Abstract

This paper attempted to answer the research question, "What determines a film's success at the domestic box office?" The authors used an OLS regression model on data set of 497 films from the randomly selected years 2005, 2006, 2007, 2009, and 2011, taking the top 100 films from each year. Domestic box-office receipts served as the dependent variable, with MPAA ratings, critical reviews, source material, release date, and number of screens acting as independent variables in the final regression. Results showed that source material, critical reviews, number of screens, release date, and some genres were statistically significant and positively contributed to a film's domestic revenue.

Introduction

Each year in the United States, hundreds of films are released to domestic audiences in the hope that they will become the next "blockbuster." The modern film industry, a business of nearly 10 billion dollars per year, is a cutthroat business (Box Office Mojo). According to industry statistics, six or seven of every ten films are unprofitable, making the business risky at best (Brewer, 2006). Given this inherent risk, how do film studios decide which films to place their bets on? Are there common factors, such as critical reviews, MPAA rating, or production budget, which explain one film's monetary success relative to another? This question forms the basis of this research project. To answer it, we estimated an Ordinary Least Squares regression that attempted to explain the monetary success of the top films in five years out of the past decade. This regression expanded our original dataset, which used 100 randomly selected films from 2004. This paper proceeds in four steps: first, the current economic literature regarding the film industry is reviewed and analyzed to assess the current project's contribution; second, the theory and functional form of the model are explained, including the expected signs of each of the independent variables; third, the results of the final regression are interpreted; and fourth, conclusions are drawn from the results, and are interpreted with regard to the original regression project and this paper's expansion of the dataset.

Literature Review

A wealth of literature exists regarding the film industry. Generally, authors have chosen to focus on one specific variable's effect on a film's success, such as star power (Treme, 2010; Elberse, 2006; De Vany and Walls, 1999; Ravid, 1999) or Oscar nominations (Deuchert, Adjamah and Pauly, 2005) [1]. Additionally, economists have attempted to explain more broadly the reasons behind a film's monetary success (Brewer, 2006; Collins, Hand, and Snell, 2002), including many variables within their models. In developing the theoretical model for this project, papers considering both of these general topics were used to determine which variables were most crucial to overall domestic film box office receipts. Once initial findings were made, the dataset was expanded to test these conclusions on a larger scale.

A large section of the literature surrounding the film industry is qualitative, rather than quantitative, focusing on the theoretical underpinnings of a film's success rather than actually running a specific econometric regression on the subject. These papers and articles provided a great background of knowledge, especially regarding potential independent variables. Indeed, Cucco's (2009) article regarding the opening-weekend distribution strategy used by film studios proved particularly helpful later in the decision to use a proxy variable for a film's production budget. Cucco (2009) found that this strategy was the best way to minimize the high uncertainty

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[1] In this project, starpower refers to the presence of well-known actors and actresses in a film, particularly those who are considered "A-list" stars.

that exists prior to a film's release, and that there was a significant theoretical relationship between the number of opening screens and the amount of money the film studio had spent in producing the film. Additionally, the article suggested potential pitfalls that could arise in an econometric regression that were echoed in other papers (Brewer, 2006), specifically multicollinearity between independent variables. De Vany and Walls (1999) and Ravid (1999) were particularly concerned about this issue as well, connecting starpower to a number of other independent variables. Multicollinearity did indeed become an issue with the original dataset, resulting in the omission of several variables. In the expanded regression, some of these variables were excluded to avoid a similar scenario.

Empirically, authors have used a variety of procedures to attempt to determine the effect of various variables on film revenue. Many of these papers used advanced econometric techniques, due the unique nature of the film industry. As stated by Collins, Hand, and Snell (2002), the film industry suffers from unbounded and possibly infinite variance (352). This can be attributed both to the limitless creative nature of the art form and the fact that films are purely heterogeneous – no two films will ever be exactly the same. While Collins, Hand, and Snell (2002) used a success threshold model, other authors at times used non-parametric and two-path models of film success (Walls, 2009; Holbrook and Addis, 2008) with varying results. Most often, researchers found that starpower, production budgets, and sequels contributed positively to a film's revenue. Though the advanced nature of these calculations did limit the usefulness of the articles as they related to model specification, they remained an essential part of the overall literature due to their insight on the theory behind the variables, and therefore essential to the development of this regression.

However, a few incorporated the use of OLS. These articles, *A Blueprint for Success* by Stephanie Brewer (2006) and *What Makes a Blockbuster? Economic Analysis of Film Success in the United Kingdom* by Collins, Hand and Snell (2002), were essential to the development of this paper's theoretical model. While the analysis by Collins eventually led the team to abandon OLS, findings still promoted the inclusion of a variable based on critic reviews (2002, 352). Most helpful however, was Brewer's OLS regression of a cross-section of films from 1997-2001 (2006). The research team performed three OLS regressions in order to determine the reasons behind a particular film's success at the domestic box office. These regressions distinguished between variables available to an audience before a film's release (ex-ante) and after a film opens in theaters (ex-post, for example word-of-mouth and award nominations), in order to determine how well a film's success can be predicted prior to and after opening night (Brewer, 2006). Results from the ex-ante model found that prior to a film's release income was a positive and statistically significant indicator of a film's success (Brewer, 2006). In contrast, the results of the ex-post model showed that peak screens, award nominations, star power, and word-of-mouth were significant positive determinants of success. Both regressions found statistically significant and positive results for production budget, critical reviews, and summer/holiday release dates.

Generally, the results found support the findings of much of the literature on the subject, and provide a great basis for this paper's new model specification. In particular, the tests performed to detect major weaknesses in the model specification (e.g. heteroskedasticity) were helpful, which gave an indication of problems this project could encounter. Though an ex-ante/ex-post structure was unnecessary when this project's goal is simply to predict total revenue, it remains the single most important and relevant article to the project.

After reviewing the literature on the subject, it became clear that this project contributes to the literature by using a new and recent data set that better reflects current film preferences from within the last several years. Even the most recent papers on film revenue use data from the late 1990's, with a few venturing into the early 2000's (Brewer, 2006; Collins, Hand, and Snell, 2002; Holbrook and Addis, 2008). Special effects and computer technology have come a long way in the last ten years, and may have contributed to a change in consumer tastes and preferences for certain types of films. By using a data set which examines the top grossing films from five given years, this project will be able to gauge if the variables that traditionally predict box-office success have changed over time.

Data

Our study analyzed a dataset of 497 films released in the United States in the years 2005, 2006, 2007, 2009, and 2011. In order to determine the variables which determine the box office success of the most popular films (i.e. the most successful films in a given year), the researchers chose to randomize the years of the dataset rather than the films within each year. Five years from the last ten (2001-2011) were randomly selected, and from those five randomly selected years the top 100 films from each respective year were taken and incorporated into one large unstructured dataset. This method proved an effective way to answer the research question as it focused on the most profitable films and attempted to explain their success, rather than finding similarities between very small and very large random films, something which would occur if the films from each given year were randomly selected. Data for variables was obtained from websites Box Office Mojo, The Internet Movie Database, and Rotten Tomatoes.

Variables and hypotheses

Our dependent variable, real domestic box office receipts (DOMESTIC_GROSS), is the revenue a film grossed during its theatrical release, controlled for inflation. Following Collins (2002) the variable was logged as the literature notes that there is a large disparity in film revenues, with roughly 80%-85% of total film revenue coming from the top 20% of films. (De Vany and Walls, 1999).

A film which is a sequel or belongs to an established property will have a leg up on the competition at the time of its release. For our purposes, a film was classified as a sequel if it was a true sequel to a previous film in a series, or if it was an adaptation of a work in another medium, such as a television show, novel, comic book, video game, etc. The dummy variable SEQ captured said effects, with a value of 1 if the film was a "sequel."Additionally, a previous film's success should also affect a future film's success. For this reason, we included the domestic gross of the sequel's predecessor to see how important a previous film's success was to a sequel's success with the variable PREVSEQ. Both of these variables are expected to have a positive effect on domestic gross.

One would intuitively expect that different genres likely draw different audiences. Some of the literature noted that, empirically, different genres do not necessarily perform better or worse than others. Indeed, Brewer (2009) states that "when holding a light to the box office numbers, however, evidence shows that this suggestion may not hold to be true." Despite this, it seemed a crucial distinction to include in the regression. The genres included in the study are action (ACTION), science fiction (SCIFI), comedy (COM), documentary (DOC), foreign (FOREIGN), romance (ROM), adventure (ADVENT) and horror (HORROR). All of these were input as dummy variables, with drama being the excluded genre. Action, science fiction, comedy, and adventure were expected to have positive effects, with the remaining genres expected to have negative effects.

Another variable whose significance is questioned in the literature but warrants inclusion was a measure of the star power attached to a film project. Brewer (2009) notes that regressions find star power to be insignificant, supporting the rent capture hypothesis that stars capture their market value through large salaries and do little to affect the profitability of films. As with genres, one naturally expects a greater quantity of stars to increase a film's appeal, so the variable was included. In an attempt to separate commercial from critical darlings, the People's Choice Awards were used as a starting point as opposed to a, for lack of a better term, "highbrow" award, such as the Oscars. A film received a 1 for every starring actor who had been a People's Choice nominee in a screen related role (television or film) between the years of 2001-2003. A possible consequence of using this method was the exclusion of cross-media stars e.g. musicians or athletes, a cost of not having access to an all encompassing measure of celebrity. The expected effect of PCA was positive.

Ratings obviously play an important role in determining film revenues, as certain ratings can both say something about the nature of a film and can restrict the market of the film. As the study was based on domestic releases, the Motion Picture Association of America's (MPAA) system of classification was used. A film with a PG, PG-13, R or UR rating was assigned a 1, with a G rating being the excluded category. A PG or PG-13 rating was expected to have a positive effect. Many popular, successful family films have had PG ratings, with PG-13 ratings being seen as very lucrative due to their ability to offer more mature subject matter without preventing who can get into the film. R and UR ratings were expected to have negative effects.

While some of the literature speculated that an R rating creates a sort of "forbidden fruit" effect, it still places a restriction on who can attend a film or purchase a ticket (No one under 17 admitted unless with a parent or guardian) (Collins, Hand, and Snell, 2002). A negative effect was expected for an unrated film (UR) as most films with that rating were expected to be small release films that wouldn't be able to gain large audiences.

Films with positive reviews would be expected to perform better than films which receive negative reviews. Some of the literature speculated that good reviews may signal artistic rather than entertainment value (Brewer, Kelley, and Jozefowicz, 2009), implying that films that receive lots of critical praise may in fact suffer at the box office. While this may occur, it seems much more intuitive that films of a better quality will be more successful at the box office. Critical reviews were sourced from the review aggregator site Rotten Tomatoes, which provides the amount of positive reviews as a percentage. These scores were used for the RVW variable. The relationship between good reviews and box office revenue was expected to be positive.

Traditionally, studios position high quality films or films with a large amount of hype behind them for release in the summer months or during the holiday season. The dummy variables SUM and WIN were used if films were released in the summer or winter seasons, respectively. More specifically, films received a 1 for SUM if released in May, June, or July (August is excluded as studios usually relegate weaker films to this month), and a 1 for WIN if released in November or December. Both SUM and WIN are expected to have positive effects.

Production budget was held by the literature to be a very important variable, since it can capture the costs of expensive actors or special effects (Brewer, 2009). Unfortunately, accurate and complete budget information proved to be very elusive, as movie studios are notoriously secretive about this information. The number of screens a film premiered on (SCRNS) was used as a proxy for budget, with the reasoning being that studios will want to get the most out of their larger investments and so will attempt to get said expensive films on a relatively larger amount of screens than lower cost films.

Model

Three models were constructed for this regression. The different iterations reflect an attempt to remove collinear variables as well as provide some symmetry with the authors' previous study. Before running the first regression, several variables were removed from the model because of the nature of the data sample. While SEQ was included as a dummy to determine whether a film belonged to a preexisting work, either as a sequel, adaptation, etc, PREVSEQ, the gross of the antecedent film in a series, was dropped from the model over concerns that its influence was arbitrary. Indeed, a good handful of films were true sequels, but the vast majority of the sample was adaptations or original works, thus earning a value of 0. Adaptations demonstrate well the potential irrelevancy of the variable, as popular novels brought to the screen would receive a value of 0, but often put up record breaking numbers for domestic gross. Due to the large range and theoretically ineffective nature of the variable, it was left out of the model.

While data was collected for the star power variable, PCA, it was ultimately dropped from the model due to a concern that it did not accurately reflect the celebrity attached to any given film. For example, George Clooney is arguably one of the most popular actors in film, yet using the PCA metric of measurement resulted in none of his films within the sample earning a value above 0. Additionally, the PCA nominees seemed to lag behind the films which they were likely being nominated for. Lastly, the literature seemed unsure of whether stars make hit films or hit films make stars. Given the ambiguity of the variable's influence and the inconsistencies of our qualifications, PCA was omitted from the model.

Additional variables that were excluded from the model include UR from the "ratings" set of dummies, and FOREIGN, from the genre dummies. UR was removed as there were no unrated films within the 500 film sample. Of these films, *Pan's Labyrinth* was the only foreign film. In an effort to prevent the FOREIGN variable from stripping away any of the significance from the omitted variable, DRAMA, *Pan's Labyrinth* and FOREIGN were dropped.

MODEL 1-

$$\log(\text{DOMESTIC\_GROSS}) = \beta_0 + \beta_1(\text{SEQ}_i) + \beta_2(\text{ACTION}_i) + \beta_3(\text{ADVENT}_i) + \beta_4(\text{HORROR}_i) + \beta_5(\text{COM}_i) + \beta_6(\text{ROM}_i) + \beta_7(\text{SCIFI}_i) + \beta_8(\text{DOC}_i) + \beta_9(\text{PG}_i) + \beta_{10}(\text{PG13}_i) + \beta_{11}(\text{R}_i) + \beta_{12}(\text{UR}_i) + \beta_{13}(\text{RVW}_i) + \beta_{14}(\text{SUM}_i) + \beta_{15}(\text{WIN}_i) + \beta_{16}(\text{SCRNS}_i) + \beta_{17}(\text{REC}_i) + \varepsilon_i$$

There was a concern that the GENRE variables might be collinear with the ratings variables. Certain genres attract certain ratings, something that could be found by examining the data. For example, many dramas and horror films attract R ratings, while lighter fare, i.e. some comedies and children's movies usually gets pegged with a PG rating. As the ratings variables were not statistically significant while a majority of the GENRE variables from Model 1's regression were, the former were dropped for the second model.

MODEL 2 –

$$\log(\text{DOMESTIC\_GROSS}) = \beta_0 + \beta_1(\text{SEQ}_i) + \beta_2(\text{ACTION}_i) + \beta_3(\text{ADVENT}_i) + \beta_4(\text{HORROR}_i) + \beta_5(\text{COM}_i) + \beta_6(\text{ROM}_i) + \beta_7(\text{SCIFI}_i) + \beta_8(\text{DOC}_i) + \beta_9(\text{RVW}_i) + \beta_{10}(\text{SUM}_i) + \beta_{11}(\text{WIN}_i) + \beta_{12}(\text{SCRNS}_i) + \beta_{13}(\text{REC}_i) + \varepsilon_i$$

Finally, in an attempt to create some congruency between this and the authors' previous study, a minimalist model was used. SUM and WIN were included as they seemed relevant given this data sample's large number of summer blockbusters and holiday releases.

MODEL 3 –

log(DOMESTIC_GROSS)

$= \beta_0 + \beta_1(SEQ_i) + \beta_2(PG_i) + \beta_3(PG13_i) + \beta_4(R_i) + \beta_5(SUM_i) + \beta_6(WIN_i) + \beta_7(RVW_i) +$

$\beta_8(SCRNS_i) + \varepsilon_i$

MODEL 1 RESULTS

Variable	Coefficient	t-Stat
C	16.41961	88.04319
SEQ	0.099608	1.915629
ACTION	0.160615	1.789688
ADVENT	0.104207	1.033101
HORROR	-0.082557	-1.103411
SCIFI	0.094776	0.674428
ROM	-0.074997	-0.871052
COM	0.187442	2.641092
PG	-0.068832	-0.686509
PG13	0.079608	0.780594
R	-0.128086	-1.171238
RVW	0.008339	8.362295
SUM	0.257660	4.190290
WIN	0.293985	4.902165
SCRNS	0.000326	8.462886
REC	0.046464	0.531858

R-Squared	.451262
Adjusted R-Squared	.434150
F-statistic	26.37050

MODEL 2 RESULTS

Variable	Coefficient	t-Stat
C	16.42116	107.1165
SEQ	0.098040	1.902746
ACTION	0.177205	1.862546
ADVENT	0.095410	1.042560
HORROR	-0.116643	-1.484768
SCIFI	0.133381	0.925838
ROM	-0.021767	-0.264001
COM	0.176414	2.472098
RVW	0.007797	7.622120
SUM	0.276323	4.317731
WIN	0.279438	4.544862
SCRNS	0.000329	8.405026
REC	0.055554	0.631851

R-Squared	.434445
Adjusted R-Squared	.420423
F-statistic	30.98310

MODEL 3 RESULTS

Variable	Coefficient	t-Stat
C	16.43253	90.77899
SEQ	0.084533	1.643997
PG	-0.069119	-0.693499
PG13	0.040435	0.424200
R	-0.175403	-1.744063
RVW	0.008435	8.794605
SUM	0.288487	4.717130
WIN	0.310602	5.163215
SCRNS	0.000351	9.311299
REC	0.074892	0.848848

R-Squared	.431991
Adjusted R-Squared	.421494
F-statistic	41.15342

As evidenced above, the R^2 and the adjusted R^2 values essentially decline with each subsequent model, while the F-statistics rose in value. Of the models, model 2 was chosen as being superior, due to its large number of statistically significant variables and comparative theoretical strength. It had an adjusted R^2 value of .434445 and an F-statistic of 30.98310. As hypothesized, (SEQ) had a positive effect on (DOMESTIC_GROSS), with a result that suggests a film will see a 9.8% increase in its revenue if it belongs to an established property. Of the genre variables, only (COM) was significant.

Both (RVW) and (SCRNS) were positive and statistically significant. Additionally, (RVW) had a greater estimated effect than the number of screens a film premiered on. Additionally, both (SUM) and (WIN) were statistically significant in this study. If a film was released in the holiday season, it could expect to see a 27.9% increase in revenue, while a summer release would bring an expected 27.6% increase. This further reinforces the idea that films released within these two time periods do significantly better at the box office. Lastly, the dummy variable used to identify films released within the Great Recession, (REC), was not statistically significant.

Conclusion

The results of our study suggest that previous source material, positive reviews, a large number of screens for a premiere, and whether a film was released during the summer or holiday season have positive and statistically significant effects on the domestic revenues of a film. Additionally, comedy films tend to experience positive box office success, though the effect of other genres is inconclusive.

Lastly, we conclude that the MPAA rating of a movie has little to no effect on its box office success. In every regression model, multiple ratings variables were insignificant, and the models seemed to function better without their inclusion. These findings correspond to other studies done on the subject; indeed, almost all of our significant variables were also confirmed by Brewer's regression in 2006. We therefore conclude that even though the film industry is inherently risky, certain attributes of a film can significantly increase its likelihood of domestic box office success.

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