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Factors Affecting the Financial Success of Motion Pictures: What is the Role of Star Power?

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Abstract

In the mid-1940s, American film industry was on its way up to its golden era as studios started mass-producing iconic feature films. The escalating increase in popularity of Hollywood stars was actively suggested for its direct links to box office success by academics. Using data collected in 2007, this paper carries out an empirical investigation on how different factors, including star power, affect the revenue of 'home-run' movies in Hollywood. Due to the subjective nature of star power, two different approaches were used: (1) number of nominations and wins of Academy Awards by the key players, and (2) average lifetime gross revenue of films involving the key players preceding the sample year. It is found that number of Academy awards nominations and wins was not statistically significant in generating box office revenue, whereas star power based on the second approach was statistically significant. Other significant factors were critics' reviews, screen coverage and top distributor, while number of Academy awards, MPAA-rating, seasonality, being a sequel and popular genre were not statistically significant.

JEL: C01, L83, Z11
Keywords: star power, motion picture industry, box-office earnings, academy awards

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1. Introduction

"'A guy stranded on an island' without Tom Hanks is not a movie. With another actor, (the movie 'Cast Away') would gross $40 million. With Tom Hanks it grossed $200 million. There's no way to replace that kind of star power."

- Bill Mechanic, Former Chairman of Twentieth Century Fox

Hollywood became the birth place of movie-stars ever since the American film industry won the quality race against its European counterpart, owing to the introduction of the expensive feature films in the mid-1940s. Despite the fact that contracted stars saved major film studios with their significant financial achievement during the studio era, scholars found no direct link between star power and box office success due to the subjective nature of consumer demand in the film industry. According to Box office Mojo website, the top gross earning film Home Alone enjoyed astonishing box office revenue of $285million in the U.S. despite featuring virtually no stars; while star Nicholas Cage starred in the film Fire Birds which yielded only $14.7million in box office revenue. This simple example indicates the need to investigate whether Hollywood movie stars generate top revenue grossing films in motion pictures industry.

There are also other significant factors which affect box office revenue. Several scholars (Terry et al. (2005), De Vany & Walls (1996 & 1999)) suggest that the unique existence of high uncertainty in motion picture industry results from the fundamental change in demand and tastes among vast movie viewers. For this reason, there is no definite formula for success for a movie in Hollywood.

To our knowledge, Litman (1983) was the first person to investigate the relationship between box office revenue and different variables, including critics' reviews, genre, and season of release. Ravid (1999) has looked at how the level of restricted contents such as Motion Picture Association of America (MPAA) ratings, influence the financial success of a film. The author later claimed that a film gains more box office revenue if they were 'family friendly'. Levene (1992) focuses more on qualitative variables based on a study with a group of university students. He suggests that critic' reviews rank after variables such as word-of mouth and acting ability. On the other hand, Dodds and Holbrook's (1988) study estimates that the average Oscar-nominated film remained on the chart for almost three months longer than the average non-nominated film.

The main aim of this paper is to explore whether 'movie-stars' have the power in influencing box office revenue. This information will be useful when film makers have a need to exploit star power as a unique product to boost box office. Due to the

ever-changing dynamics in consumer demand, no one knows the right formula to create a blockbuster film and there remain many questions unanswered: How should star power be defined? Would star power increase or decrease over time? Is there any specific aspect in which star power is more directly related to financial success of a film?

We carry out an econometric analysis using simple Ordinary Least Squares based on films produced in the US. Based on literature, each of the variables that are important to this paper is discussed in more detail in Section 2. In addition to star power, we investigate the effect of other variables such as screen coverage, critical review, budget, Academy awards won or nominated, the size of the distributor, genre, date of release and MPAA-rating.

Empirical results from existing literature show diverse findings of star power in terms of its impact on a film's theatrical revenue. Simonet (1980) conducted multiple regression analysis and found no significant influence of star power in generating high box office revenue. Influential paper by Ravid (1999) also concludes that stars play no role in the financial success of a film. Other scholars (Prag and Casavant (1994) Rosen (1981), Walls (2009)) find positive relationship between the two.

Defining star power holds a subjective nature that makes it difficult to quantify and measure. Two different approaches for the measurements of star power are used in the regression analysis. The first method to measure star power is based on previous literature - the number of nominees and winners of Academy Awards for all key players in each film before our sample year, where the awards considered are for Best Actor/Actress, Best Supporting Actor/Actress and Best Director. This allows us to understand whether stars' success in the past in terms of the amount of Academy Award nominations and awards won, influences financial success in their future films.

The second method to measure star power is in terms of movie stars' earning power, which is defined as the average value of box office revenue generated throughout all key players' entire acting careers before our sample year. The data for the second method is collected from the website Box Office Mojo and involved a lot of data cleaning before statistically significant functional form is found for this analysis. To our understanding, this approach has never been used before by previous scholars. It would be interesting to see whether measuring star power in terms of the star's earning power offers a better indication than the first method regarding the impact on box office revenue of a film.

The regression analysis has provided some interesting results using the two different measurements as proxies for star power. We do not find star power to be statistically significant using the first approach, which is in line with Ravid's (1999) results. Stars who have been recognised by Academy Award do not necessarily

guarantee financial success of a film. However, the second approach that measures star power in terms of average box office revenue throughout their career is found to be statistically significant. This confirms the finding that the future success of a movie star is more closely linked with their earning power. The result is not only consistent with Rosen (1981) and Walls's (2009) studies, but also supports John et al. (2003) that the success of a movie director (who is one of the key players in a film) is based on his/her performance throughout the entire career path.

In addition to star power, it is found that screen coverage, being distributed by a large distributer and critical reviews play a statistically significant role in increasing box office revenue. However, MPAA-ratings, popular genre, nomination or winning of academy awards, date of release and budget do not play a statistically significant role in affecting box office revenue.

The rest of the paper is structured as follows: Section 2 introduces the variables; explains the data collection process and the functional form used for the empirical analysis. Section 3 presents and discusses the results, while Section 4 concludes the findings and makes suggestions for future studies.

2. Data and Methodology

The analysis in this paper will focus only on movies produced in the United States which were released in 2007. In order to avoid large outliers arising from the introduction of cinematic technology such as 3D movies and availability of movies for illegal online viewing, 2007 was chosen as the sample year. We carry out an econometric analysis to investigate whether star power influences the success of movies.

2.1 Variables

The dependent variable indicates the financial success of a movie. The explanatory variables include other control variables in addition to two variables which capture star power.

Dependent variable - Revenue

The first variable to be discussed is the dependent variable, *Revenue*. De Vany and Walls (1999, 2002 and 2004) show that revenues in the movie industry follow a heavy-tailed (Pareto) distribution, as opposed to the standard normal probability distribution. The 'fractal-like' distribution is characterized by high skewness in revenue, as a result of a small fraction of films capturing most of revenue in the

industry. Litwak (1986) described it as 'home-run business (blockbusters)'. For example, the top 20% of films earn 80% of the revenue in North America.

In addition, it must be stressed that profits arguably provide more direct information about the financial success of a film, but direct measures of profits remain difficult to obtain. This is why the study relies on box office revenue as the most suitable index for financial success of a film. Due to the purpose of the study, this variable measures only domestic box office revenue excluding rental sales in America. Therefore all movie observations produced outside the origin of the U.S. are dropped from the sample. The data for box office revenue are collected from Mojo Box Office website and recorded in million dollars.

Star Power

The primary explanatory variable in our empirical analysis is star power. Measuring star power to determine the financial success of a film remains an active field of research. Quantifying star power is challenging not only due to its subjective nature, but also the lack of information on salaries, back-end-deals (Elberse (2007)) and compensation packages (Gumble et al. (1998)). Therefore it is not surprising to see a variety of findings depending on scholars' approach.

Caves (2003) states that complex goods such as motion pictures are produced from many creative inputs, therefore it is hard to examine the direct impact of individual actor/ actress on the success of a movie. The definition of 'movie-stars' essentially boils down to an individual's opinion towards a specific actor/actress at the end of the day. This means an introduction of bias would be inevitably unavoidable when star power is included as one of the independent variables in the regression.

Scholars attempt to tackle the quantification problem of star-power by using different proxy variables. Several researchers measure star power as a dummy variable, where a film is given a value of one if all cast member who have won Oscar for Best Actor/Actress at least once, or been involved in a top-ten grossing movie before the sample year (Litman & Ahn (1998), Ravid (1999), Basuroy et al. (2003)). On the other hand, Simonet (1980) uses the number of awards won by the key players. Ravid (1999) uses budget to quantify star power. Additionally, charts are used as one of the most useful indicator for star power such as Premier's annual listing of the 100 most powerful people in Hollywood. Elberse (2007) uses the information about a movie's expected performance before and after the casting announcement on Hollywood Stock Exchange (www.HSX.com), which estimates the value of a movie by registered users.

Austin and Gordon (1987) discovered a weak relationship between movie attendance and Academy Award of Artist Ratings. Ravid (1999) and Weinstein (1998)

claim that stars act as a signalling device to the audience indicating the quality of the film. However, they eventually concluded that financial success of a film does not depend on stars. In contrast, Rosen (1981) found positive correlation between stars and box office revenue as small differences in a movie-star's quality would result in large difference in earning of movies. Walls (2009) strengthens this finding by showing that the average impact of including a star in a movie raises profits by $6.5 million.

In this paper, we use two different approaches to measure star power in attempt to capture the role of Hollywood star in determining the financial success of a movie-The first measurement, *Star Power* 1, which is based on the number of Academy Award nominations and award won by key players in a film. The second measurement, *Star Power* 2, is based on the earning power of players in a film. Detailed explanations of these two different approaches are presented below.

Star Power 1

John et al. (2003) assume that the success of a movie director is based on his/her performance throughout the entire career path. In our analysis, the first method combines the above assumption with an Academy Award approach in defining a star's success, represented by *Star Power* 1. It is defined as the sum of all nominations and awards won for top-awards as categorized by the IMDB website, which are Best Actor/Actress, Best Supporting Actor/Actress and Best Director.
It is important to note that this data is collected before 2007 because the number of Oscar nomination and award won will also be taken into account in another variable in the same sample year.

Star Power 2

A film's star power is not fully represented by star power 1. Actor Tom Cruise has not won any Academy Award but has been nominated several times for best supporting actor. Nonetheless, the average life time gross earnings per film in which he acted yields an astonishing $160 million in real terms according to Box office mojo. In this case, a natural Tom Cruise fan would automatically give him significant star power regardless of his acting abilities recognised by Academy awards. Nelson and Glotfelty (2012) point out some stars have more success than others.

We believe the second method will act as a better measure of star power. This approach aims to quantify star power by using the average domestic box office revenue of all the films in which the key players have been involved in their entire career before 2007.

Bing (2002) raises the possibility of star power multiplying when more than one star is cast in a film. Consequently, in order to examine the existence of such effect,

this study defines key player of a film as the actor, actress and director who are all listed on 'Director' and 'Stars' category on IMDB. The actual data of the revenue of all the films for each key player is then searched and collected from Box Office Mojo website. Therefore *Star Power* 2 is represented by the average value of the average lifetime revenue of each key player in a film that is produced in America in 2007.

To the best of our knowledge, this method has not been used previously, probably because the data collection process for this particular variable was time-consuming. The data sources for two measurements of star power are consistent because IMDB and Box Office Mojo belong to the same company.

Control Variables

Screens

The more accessible the film is to viewers, the more it could generate revenue. The independent variable *Screens* captures the screen coverage enjoyed by the film, measured by the number of screens in which the particular film is shown within the USA in the sample year. The data is collected from Box Office Mojo website. Using around 2,000 movies in their sample, Walls (2009) found increasing marginal return of financial success to screen openings.

Reviews

Using several approaches in measuring critics' reviews, such as the number of good, bad and mixed reviews a film receives in the opening weekend on Variety, Ravid (1999) concluded that critic review does have positive impact on the box office revenue regardless the nature of reviews.

However, this only indicates the amount of different types of reviews received but does not provide information about the actual quality of the film. Alternatively, we use the reviews from RottenTomatoes.com, a source suggested in Terry et al. (2005)'s study. The website summarizes both positive and negative ratings (e.g., 2/5, 7/10) from accredited critics (newspaper, magazines, and radio critics) then converts the aggregate ratings into an average value that lies between 0 and 10. This is the value given for each observation for variable *Reviews* The higher the ratings, the higher the value a film has. For example, the film The Bourne Ultimatum has a value of 8.5 indicating high popularity among the critics. Note that the approach in this paper is significantly different than Reinstein and Snyder's (2005) difference-in-difference approach, since their findings indicated that the power to influence a film's revenue is held by only a few critics, as they have already established reputation among vast reviews with uncertain quality in the market.

Distributor

Market share of box office revenue in Hollywood has been dominated by only a few top distributors. The market share of the top-six distributors (Sony/Columbia, Buena Vista, Fox, Warner Bros, Paramount and Universal) make up more than 80% of gross revenue in American film industry in 2007 (Box Office Mojo). Again using a dummy variable $Distributor$, an observation is allocated with a value of one if it is produced by any one of the top-six distributors in 2007, and zero otherwise. This useful variable reveals whether motion pictures produced by major distributors are more popular than the rest of the smaller distributors.

Ratings

Motion Picture Association of America (MPAA)-ratings classify films according to its suitability to different audiences in the following way: general audience (G), parental guidance suggested for young children (PG), parents strongly cautioned for children under 13 (PG13), audience under 17 should be accompanied by an adult (R), no one under 17 is permitted (NC17). How important is the type of film in influencing the success of films is crucial information for the producers. According to De Vany and Walls (2002), too many R-rated films are produced if revenue generating power is considered, but they explain that it is in order to demonstrate and acquire prestige. Basuroy et al. (2003) suggests that $Ratings$ for a film is assigned a value of one if it has a MPAA-rating of R and NC-17, otherwise zero, which is also used in our study.

Sequel

Another variable of interest in this study is whether or not an observation is a movie sequel. The variable $Sequel$ is assigned a value of one if it is a movie sequel and zero otherwise. This is a useful explanatory variable because it will tell us whether film makers should reproduce the sequel using similar formula as the original. As suggested by Ravid (1999), film producers should try to remake a sequel as closely as possible to the original if it succeeds. However, a study by Walls (2009) claims that there is no guarantee of success for a sequel as the profit distribution illustrates almost the same shape for sequels and non-sequels.

Awards

Despite the fact that some papers found contradicting results using Academy Award as a tool to measure a film's success (Smith & Smith (1986), Eliashberg & Shugman (1997)), others found that an Oscar nomination or award (especially for Best Picture/Actor/Actress) would generally increase a film's probability of survival, as theatre-owners compete to book nominated or awarded films with the hope of

extending the life of film release, thus generating higher box office revenue (Dodds & Holbrook (1988), Dretzka (1998), Levene (1992)).

Ravid (1999) treats Academy Award as a dummy variable: where a film with at least one actor, actress or director has been nominated or won an Academy Award is one, zero otherwise. However, as suggested by the same author, in our analysis, Awards is measured using the sum of all nominations and actual award won by the particular film, where a nomination is appointed with a numerical integer of one and two for an Oscar nomination and win. This measures the effect of Academy Awards other than the ones which measure star power such as Best Achievement in Makeup or Best Achievement in Visual Effects. There are obviously other awards that signal the value of professional recognition such as the Golden Globe Award but this study only focuses on the impact of Academy Awards on box office revenue.

Budget

The amount of budget allocated for a film is shown to be an important determinant according to some literature (Ravid (1999), Basuroy et al. (2003)). It also controls for the amount that has to be spent on key players, screen coverage and distributors so that we can discern the effect of all these variables. The data for $Budget$ (in $ million) is collected from Box Office Mojo website. It must be stressed here that budget is based only on estimation because direct information such as salaries is simply too difficult to account for. For this reason, there are a large number of missing data for budget in the sample. Nevertheless, this variable is included in our analysis because of its importance.

Genre

Austin and Gordon (1987) found that movie-goers view genre as probably the most important factor determining movie attendance. They argue that viewers accumulate genre preferences based on expectations and information from the past movie-going experience for specific genres, hence affect movie choice.

Hsu et al. (2014) commented that several archival sources show various classifications on genre for the same film in order to 'cross the genre boundaries' in an attempt to maximize box office revenue by attracting all types of movie-goers. For example, while the film Knocked up is classified as a 'romantic comedy' on Box Office Mojo, it is classified under 'drama', 'comedy' and 'romance' on IMDB. He finds that film distributors only cross a small number of boundaries even if it requires small effort. As a result, we classify subgenre into main genre for all observations and therefore Knocked up will be classified as 'comedy' in this study.

Fischoff et al. (1998) suggest seven most popular genres based on frequency in their data. Therefore it will be interesting to examine whether choosing a popular

genre would be positively correlated with high box office revenue; or whether less popular genres which avoid competition among other films will have an advantage. The 'popular' group consists of seven most popular genres which will take a value of one, including Drama, Comedy, Documentary, Thriller, Action Adventure, Horror and Animation while the remaining genres such as Fantasy, Foreign, Sci-Fi, Musical, Romance, War, Western, and Family are classified as 'unpopular'.

The dummy variable $Genre$ is assigned a value one of the film is one of the popular genres and zero otherwise. Figure 1 below shows the market shares of each genre-type based on frequency count in 2007.
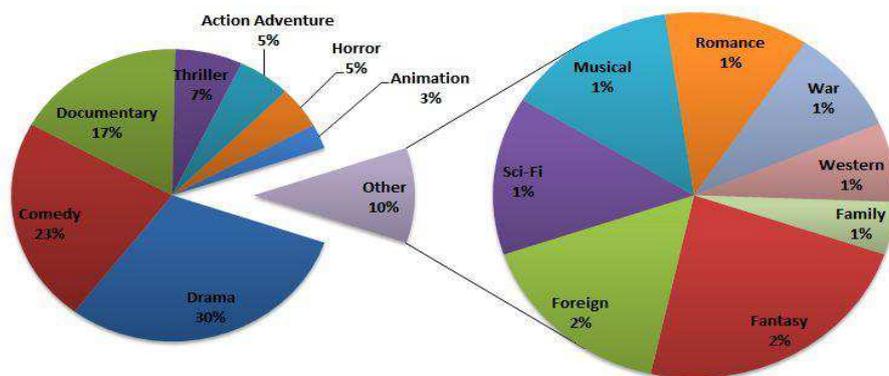

Figure 1: Market shares of individual genre-type based on frequency count in 2007

Seasonality

Nardone (1982) suggests that the motion-picture industry acts contra cyclically indicating that there are several peaks and troughs that represent seasonal fluctuation throughout the year. Furthermore, the result is also consistent with Vogel's (2010) finding, in which peak periods include Christmas, Thanksgiving, Easter and summer holidays. Some papers (Dodds & Holbrook (1988), Litman (1983)) suggest that distributors strategically delay a film's release date to the fourth quarter of the year, in order to increase the probability of awards nominations while the film is fresh in the minds of the members of the Academy when they cast their ballots. Vogel (2010) constructs a sophisticated graph of normalized weekly attendance based on films produced in the U.S. collected on Variety between 1969 and 1984. Therefore the seasonality graph provides information on the popularity of each film according to the date of release. The variable $Seasonality$ for each film is given a numerical value in decimal points between 0 and 1. For example, Midsummer being one of the peak periods in the year has a high value of about 0.85 indicating high movie attendances, perhaps due to the fact that it is in the middle of holiday season. We use the figure given by Vogel (2010) for our analysis.

2.2. Data description

The summary statistics are given in Table 1, which includes the number of observations, mean, standard deviation, minimum and maximum values for each variable. Comparatively, variables of high standard deviation with a larger difference between the minimum and maximum values are $Revenue$, $Star\ Power2$, $Budget$ and $Screens$. Therefore we have also included the natural log of these variables.

Variable	No. Obs.	Mean	Std. Dev.	Minimum	Maximum
$Revenue$ ($million)	411	22.70	51.30	0.0003	337.00
ln $Revenue$	411	13.59	3.48	5.8171	19.63
$Star\ Power1$	411	1.36	3.00	0	27.00
$Star\ Power2$ ($million)	244	57.70	35.40	0.0663	293.00
ln $StarPower2$	244	17.66	0.83	11.1019	19.49
$Screens$	411	1023.78	1293.54	1	4362.00
ln $Screens$	411	4.60	2.97	0	8.38
$Reviews$	306	5.40	1.47	2.40	8.60
$Budget$ ($million)	90	53.00	59.00	0.30	300.00
ln $Budget$	90	17.13	1.29	12.6115	19.52
$Seasonality$	411	0.61	0.13	0.36	0.97
$Awards$	411	0.22	1.09	0	12.00
$Distributor$	411	0.29	0.45	0	1
$Ratings$	411	0.40	0.49	0	1
$Sequel$	411	0.04	0.20	0	1
$Genre$	411	0.90	0.31	0	1

Table 1: Data description

First of all we ensured that the sample is balanced by automatically omitting observations if any variable contains missing data in order to avoid unbalanced sample which could potentially introduce bias and inconsistency into the model. The number of observations that we could obtain for the variable $Budget$ is only 90, compared to most other variables which stand at 411. In particular, the task gets more challenging when it comes to estimating budget for relatively unsuccessful films with domestic box office revenue below $1million, which accounted for 66.9% of data in our sample. While one could argue that the study could proceed simply by dropping budget as an independent variable; however, based on literature, it plays a significant role in terms of its impact on the total box office revenue of a film. For that reason, it is kept in the model. As a result, the final sample size is reduced down to 78 observations. We consider this to be a sufficient sample size to carry out the analysis.

2.3 The Regression Model

The Ordinary Least Squares Model

Uncertainty and volatility in demand in the movie industry provides obstacles to construct a relatively good model to examine the factors that determine the financial success of a specific film. Earlier work by De Vany and Walls (1996) show that the final distribution of total revenue undergoes stochastic dynamic processes when it comes to modelling movies, as demand alters unexpectedly through information flows. As a result, these processes lead to various distributions such as the uniform, the geometric, the Pareto, and the log normal. The authors later extended their work (De Vany and Walls (1999)) in which they believed that the most suitable model for the disparity of motion pictures revenues is the estimated Pareto rank distribution.

In order to avoid inaccurate results caused by using discretised data without a large sample size, we use probability distribution to model how the probability mass is shifted with the changes of variables. Hence we use the more traditional Ordinary Least Square (OLS) for regression analyses because it is the simplest model to obtain unbiased, consistent and accurate results (Wooldridge 2006) It helps us achieve our main objective, which is whether Star Power plays a key role in generating revenue from local cinemas.

$$\ln Revenue_i = \beta_0 + \beta_1 StarPower1_i + \beta_2 \ln StarPower2_i + \beta_3 \ln Screens_i +$$
$$\beta_4 Reviews_i + \beta_5 Distributor_i + \beta_6 Ratings_i + \beta_7 Sequel_i + \beta_8 Awards_i +$$
$$\beta_9 \ln Budget_i + \beta_{10} Genre_i + +\beta_{11} Seasonality_i + u_i \qquad (1)$$

Equation (1) is the basic model that is regressed to analyse the factors explaining the variations in Box office revenue. The model contains all the explanatory variables based on empirical evidence discussed in Section 2.1 including both measurements of star power, since essentially they are two different explanatory variables that could be investigated.

The variables should provide a closer fit to the model if the dependent variable, *Revenue* is transformed into natural log form (Terry et al. 2005). This does not only allow non-linear relationship between domestic gross revenue and the dependent variables, but also corrects for outliers that exist in the sample because of the top-grossing films. The same transformation has been done to Budget and Star Power 2 since these variables are measured in numerical values.

In addition to that, we also decided to have the variable $Screens$ in natural logs. This decision is supported by the values in Table 1 where the variance is comparable with other variables in the model as well as the scatter plot graph shown in Figures 2a and 2b. The $y-axis$ of Figures 2a and 2b represent $Revenue$ and ln$Revenue$ respectively with the $Screens$ on the $x-axis$ and a line connecting the median points for each point on the $x-axis$.
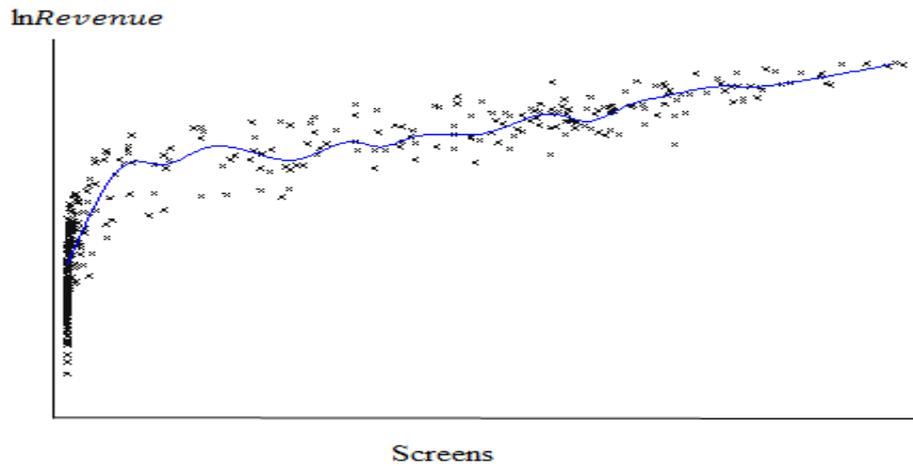
Figure 2a: ln$Revenue$ on $Screens$
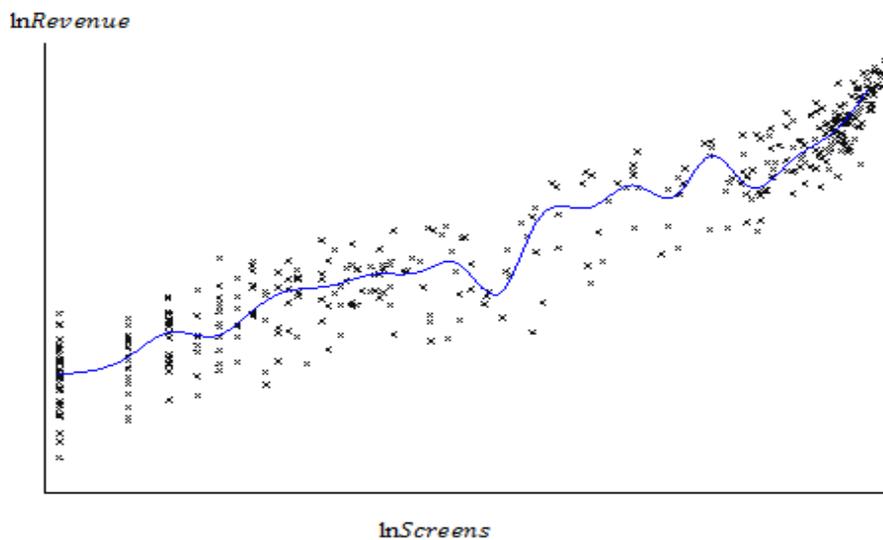
Figure 2b: $lnRevenue$ on ln$Screens$

First we checked whether there is multicollinearity between the explanatory variables. The correlation between the variables confirms we do not have to worry about this problem. The largest correlation is between $Screens$ and $Budget$ of

13

0.73. Since we use a single-period data set in this paper, there exists no problem of autocorrelation. The regressions are run with robust standard errors in order to avoid heteroscadasticity problems so that the results are consistent and unbiased.
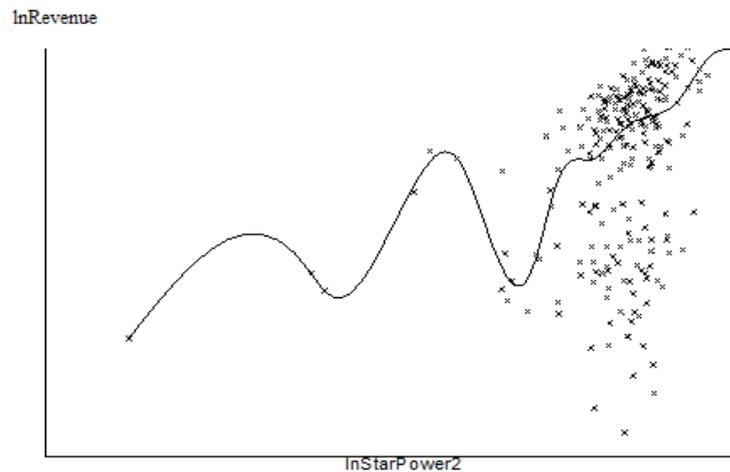
Figure 3: $\ln Revenue$ on $\ln StarPower2$
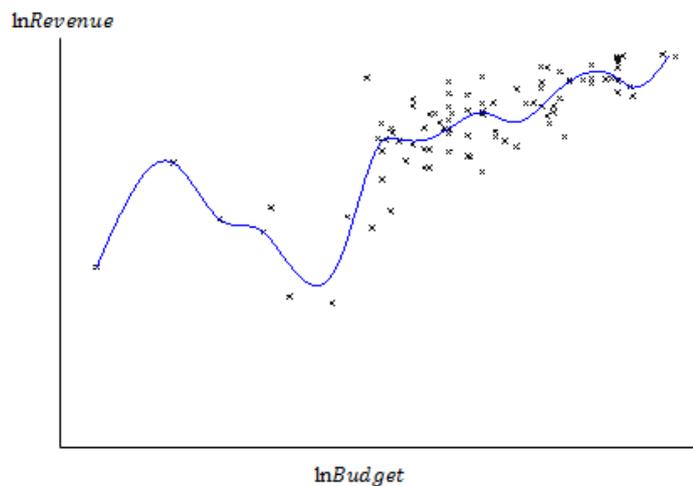
Figure 4: $\ln Revenue$ on $\ln Budget$

The results of the regression analysis according to equation (1), is presented in Model II in Table 2 which follows in Section 3. Its explanatory power is quite high with R^2 being 0.8223. However, the Ramsey RESET test for omitted variables and functional form indicated that we cannot reject the hypothesis that the model having no omitted variables. Walls (2009) dealt with this issue by choosing a non- parametric model to carry out the analysis.

Various functional forms were tried, and the best solution we decided on is given in equation 2. The variables $\ln StarPower2$ and $\ln Budget$ are raised to the power 2, whereas the variable $\ln Screens$ has been raised to the powers 2 and 3. Figures 2b, 3 and 4 indicate that these changes to the functional form are reasonable. Figure 3 and Figure 4 have on the x-axis $\ln StarPower\,2$ and $\ln Budget$ respectively and $\ln Revenue$ on the y-axis.

$$\ln Revenue_i = \beta_0 + \beta_1 StarPower1_i + \beta_2 \ln StarPower2_i + \beta_3 \ln StarPower2_i{}^2 +$$

$$\beta_4 \ln Screens_i + \beta_5 \ln Screens_i{}^2 + \beta_6 \ln Screens_i{}^3 + \beta_7 Reviews_i +$$

$$\beta_8 Distributor + \beta_9 Ratings_i + \beta_{10} Sequel_i + \beta_{11} Awards_i + \beta_{12} \ln Budget_i +$$

$$\beta_{13} \ln Budget_i{}^2 + \beta_{14} Genre_i + \beta_{15} Seasonality_i + u_i \tag{2}$$

The Ramsey test shows insignificant F-statistics at the 1%, 5% and 10% significance level which suggests that the null hypothesis of the functional form being correctly specified is not rejected. So we conclude that there is no misspecification in the functional form.

Finally, we checked whether the residuals are normally distributed with an expected value of zero. According to the skewness-kurtosis test, the probability of skewness is 4.7% and the probability of kurtosis is 0.61%, which reasonably confirms it is indeed so. The distribution of the residuals is given in Figure 5. We can conclude that the data collected delivers a relatively good model for this analysis. The results of the OLS regression of equation 2 are presented in Models III and IV in Table 2.
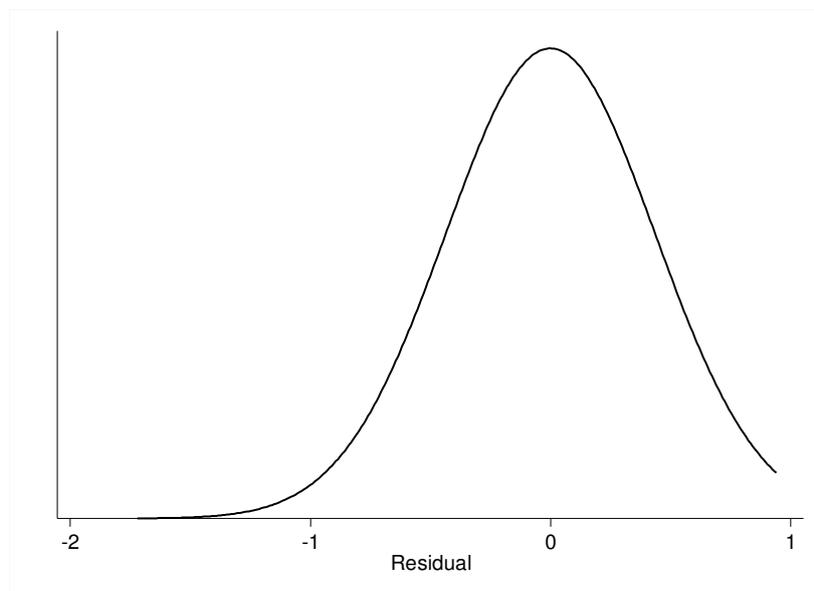

Figure 5: Distribution of the predicted residual $\hat{u}_i$

3.   Regression Analysis and Results

The relevant results of the Ordinary Least Squares regression analysis of equations (1) and (2) are presented in Table 2, including adjusted R^2, estimated coefficients of each independent variable and the respective robust standard errors in parenthesis. The level of statistical significance is indicated by the superscript *, ** and *** which refer to the variable being statistically significant at 10%, 5% and 1% respectively.

The objective of this exercise is to check whether the involvement of 'Stars' in a film significantly increases the revenue it generates. Model 1 checks the effect of only the two variables capturing this and finds that $Star\ Power$ 1 has no significant effect, while Star Power 2 is highly significant at the 1% level. Model II, includes all the control variables in equation (1) where we find that $Screens$ is highly significant at the 1% level while $Review$, $Distributor$, $Ratings$ and $Sequel$ are significant at the 10% level. The variables $Awards$, $\ln Budget$, $Genre$ and $Seasonality$ are not statistically significant.

The discussion of the results is based on Model III in Table 2 which gives the results of the Ordinary Least Squares regression of equation 2. The R^2 indicates that 89.82% of the dependent variable (natural log of the revenue generated by films in the US domestic box office) is explained by the independent variables.

We find that the number of Oscar nominations and wins by key contributors to the film does not play a big role in the financial success of a film as indicated by $StarPower1$ which turned out not to be statistically significant even at the 10% level. However, $Star\ Power$ 2 is highly significant at 1% level according to our analysis. A percentage increase in $Star\ Power$ 2 (i.e. if on average a film involving a key player generated a 1% higher revenue previously) results in 9.4 percent increase in total revenue of a film produced within the USA. Furthermore, $\ln StarPower2^2$ is negative, which indicates that the increase is at a decreasing rate.

These results confirm the theory that star power as a variable remains extremely difficult to measure, especially due to the changing tastes of the vast audience for the stars over time. This also supports the literature that actors, actresses and directors who have been nominated or won Oscars in the past might not necessarily carry the power to generating revenue. Furthermore, research has shown that Oscar nominees and winners do not guarantee high box office revenues because actors without the Oscar label might be even more popular to the general audience. Based on this intuition, it is no surprise to see a much better result has been generated using the logarithmic form of average life-time gross revenue per player as the second proxy.

$\ln Revenue_i$	I	II	III	IV
$StarPower1_i$	0.0482653	$-0..0076197$	0.0055057	0.0054614
	(0.0400611)	(0.0153643)	(0.01121)	(0.0121964)
$\ln StarPower2_i$	1.375356***	0.6341087***	9.047229***	8.047805***
	(0.2013832)	(0.1556165)	(3.475114)	(2.568057)
$\ln StarPower2_i{}^2$			-0.2420904**	-0.2130399***
			(0.0969937)	(0.0716906)
$\ln Screens_i$		0.9349422***	31.73573***	30.33723***
		(0.1421066)	(5.753124)	(6.241135)
$\ln Screens_i{}^2$			-5.315089***	-5.094988***
			(0.9368583)	(1.018563)
$\ln Screens_i{}^3$			0.2967855***	0.2853283***
			(0.0498002)	(0.0543004)
$Review_i$		0.1059554*	0.1268343***	0.1692642***
		(0.0622761)	(0.0462068)	(0.0425012)
$Distributor_i$		0.3427787 *	0.2760973*	0.3378339**
		(0.1862436)	(0.1410945)	(0.140068)
$Ratings_i$		0.310738 *	0.1335512	
		(0.1699701)	(0.141577)	
$Sequel_i$		0.3202963 *	0.0271116	
		(0.1709179)	(0.1395181)	
$Awards_i$		0.0491763	0.0514539	
		(0.0368469)	(0.0359568)	
$\ln Budget_i$		0.1589283	-0.7889426	-1.301718
		(0.120284)	(2.828199)	(2.731829)
$\ln Budget_i{}^2$			0.0151289	0.0308931
			(0.0804448)	(0.0775969)
$Genre_i$		-0.1585415	-0.1852491	
		(0.2326261)	(0.1725988)	
$Seasonality_i$		-0.137646	0.5039076	
		(0.562441)	(0.4772061)	
$Constant$	-9.111609	-4.687071	-124.0622	-108.3941
	(3.537632)	(2.989204)	(32.15145)	(27.32002)
R^2		0.8223	0.8982	0.8886
Observations		78	78	78

Table 2: Results of the from Ordinary Least Squares analysis

Next we look at the variables responsible for how the film is advertised and enabled it to reach the viewing public to generate income. Even though we control for both screen coverage and the distributor, both turn out to be significant. Screen coverage is found to be more important in generating revenue than who does the distribution, even though that also plays an important role. The variable $\ln Screens$ is highly significant at the one percent level of significance. A percentage increase in the number of screens in which the films are telecast will increase revenue by 37.1% on average.

As indicated by the parameter for the variable, $Distributor$, a film distributed by one of top-six distributors (Sony/Columbia, Buena Vista, Fox, Warner Bros, Paramount and Universal) will increase revenue by approximately 31.8 percent and this is significant only at the 10% level. Major distributors have higher budgets, resources and experience which strategically aim to produce high gross revenue films compared to the smaller distributors in the American motion pictures industry.

Another explanatory variable that is highly significant at the 1% level is $Reviews$. Serving as a reliable word of mouth, Critical reviews play a significant role in a film's financial success. It signals and criticises the quality and recognition of a film among vast number of competitors in the market, hence drives the demand for that particular film. This result is contrary to what is found by the influential paper Ravid (1999), who used a different indicator to capture this variable. A one-unit increase in $Reviews$ (recall that RottenTomatoes.com gives an average rating value ranging from 0 to 10 that is rounded to one decimal place), it will increase the box office revenue of a film by approximately 13.5%.

The results are robust even when we drop the control variables that are not significant even at the 10% level in the Model IV.   These variables are $Ratings$ and $Sequel$ along with $Awards$, $\ln Budget$, $Genre$ and $Seasonality$.

We find that budget does not play a significant role in generating revenue. The amount of money that is invested does not matter significantly in generating revenue. Also, whether or not a film is classified as R/NC-17 does not have a significant impact on the revenue generated by the film, nor do popular genres. Surprisingly, the time of release and being a sequel also turn out to be not statistically significant.

Importantly, the variable $Award$ is not statistically significant even at the 10% level suggesting that Oscar nomination or win does not significantly increase box office revenue of motion pictures. This result is not surprising, given that $Star\ Power$ 1 (which captures the previous success in securing academy awards by key players) was also found to be not significant.

4. Conclusion

According to the empirical investigation, we find that the approach to measuring star power based on the number of Academy Awards nominations and wins show no significant correlation to box office success. On the other hand, the alternative approach we used to measuring star power: the average box office revenue generated by films involving an actor/ director during their career up to the year in question - was found to significantly increase revenue. Overall, despite the approach of number of Academy Awards nominations and awards won is not statistically significant, the results confirm our hypothesis. We can conclude that star power indeed has a strong positive impact on domestic box office revenue in the Motion Pictures industry in Hollywood. The findings suggest that due to the subjective nature of star power, vast number of movie-goers have their own unique perception towards the true definition of movie-stars, which cannot be simply signalled by the recognition of Academy Awards. For example, the key players involved in the top box office revenue grossing film Spider-man 3 have not received any Academy Award nominations, but yielded an astonishing domestic box office revenue of $336.5 million.

Future research can focus on the effect of individual stars and the interdependencies between stars, which has been ignored in previous studies. Nowadays a substantial proportion of revenue of a film is also generated through television rights, DVD sales and membership-based online websites. Including post-cinema sales as a variable would provide a better understanding on the success of a film. Despite the fact that difficulty remains in obtaining data about budget and actual costs of a film, profit would serve as a better dependent variable to indicate the financial success of a film.

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http://www.mpaa.org/ratings

http://www.rottentomatoes.com

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www.HSX.com

```
. corr  starpower1 starpower2 academyaward criticreiew genre mpaaratings sequel releasedate budget screencoverage di
> stributor
(obs=78)
```

	starpo~1	starpo~2	academ~d	critic~w	genre	mpaara~s	sequel	releas~e	budget	screen~e	distri~r
starpower1	1.0000										
starpower2	0.0871	1.0000									
academyaward	0.1883	0.0725	1.0000								
criticreiew	0.0620	0.0365	0.4888	1.0000							
genre	0.0396	-0.1892	-0.0828	-0.1904	1.0000						
mpaaratings	-0.1319	0.2453	0.1125	0.1013	0.1978	1.0000					
sequel	-0.0626	0.3418	0.0557	-0.0028	0.0452	0.0764	1.0000				
releasedate	0.0454	0.2138	0.1277	0.0558	-0.0373	0.2512	0.0915	1.0000			
budget	0.0765	0.6314	0.1550	-0.0088	-0.1450	0.2100	0.5360	0.0909	1.0000		
screencove~e	0.0697	0.6104	0.0599	-0.1461	0.0304	0.1757	0.4202	0.1321	0.7327	1.0000	
distributor	-0.0691	0.2448	0.1074	-0.0919	-0.0084	0.1314	0.0699	0.1560	0.2623	0.3895	1.0000

```
. reg  lnrevenue starpower1 lnstarpower2 academyaward criticreiew genre mpaaratings sequel releasedate lnbudget lnsc
> reencoverage distributor, robust

Linear regression                                          Number of obs =       78
                                                           F( 11,     66) =    40.01
                                                           Prob > F       =   0.0000
                                                           R-squared      =   0.8223
                                                           Root MSE       =  .62135

                           Robust
  lnrevenue  |    Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  starpower1 |  -.0076197  .0153643    -0.50   0.622    -.0382955    .023056
lnstarpower2 |   .6341087  .1556165     4.07   0.000     .3234103    .944807
academyaward |   .0491763  .0368469     1.33   0.187    -.0243909   .1227434
  criticreiew|   .1059554  .0622761     1.70   0.094    -.0183829   .2302937
       genre |  -.1585415  .2326261    -0.68   0.498    -.6229946   .3059115
  mpaaratings |   .310738   .1699701     1.83   0.072    -.0286182   .6500941
      sequel |   .3202963  .1709179     1.87   0.065    -.0209523    .661545
  releasedate|  -.137646    .562441    -0.24   0.807    -1.260596   .9853036
    lnbudget |   .1589283   .120284     1.32   0.191    -.0812264   .3990831
 lnscreenco~e |   .9349422  .1421066     6.58   0.000     .6512171   1.218667
  distributor|   .3427787  .1862436     1.84   0.070    -.0290686    .714626
       _cons |  -4.687071  2.989204    -1.57   0.122    -10.65521   1.281066

. ovtest

Ramsey RESET test using powers of the fitted values of lnrevenue
       Ho:   model has no omitted variables
                  F(3, 63) =       6.27
                  Prob > F =      0.0009
```

```
. reg  lnrevenue starpower1 lnstarpower2 academyaward criticreiew genre mpaaratings sequel releasedate lnbudget lnsc
> reencoverage distributor lnscreencoveragesq lnscreencoverage3 lnstarpower2sq lnbudgetsq, robust

Linear regression                                      Number of obs =      78
                                                       F( 15,    62) =  212.02
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8982
                                                       Root MSE      =  .48522
```

lnrevenue	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
starpower1	.0055057	.01121	0.49	0.625	-.0169027	.0279141
lnstarpower2	9.047229	3.475114	2.60	0.012	2.100575	15.99388
academyaward	.0514539	.0359568	1.43	0.157	-.0204227	.1233306
criticreiew	.1268343	.0462068	2.74	0.008	.0344683	.2192003
genre	-.1852491	.1725988	-1.07	0.287	-.5302692	.159771
mpaaratings	.1335512	.141577	0.94	0.349	-.1494571	.4165596
sequel	.0271116	.1395181	0.19	0.847	-.251781	.3060043
releasedate	.5039076	.4772061	1.06	0.295	-.4500137	1.457829
lnbudget	-.7889426	2.828199	-0.28	0.781	-6.442432	4.864547
lnscreenco~e	31.73573	5.753124	5.52	0.000	20.2354	43.23607
distributor	.2760973	.1410945	1.96	0.055	-.0059465	.5581411
lnscreenco~q	-5.315089	.9368583	-5.67	0.000	-7.187842	-3.442336
lnscreenco~3	.2967855	.0498002	5.96	0.000	.1972363	.3963346
lnstarpowe~q	-.2420904	.0969937	-2.50	0.015	-.435978	-.0482027
lnbudgetsq	.0151289	.0804448	0.19	0.851	-.1456779	.1759357
_cons	-124.0622	32.15145	-3.86	0.000	-188.332	-59.79234

```
. ovtest

Ramsey RESET test using powers of the fitted values of lnrevenue
       Ho:  model has no omitted variables
            F(3, 59) =      2.15
            Prob > F =      0.1035




. predict ResFilmGenre, r
(333 missing values generated)

. sktest ResFilmGenre

              Skewness/Kurtosis tests for Normality
                                                 ——— joint ———
     Variable |   Obs   Pr(Skewness)   Pr(Kurtosis)  adj chi2(2)    Prob>chi2
```

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
ResFilmGenre	78	0.0470	0.0061	9.78	0.0075

```
. reg lnrevenue starpower1 lnstarpower2 lnstarpower2sq lnscreencoverage lnscreencoveragesq lnscreencoverage3 criticr
> eiew distributor lnbudget lnbudgetsq, robust

Linear regression                                    Number of obs =        78
                                                     F( 10,    67) =   373.19
                                                     Prob > F      =   0.0000
                                                     R-squared     =   0.8886
                                                     Root MSE      =   .48825
```

lnrevenue	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
starpower1	.0054614	.0121964	0.45	0.656	-.0188828	.0298055
lnstarpower2	8.047805	2.568057	3.13	0.003	2.921943	13.17367
lnstarpowe~q	-.2130399	.0716906	-2.97	0.004	-.356135	-.0699448
lnscreenco~e	30.33723	6.241135	4.86	0.000	17.87987	42.79459
lnscreenco~q	-5.094988	1.018563	-5.00	0.000	-7.128048	-3.061927
lnscreenco~3	.2853283	.0543004	5.25	0.000	.1769443	.3937124
criticreiew	.1692642	.0425012	3.98	0.000	.0844314	.254097
distributor	.3378339	.140068	2.41	0.019	.0582569	.6174109
lnbudget	-1.301718	2.731829	-0.48	0.635	-6.754473	4.151036
lnbudgetsq	.0308931	.0775969	0.40	0.692	-.1239909	.1857771
_cons	-108.3941	27.32002	-3.97	0.000	-162.9251	-53.86315