perfect filming conditions. By the 1920s, the majority of American studios produced films in the Hollywood area.

With the wide introduction of sound in the late 1920s and ever-increasing popularity of films, cinema moved into the studio era by the mid 1930s. Despite lasting roughly ten years, four films of this era make the top ten of American Film Institute's top 100 American films: Citizen Kane [#1], Casablanca [#3], Gone with the Wind [#6], and The Wizard of Oz [#10] (American Film Institute, 2007). In fact, when adjusted for inflation, Gone with the Wind is still the all time highest grossing movie at the box office. Five major studios (MGM, Paramount Pictures, RKO, Warner Bros., and Twentieth Century Fox) flourished during this period. The practice of the time was for each studio to have its own specific actors, creative teams, and even theaters; thus, it was easy for an individual to distinguish between a MGM movie and a Warner Bros. movie or any of the other big five. According to data collected from the Internet Movie Database (IMDB), by the mid 1940s film popularity was at its height with studios producing somewhere around 1000 movies per year, and 90 million Americans per week attended the movies.

In contrast, during 2007 approximately 28.3 million Americans per week (MPAA, 2007) attended movies.

The studio era of cinema ended at the end of the 1940s with the introduction of television and the decision in United States v. Paramount Pictures (1948). This case found the major studios in violation of the Sherman Antitrust Act and forced separation of the production, distribution, and exhibition of films. This ruling prohibited the practice of block booking, or selling multiple films to a theater as a unit and gave theaters the ability to view films before agreeing to show them. Many changes ensued, one of which released actors and creative staff from standing contracts with each studio, allowing actors to sign contracts on a per film basis. With this modification, budgets soared, and the increasing budgets coupled with competition from home television pushed studios to focus on producing spectacles to which television could not compare.

This transformation of the industry pushed cinema into the director era by the mid 1950s. This era is identifiable by the increased attempts at producing the modern blockbuster and increased control given to flourishing directors. Another factor that shaped this era was the disappearance of government censorship with the landmark decision made by the U.S. Supreme Court in the Joseph Burstyn, Inc. v. Wilson (1952). This decision protected film, as a form of art, under the First Amendment. Success of movies such as *The Godfather*, *Jaws*, and *Star Wars* urged studios to pour more resources into fewer films and gave movie directors of the time a great deal of power but also greater risk. The director of the film *Heaven's Gate* single handedly bankrupted the studio United Artists due to his extravagant overspending.

As studios reclaimed control over films from the directors, cinema delved into the contemporary era. For the larger studios, the contemporary era has focused on risk management through a reliance on blockbusters supplemented with independent films that have smaller budgets. On the blockbuster end, film studios work to combine big-name actors, directors, and producers with large budgets to produce movies that appeal to the masses, in the hope that they will bring in more than enough revenue to cover their costs. Besides relying on big names and big money, the parent divisions of the "big six" studios (Warner Bros. Pictures, 20th Century Fox, Paramount Pictures, Columbia Pictures, Walt Disney Pictures/Touchstone Pictures, Universal Studios) have subsidiary companies which bring together smaller budgets and lesser known actors and directors. Some of these subsidiaries aim to produce films that may appeal to the critics or receive award nominations (e.g. Fox Searchlight Pictures).

In some senses, the current system appears to be working for the industry. The number of tickets sold increased roughly four percent from 1980 to 2009, while real gross revenue is nine times higher in 2009 than it was in 1980 (Figure 1 below). The big six film studios accounted for roughly 95 percent of the total gross revenue from 1995 to 2010, even though they only accounted for roughly 30 percent of films distributed (www.the-numbers.com). Other studios, categorized as the "mini-majors" or as independents, meanwhile, accounted for 70 percent of the films distributed for this period. The conglomerate companies of the big six may release 15 to 20 films in a given year, and they count on spreading risk over these films. The mini-majors and independent studios each release far fewer films in a given year and thus have a greater

amount of risk vested in each film. The mini-majors and independent studios are always hoping to hit the jackpot with one big film.

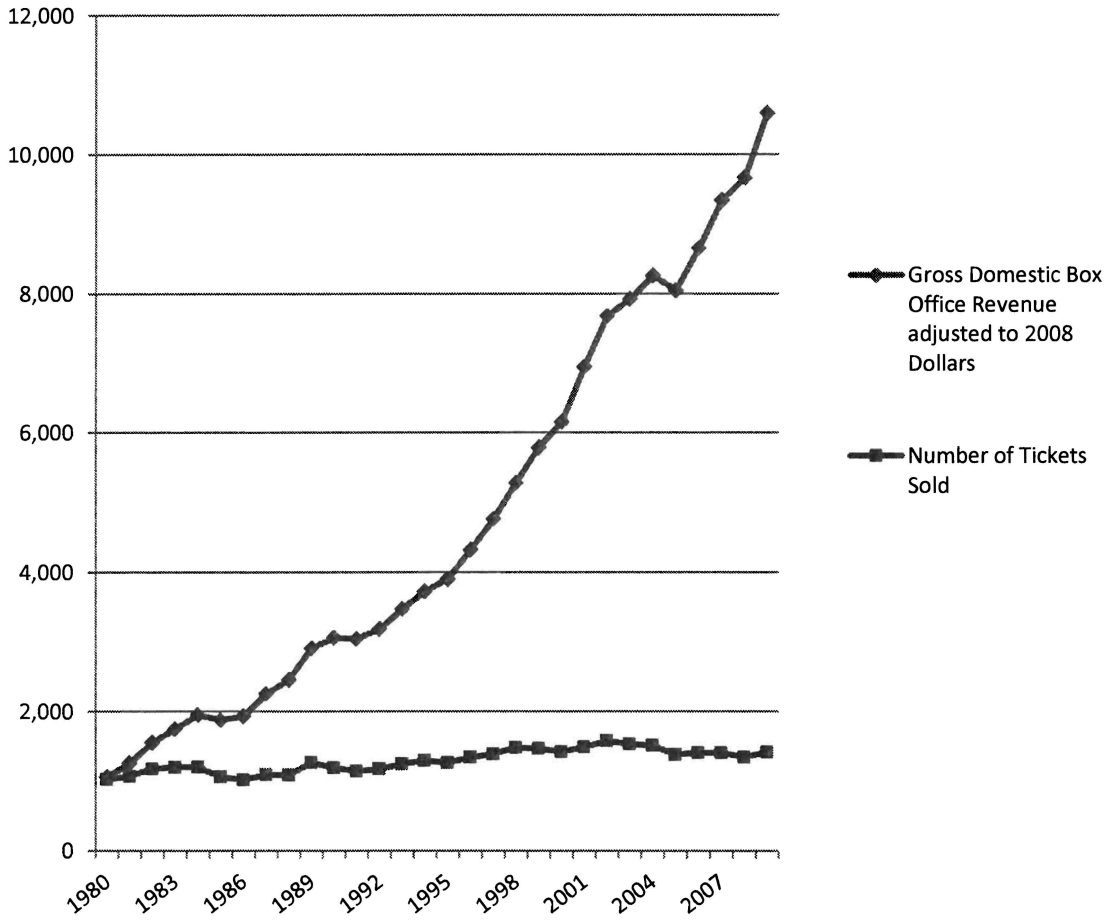

Figure 1 - Real gross revenue vs. number of tickets sold (1980-2009)

Literature Review and Consideration of Variables

In determining which factors influence the box office success of individual movies, scholars and non-scholars alike have considered a vast array of different possibilities and problems. In the past 20 years, a good deal of research on box office success emerged in the fields of economics, psychology, communications, and marketing.

The field of film studies and those intimately familiar with the movie industry also made contributions toward the study of the business side of Hollywood. Eliashberg, Elberse, and Leenders (2006) reviewed the body of motion picture industry research and sorted the research into three phases: the production phase, the distribution phase and the exhibition or retail phase. In each category, they provided research questions for future studies to answer. This work contributes to the growing pool of research by using unique data and applying an economic approach to determine the factors that affect the opening weekend success of a movie.

One may speculate that a movie's opening weekend success should depend on the production budget, the creative team (i.e. actors, directors, producers, screenwriters), advertising, critical review, characteristics of the screenplay itself (i.e. genre, if it is a sequel or prequel, MPAA rating it receives), the "quality", and the pattern of distribution of the movie. Characteristics of the weekend itself may also influence opening weekend success, as the box office has certain general high points and low points during a given year and competition among films varies from week to week. Variables that can somewhat simply be categorized or quantified include production budget, advertising budget, distribution pattern, genre, MPAA rating, whether the movie was a sequel, and whether the movie was a remake. Other variables, such as creative team, competition, quality, and critical review are less simple, and thus require additional thought.

The creative team that puts together a movie has the potential to influence its success based on public popularity alone. If the audience likes a specific director or actor, they may attend the movie regardless of its critical reviews or other expected success markers. This was the basis of the work done by De Vany and Walls (1999), as

well as Basuroy et al. (2003) and others. Examining the effect of budget and star appearances, Basuroy et al. (2003) determined that large budgets and star power seem to blunt the negative impact of bad reviews. Sochay (1994) and Prag and Casavant (1994) both found star power to positively impact box office receipts, as did Litman and Ahn (1998). Litman (1983) found that having a 'star' had no significant impact on box office receipts. Research has defined the variable "star power" in a variety of ways. Sochay (1994), Litman (1983), Litman and Kohl (1989), and Litman and Ahn (1998) defined a 'star' as an actor or actress that was one of the Top 10 box office stars as measured in a poll of theater exhibitors for the two years prior to the film's release. Ravid (1999) considers two different 'star power' variables; one variable was equal to unity if any cast member had won an Academy Award, and the other was equal to unity if any cast member had participated in a top-ten-grossing movie in the year. Ravid finds evidence that rather than acting as a signal of project quality and thus increasing the profit or return on investment for a given film, 'stars' essentially capture their economic rent in their higher pay, which is accounted for, in part, in the production budget.

De Vany and Walls (1999), De Vany (2004), and Walls (2009) all considered a movie to have a star's presence if an actor or director in the film appeared on *Premier*'s annual listing of the hundred most powerful people in Hollywood or on James Ulmer's list of A and A+ actors. De Vany and Walls (1999) admit that strategic choices made by creative teams may increase a movie's chance of success; however, when they examine revenue and movie data against theory, they ultimately conclude that a movie is made a success due only to quirks of audience preferences and that 'star power' and marketing cannot alter this fact. De Vany and Walls discover that the probability distribution of

box-office revenues, as well as that of profits, has an infinite variance. They found infrequent blockbusters to dominate the mean. Because of this, they argue that revenue forecasting has negligible precision and models of risk management that studios use lack foundation in theory. De Vany (2004) reexamines the blockbuster strategy using a probability modeling technique and find evidence of decreasing returns to budget, opening screens, and stars.

Ginsburgh and Weyers (1999) analyzed a set of movies to determine how critics and consumers have evaluated certain movies over time. They considered two types of movies: ones consumers chose to be of 'high quality' over time and movies that had received Academy Awards for being of 'high quality'. They found that: (1) Quality evaluations made by the U.S. Academy are temporary, implying that perception of what quality is changes over time; and (2) Consumers appear to be more time-consistent with their evaluations, and although consumers and experts appear to agree when movies first come out, there is less agreement some years later. Ginsburgh and Weyers (1999) explain, "...the two groups seem either to value different attributes or value differently the same attributes" (p. 278). On the notion of quality, Sedgwick (2002) explains that in most markets, quality goods carry higher prices showing the willingness and ability of certain consumers to pay more for perceived differences in utility. For movies, this is not the case; though there may be discounts for certain groups of people, theaters generally price all movies shown at a given time in a given day similarly. Some consumers may look to creative teams that have produced 'high quality' in the past, while many others rely on film critics to relay what they determine to be of 'high quality'.

In 2007, 69 percent of the movie-going population went less than once a month (MPAA, 2007). If we consider that many people learn about new movies from movie previews, and since distributors released roughly 600 movies during 2007, it is easy to deduce that most individuals received relatively little information about most movies. One could logically assume that the ability of film critics to preview movies would give them substantial market power. Several researchers have written about the influence of critics. Moviegoers may look to critics for more information about individual movies, and some may trust that critics can properly assess quality. King (2007) cites the accessibility of film reviews, the objectiveness of film critics, and the fact that film critics consider themselves advisors to their readers as factors for the considerable market power of film critics. He discusses marketing effects, word-of-mouth recommendations, and preferential differences between critics and average moviegoers as potential dampening effects.

Although the argument for the influence of critics on the box office is strong, results from research are mixed. Eliashberg and Shugan (1997) found a statistically insignificant relationship between critical reviews and box office revenues during the first four weeks that a movie showed in theaters, but they found that critical reviews do tend to correlate with total cumulative box office revenues. Reinstein and Snyder (2005) found that a positive review has an influence on opening weekend box office revenue and increases its total box office revenue. Basuroy et al. (2003) found mixed results with respect to the role of critics as influencers or predictors and found that in the first week of a film's run, the negative impact of a bad review is significantly greater than the positive impact of a good review. King (2007) also showed mixed results.

Prag and Casavant (1994), on the basis of the preliminary analysis by Smith and Smith (1986), provided one of the first thorough examinations of the determinants of film revenues (or 'rents', which are the amounts of money received by the studio from domestic and foreign box office receipts) in the motion picture industry. Data were collected from *Variety* magazine. In their large sample (n = 652), they found 'negative cost' (the cost of producing the initial negative of the final film), being a sequel, star power, winning an Academy Award, and quality (as determined by critic appraisal) to positively affect a film's financial success. They found that being categorized as a drama had a negative impact on a film's financial success. For a smaller subset (n = 195), for which 'prints and advertising' cost was available, the 'prints and advertising' variable was positive and significant; however, star power, negative cost, and winning an Academy Award were no longer significant. In consideration of these results, Prag and Casavant (1994) further modeled 'prints and advertising' and found 'negative cost', star power, winning an Academy Award, and being a comedy or action film to be positive factors on the prints and advertising model. MPAA ratings were found to be insignificant in all models.

Sochay (1994) sought the determinants of domestic financial success and measured performance by considering domestic box office receipts and the 'length of run' as an alternative measurement of success. This work, based on Litman (1983) and Litman and Kohl (1989) considered factors influencing financial success, including genre, star power, MPAA, distributor, release date, pattern of release, critical reviews, Academy Award nominations and wins, and variables to measure the amount of competition a movie is up against during a given week. With respect to MPAA ratings

and genre classifications, Sochay found little evidence of their impact on domestic box office receipts. Star power, critical reviews, Academy Award nominations or wins, and screens all had a positive impact on domestic box office reviews. Movies released during the Christmas or summer season had, on average, significantly larger domestic box office receipts, while films released during the Easter time frame had, on average, significantly smaller domestic box office receipts. The competition variables considered were concentration ratios (CR4, CR8, and CR10) which Sochay derived by adding revenues for the top 4, top 8 and top 10 movies each week as a percentage of total movie revenues for the week of interest. Sochay found all to have a significant, negative impact on box office receipts, with the CR10 variable best explaining variance in box office receipts.

Based on work done by King (2007) and Reinstein and Snyder (2005), Muser (2008) examined the total box office revenue and the opening weekend box office revenue of movies released in 2007, focusing on their relationship with critical ratings compiled through www.metacritic.com. The study developed an opening weekend box office revenue model and a total box office revenue model. Independent variables included the running life of the movie in weeks, a composite critic score, the number of screens on which the movie opened, the genre of the movie, the MPAA rating of the movie, the quarter in which the movie opened, the budget of the movie, and whether or not the movie was a sequel or remake. The models, when they included budget data, explained about 90 percent of the variation in revenues. The critic variable was strongly significant and positive in both models. However, a small sample size (122 movies) and endogeneity were both significant issues with that study.

Data and Summary Statistics

For the current study, the initial dataset consisted of 1644 movies released between 1996 and 2007. Data for each movie was collected from Internet Movie Database (imdb.com) and Rotten Tomatoes (rottentomatoes.com). From imdb, the following data were collected: opening weekend revenue (OWR), date of release, number of screens on which the movie opened (OWS), budget (BUD), genre(s), and MPAA rating (G, PG, PG13, R, NC17, and Unrated). The budget variable from imdb.com is the production budget according to the production studio.[1] The Rotten Tomatoes website (www.rottentomatoes.com) provided the Rotten Tomatoes critic rating, genre, directors, and up to four additional actors. Lists of Academy Award winners and nominees were compiled from Wikipedia.org for the following awards: Best Actor, Best Actress, Best Director, Best Supporting Actor, and Best Supporting Actress. A description of variables can be found in Table 1 below.

To determine genre, the Rotten Tomatoes genre was considered the primary genre, and most films had an initial genre in one of the following categories: Action/Adventure, Children/Family, Comedy, Drama, Horror/Suspense, Science-Fiction/Fantasy, and Thriller. For films that did not have one of those listed as the primary genre, a secondary genre was determined by consulting a combination of IMDB.com, Wikipedia.com, and Allmovie.com. Observations that did not have one of the previously mentioned seven genres listed as their secondary genre were then dropped.

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[1] Ideally, a variable for advertising budget would also be incorporated in the model. Since distributors and exhibitors share the cost of advertising and only limited public data is available for advertising costs, this work was unable to develop a variable for advertising.

Since the focus for this study was wide release movies, films that opened on fewer than 1000 screens were also dropped. Dropping films that were rated by fewer than 25 critics on RottenTomatoes.com brought the final number to 1116 films. For this subset, summary statistics on the non-dummy variables are shown in Table 2 and frequency statistics for the genre dummy variables and MPAA rating dummy variables are shown in Table 3.

Table 1 - Description of variables

Variable	Description
ORPS	Opening weekend revenue per screen
BUD	The production budget of the film in 2008 dollars
RTrate	Rotten Tomatoes critic rating for the film
Genre	Dummies for Action/Adventure, Children/Family, Comedy, Drama, Horror/Suspense, Sci-Fi/Fantasy, and Thriller
MPAA Rating	Dummies for the MPAA ratings, which include G, PG, PG13 and R
Holiday	Dummy for if the movie was released between Nov. 22nd and Jan. 4th
Summer	Dummy for if the movie was released between May 25 and Sept. 5
BDIRN	Dummy for if the film's director was nominated for an Academy Award for Best Director in the previous n years, where n = 2, 3, 4, 5, and 1000
BACT2	Dummy for if one of the film's actors or actresses was nominated for an Academy Award for Best Actor or Best Actress in the previous 2 years
BSUPACT2	Dummy for if one of the film's actors or actresses had was nominated for an Academy Award for Best Supporting Actor or Best Supporting Actress in the previous 2 years

Previous work by the author estimated opening weekend revenue and considered the number of screens on which a movie opened to be an influencing factor. Since it is very likely that many of the variables thought to impact opening weekend revenue would

also influence the number of screens a film was opened on, this work takes a new direction in attempting to estimate the opening weekend revenue per screen. Since the opening weekend revenue per screen and budget displayed high levels of skewness and kurtosis, it was determined that a log-log model would perform better than a linear model.

Table 2 - Summary statistics

Variable	Description	Full Sample			Random Sample		
		Mean	50% Percentile	Std. Dev.	Mean	50% Percentile	Std. Dev.
ORPS	Opening weekend revenue (in 2008 dollars) per screen	7,446	6,095	5,413	7,027	6,489	5,696
BUD	Budget in millions of 2008 dollars	54.8	42.7	42.4	61.8	49.7	48.9
RTrate	Rotten Tomatoes critic rating	43.6	41	25.4	45.6	43	25.1

Table 3 - Tabulation of genre and MPAA rating for full sample

	G	PG	PG13	R	Total
ActAdv	0	21	113	82	216
Child	29	49	0	0	78
Comedy	4	60	200	92	356
Drama	1	20	108	127	256
Hrrsus	0	0	31	90	121
SciFsy	0	12	40	19	71
Thrillr	0	0	6	12	18
Total	34	162	498	422	1116

Model and Hypotheses: Full Data Model

Based on work done by De Vany (2004), Litman and Ahn (1998), and Sochay (1994), all of which began by using a similar basic regression model, the following initial regression model was formulated:

$$(1)\ \log ORPS_i = \beta_1 + \beta_2 \log \text{Bud}_i + \beta_3 \log \text{RTrate}_i + \beta_4 \text{Holiday}_i + \beta_5 \text{Summer}_i + \beta_6 \text{BDIRN}_i + \beta_7 \text{BACT2}_i + \beta_8 \text{BSUPACT2}_i + \Gamma[Genre, MPAA]_i + \mu_i$$

Where i indexes movies, Holiday and Summer are indicator variables, and Γ is a vector of parameters corresponding to the coefficients on the sets of explanatory variables indicating genre and MPAA rating. Further description of the variables is provided in Table 1 above.

When estimating the model using OLS, omitted dummy variables include Drama and the MPAA rating R. Academy Award recognition was considered for the two years prior to the release of the film in question following Sochay (1994). Although Sochay also considered only the two years prior to the release of a film to determine if the director had received Academy Award recognition, this work ran the model with six variations of the "Best Director" dummy variable, in which the number of prior years considered for directors varied. Since directors have a larger amount of control over film quality than any particular actor does, it is possible that an Academy Award would act as an indicator of quality for a longer amount of time for directors. Aside from that hypothesis, the model will be used to test the following hypotheses against the null of no effect:

- H1: βRTrate > 0

As found in previous work, it is expected that a compiled critical review, as the one from RottenTomatoes.com, will significantly and positively influence opening weekend revenue per screen.

- H2: $\beta Lbud > 0$

  It is expected that budget is a significant and positive influence on opening weekend revenue per screen. A higher budget generally leads to more advertising and greater hype; therefore, more moviegoers will likely attend.

- H4: $\beta BDIRN > 0$

  Since winning or being nominated for an Academy Award for best director is a signal of quality to moviegoers, it is expected that this variable will positively influence opening weekend revenue per screen.

- **H5: $\beta_{BACT2} > 0$**

  As with the previous variable, winning or being nominated for an Academy Award for best actor or actress is expected to act as a signal to consumers, and therefore a positive influence is expected.

- **H6: $\beta_{BSUPACT2} > 0$**

  Winning or being nominated for an Academy Award for best supporting actor or actress is also expected to positively impact opening weekend revenue per screen, although the impact is expected to be smaller than the impact of the best director or best actor or actress variables.

Statistical Results: Full Data Model

Coefficient and significance level estimations for important variables can be found in Table 4. Full results for the full sample model can be found in Table 6 in the appendix. Results are reported for the full sample model using the dummy variable that is equal to unity if the director of a particular film in the sample had been nominated for an Academy Award in the five years prior to the release of the film in question. The variable was insignificant if considering the prior two years, significant at the ten percent level if considering the prior three years, significant at the five percent level if considering the prior four years, and significant at the one percent level if considering the prior five years. The variable was still significant at the ten percent level when considering if the director had ever previously been nominated for an Academy Award.

Results demonstrated that the number of prior years considered is important. Subsequently, regressions were also run in which the variables for Academy Award recognition of actors or actresses were varied. For both variables (best actor or actress Academy recognition and best supporting actor or actress Academy recognition) the prior n years were considered, where n varies from one through 15. A variable that captured whether the actor or actress had ever previously been nominated for an Academy Award for best supporting actor or actress and a variable that captured whether the actor or actress had ever previously been nominated for an Academy Award for best actor or actress were also implemented.

Results for the variations in years for the best actor or actress variable were interesting. When fewer than the prior five years were considered, the variable was

insignificant. When considering between six and ten years prior, the variable was significant at the fifteen percent level and when considering more than ten years prior, the variable was significant at the five percent level. However, significant variables always had negative coefficients. This could possibly indicate the somewhat fleeting success or popularity of actors and actresses. The variable indicating whether an actor or actress in the film had received Academy recognition for a support role proved to be insignificant for all prior years considered. From these results, it was determined that the models would include the actor or actress Academy recognition variable which considered the prior two years for actors or actresses. This is also what was used in Sochay (1994).

Table 4 - Estimates of log-log regression models

Log-Log ORPS – Full Sample				Log-Log ORPS – Random Sample		
Variable	Coef.	Std. Err.	P>t	Coef.	Std. Err.	P>t
Lbud	0.288	0.024	0.000***	0.272	0.054	0.000***
LRTrate	0.274	0.022	0.000***	0.201	0.050	0.000***
Holiday	-0.102	0.058	0.079*	-0.117	0.104	0.265
Summer	0.066	0.037	0.074*	0.134	0.075	0.077*
BDIR	----------	----------	----------	-0.064	0.100	0.522
BDIR5	0.247	0.081	0.002***	----------	----------	----------
BACT2	0.014	0.059	0.815	0.097	0.175	0.578
BSUPACT2	0.043	0.053	0.415	0.099	0.093	0.290
BigSix	----------	----------	----------	0.077	0.080	0.326
SeqPre	----------	----------	----------	0.281	0.102	0.006***
FX	----------	----------	----------	0.523	0.118	0.000***
Adult	----------	----------	----------	-0.097	0.078	0.214
Obs.	1114			225		
F-value	34.96			11.77		
R^2	0.3353			0.4580		

Examination of correlation between variables and examination of the variance inflation factor (VIF) levels of the model indicated no concerns concerning multicollinearity. The model did however reject the null hypothesis of constant variance at the five percent level of significance using the Breusch-Pagan/Cook-Weisberg test of

heteroscedasticity. To correct for heteroscedasticity, the model was run with robust standard errors, and those results are reported here.

In the full sample model, production budget and the rotten tomatoes rating were found to be significant at the 1 percent level. The director Academy Award variable was also highly significant. If the director was nominated for an Oscar in the previous five years, opening weekend revenue per screen is increased by a factor of $e^{0.25}$, or 1.28, on average. Both actor variables were found to be insignificant in the full sample model. The model thus implies that while a prestigious director can positively impact opening weekend revenue per screen, prestigious actors or actresses have no impact. This could be due to the fact that directors have greater control of overall quality of a given film. It is also possible that audience members look to other quality indicators for actors or actresses in films, or that popularity and not prestige is how actors and actresses impact film revenue.

Other variables of significance are the holiday and summer indicators. The goal of including these variables was to capture some of the seasonal variation; however, it is likely that a monthly or weekly variable may have captured fluctuations more accurately. It was expected that a film released during the holiday season or during the summer would on average have higher opening weekend revenue per screen. This expectation held for films released in the summer, but not for those released during the holiday season. Films released during the holiday season were found to have, on average, lower opening weekend revenues per screen than those that were not. The most obvious reason for the impact being opposite of what was expected is that the holiday season was poorly defined. Films released between the 22nd of November and the 4th of January were

considered to be within the holiday season. While Christmas, Thanksgiving, and the weekends surrounding them tend to be high movie attendance times, the rest of the dates captured by the holiday variable are not necessarily peak times. Future research will more properly define seasonal variation.

In the full sample model, films with an MPAA rating of PG13 were found to do significantly better than films with R ratings. This is not surprising when considering that films with a PG13 MPAA rating have a larger audience base than films with an R rating, but that they may contain more violence or action content than films with a rating of G or PG. Further, during recent cinema history, teens and college-age individuals have accounted for disproportionately large percentage of tickets sold, and many PG13 films may be aimed at this crowd.

Model and Hypothesis: Random Sample Model

From the initial dataset a random sample of 225 films were selected and additional data were collected for each. Summary statistics for non-dummy variables can be found in Table 2 above. For these films, data were collected regarding the distribution company, whether the film was a sequel or prequel, and whether the film production process involved an advancement in special effects technology. Data for these variables were collected from a combination of Wikipedia.org, Allmovie.com, and BoxOfficeMojo.com. The variable regarding special effects advancements is equal to unity if the film appeared on AMC (American Movie Classics) Filmsite.org's "Greatest Visual and Special Effects (F/X) – Milestones in Film" list (http://www.filmsite.org/visualeffects.html), or if they were on Wikipedia's "List of

computer-animated films" (http://en.wikipedia.org/wiki/List_of_computer-animated_films). The model is formulated as follows:

$$(2)\ \log ORPS_i = \beta_1 + \beta_2 \log \text{Bud}_i + \beta_3 \log \text{RTrate}_i + \beta_4 \text{Holiday}_i + \beta_5 \text{Summer}_i + \beta_6 \text{BDIR}_i + \beta_7 \text{BACT2}_i + \beta_8 \text{BSUPACT2}_i + \beta_9 \text{BigSix}_i + \beta_{10} \text{SeqPre}_i + \beta_{11} \text{FX}_i + \beta_{12} \text{Adult}_i + \Gamma[Genre]_i + \mu_i$$

Where i indexes movies and Γ is a row vector of parameters corresponding to the coefficients on the explanatory variables indicating genre. Information regarding the independent variables, if different from that above, can be found in Table 5 on the following page.

Table 5 - Description of Additional Variables for Random Sample Model

Variable	Description
BDIR	Dummy for if the film's director was ever nominated for an Academy Award for Best Director
BigSix	Dummy for if the film was distributed by one of the "Big Six" film companies
SeqPre	Dummy for if the film was a sequel or a prequel
FX	Dummy for if the film implemented a significant advance in special effects
Adult	Dummy for if the film included adult content, as indicated by receiving an MPAA rating of R
Genre	Dummies for Action/Adventure, Children/Family, Comedy, Drama, Horror/Suspense

When estimating the model using OLS, Drama was the omitted genre variable. In this model, since the number of directors who had been nominated for an Academy Award was very small, the variable for if a director had ever in his or her lifetime been nominated for an Academy Award was used. This model will be used to test the previous hypotheses, as well as the following hypotheses against the null of no effect:

- **H7: $\beta_{BDIR} > 0$**

  Since being nominated for an Academy Award for best director could be a signal of quality to moviegoers, it is expected that the impact of this variable will be positive.

- **H8: $\beta_{BigSix} > 0$**

  Each of the big six film studios is one part of a media conglomerate and due to their additional resources for advertisement and research, one would expect distribution by one of the big six to have a positive impact on opening weekend revenue per screen.

- **H9: $\beta_{SeqPre} > 0$**

  Sequels and prequels are often produced following a successful initial film. By duplicating many of the elements of the initial successful film, film producers or studios may attempt to ride the success of the initial film with a follow up. Further, the audience already has a set of expectations based on the initial film. This additional knowledge may make the sequel or prequel less likely to be a waste of resources (time, money) for some potential audience members. Therefore, the expectation is that being a sequel or prequel will positively influence opening weekend revenue per screen.

- **H10: $\beta_{FX} > 0$**

  Special effects are one of the major sources of technological advance within the film industry, and during the time frame from 1996 to 2008, advancements in CGI (computer-generated imagery) were significant. Most people who have attended

a film in a given year have done so infrequently. Advancements in special effects and the "spectacle" aspect are likely factors that do draw in crowds for certain films.

- **H11:** $\beta_{Adult} > 0$

  One prevailing notion in American culture is that sex and violence sells. This variable will test that notion. Although a MPAA rating of R restricts the potential audience size, so it is possible that a rating of R could have a negative impact on opening weekend revenue per screen.

Statistical Results: Random Sample Model

Coefficient and significance level estimations for important variables can be found in Table 4 above and full results for the random sample model can be found in Table 7 in the appendix. Similar to the full sample model, examination of correlation between variables and examination of the variance inflation factor (VIF) levels of the model indicated no concerns with regards to multicollinearity. Although the model failed to reject the hypothesis of constant variance at the ten percent level of significance using the Breusch-Pagan/Cook-Weisberg test of heteroscedasticity, the model did reject constant variance at the 15 percent level of significance and results here are reported with robust standard errors.

As in the full sample model, production budget and the rotten tomatoes rating were found to be significant at the 1 percent level. In the random sample model, none of the Academy Award variables was significant. For the dataset considered in the random

sample model the director's nominations over his or her entire career were considered instead of just the five years prior to the release of the film observation. This was due to the very small number of films that had directors who had been nominated in the five years prior to the release of the film. It is possible that while a nomination in the prior five years may affect opening weekend revenue per screen, the audience may not consider nominations occurring more than five years prior to the release of the film to be a signal of quality. The variable for holiday season was also no longer significant; however, as mentioned previously, the flaws in the definition of the variable likely account for this.

Of particular interest in the random sample model are the additional independent variables. Surprisingly, the variable indicating that the film was distributed by one of the "Big Six" distributors was insignificant. This result may indicate that the formulaic approach of the "Big Six" is no better at indicating success than any of the independent or mini-major studios. It could also be, however, that while the "Big Six" do not necessarily have higher opening weekend revenue per screen, they may have higher profit levels over all. The "Big Six" may also be more successful in the other markets not considered in this work (worldwide, pay TV, home video).

The variable indicating that the film was a sequel or prequel and the variable indicating an advance in special effects were both found to be highly significant positive impacts on opening weekend revenue per screen. This provides support for the argument that consumers head to the movie theater when they expect a spectacle. Surprisingly, the variable indicating adult content was not significant. One likely reason is that since those under 17 can only attend with someone 17 or older, the potential audience is limited

enough such that no impact is apparent. It is also possible that television programming, such as HBO's *The Sopranos* or *Sex in the City*, which has advanced in production quality since the late 1980s and early 1990s, is filling the adult content niche.

Discussion

The overall low explanatory power of both models indicates that while the models may provide a starting place, they are far from perfect. For the full sample model, only 34 percent of the variation in opening weekend revenue per screen can be explained by the independent variables. The random sample model provides slightly more explanatory power, with 46 percent of the variation in opening weekend revenue per screen accounted for by the model. This increase in the explanatory power of the random sample model as compared to the full sample model is one indicator that additional variables likely need to be taken into account; some of which have been mentioned previously: Popularity of actors or actresses and a new indicator for seasonal changes. Data about distributor, sequel or prequel, and special effects, as well as data on films released in 2008 and 2009, should also be collected on a larger scale to examine more robustly.

Several new variables should also be considered in the future. Websites, such as twitter.com, now provide an opportunity potentially to capture "buzz" and word-of-mouth effects. While the process of collecting the data could prove onerous, it is now possible to capture data that has not been easy to capture previously. The Hollywood Stock Exchange (hsx.com), where you can "Trade Movies, Stars & More," is another site that is providing a whole new set of data to analyze. It will be possible to measure the success of a film while it is still in the production phase based on news and

announcements. Analysis of the worldwide box office and of the 3D film market will also be desirable, as both have been growing markets.

More accurate modeling options should also be considered in the future. Walls (2009) uses a nonparametric kernel regression estimation method, and obtains a model that fits his data better than the standard logarithmic model. The advantage of this type of model is that it allows the impact of independent variables to vary over their domain. This technique would also remove specification error as a potential problem.

Conclusion

Although the results found by this work echo some previous work, it builds on past work by considering determinates of opening weekend revenue per screen, as opposed to determinates of gross revenue. Several new variables, including the Rotten Tomatoes critic rating and a variable to capture advances in special effects, were also defined. Though the models provide a limited amount of explanatory power, some factors were identified as having an important significant impact. Budget is hardly surprising as an impacting factor, but this work did find critics to impact opening weekend revenue per screen, contrary to the argument that audience members and critics prefer different fare. Other factors, such as advances in special effects and distribution company, were identified as variables to consider with a larger dataset. With public and academic interest aroused in the film industry, it is unlikely that research within this area will dry up any time soon.

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Appendix

Table 5 - Robust Results for Full Sample Model

Number of obs = 1114
F(16, 1097) = 34.96
Prob > F = 0.0000
R-squared = 0.3353
Root MSE = .5485

Log ORPS	Coef.	Robust Std. Err.	t	P>|t|	[95%	Conf. Interval]
lrbud	0.288471	0.023556	12.25	0	0.24225	0.334692
lrtrate	0.273873	0.022343	12.26	0	0.230034	0.317713
Holiday	-0.10211	0.058095	-1.76	0.079	-0.2161	0.011882
Summer	0.065885	0.036853	1.79	0.074	-0.00643	0.138196
BDir5	0.247345	0.080859	3.06	0.002	0.088688	0.406001
BAct2	0.013715	0.058675	0.23	0.815	-0.10141	0.128844
BSupAct2	0.04317	0.05289	0.82	0.415	-0.06061	0.146948
g	0.08363	0.117583	0.71	0.477	-0.14708	0.314342
pg	-0.02607	0.059984	-0.43	0.664	-0.14376	0.091629
pg13	0.101915	0.038834	2.62	0.009	0.025718	0.178113
actadv	0.194549	0.04835	4.02	0	0.099681	0.289417
child	0.032429	0.098816	0.33	0.743	-0.16146	0.226319
comedy	0.145333	0.048022	3.03	0.003	0.051108	0.239558
hrrsus	0.336996	0.061047	5.52	0	0.217213	0.456778
scifsy	0.305922	0.07889	3.88	0	0.151131	0.460714
thrillr	0.018556	0.132713	0.14	0.889	-0.24184	0.278955
_cons	2.470078	0.404388	6.11	0	1.676617	3.263539

Table 6 - Robust Results for Random Sample Model

Number of obs = 225
F(15, 209) = 14.98
Prob > F = 0.0000
R-squared = 0.4580
Root MSE = .50064

Log ORPS	Coef.	Robust Std. Err.	t	P>|t|	[95%	Conf. Interval]
lrbud	0.271814	0.054363	5	0	0.164644	0.378983
lrtrate	0.201355	0.050401	4	0	0.101995	0.300715
Holiday	-0.11667	0.104291	-1.12	0.265	-0.32226	0.08893
Summer	0.133551	0.075196	1.78	0.077	-0.01469	0.28179
BDir	-0.06399	0.099871	-0.64	0.522	-0.26087	0.132898
BAct2	0.097462	0.174801	0.56	0.578	-0.24714	0.44206
BSupAct2	0.098543	0.09293	1.06	0.29	-0.08466	0.281742
bigsix	0.077427	0.080245	0.96	0.336	-0.08077	0.23562
seqpre	0.280957	0.101679	2.76	0.006	0.080509	0.481406
FX	0.523364	0.1177	4.45	0	0.291332	0.755396
Adult	-0.09709	0.077821	-1.25	0.214	-0.2505	0.056327
actadv	0.194989	0.095155	2.05	0.042	0.007403	0.382575
child	-0.11263	0.145891	-0.77	0.441	-0.40024	0.174973
comedy	0.239945	0.104257	2.3	0.022	0.034414	0.445476
hrrsus	0.488369	0.120421	4.06	0	0.250973	0.725764
_cons	2.932933	0.949391	3.09	0.002	1.061324	4.804543