Prelaunch Advertising for Movies: An Econometric Analysis of Demand and Supply

Abstract

This research examines how pre-launch advertising affects movie demand and studios allocate pre-launch advertising budgets. Using weekly data on box-office revenues, advertising expenditures, and movie characteristics (studio, budget, genre, star value, critics' ratings, etc.) for 1,276 U.S. movies (2019-2012), we employ a logit diffusion model to show that pre-launch advertising significantly impacts demand, with an average elasticity of 0.35 across major studios. On the supply side, structural econometric models reveal studios maximize total expected profit across their yearly slate. Four policy experiments explore managerial implications of the advertising model.

Keywords: Advertising, Movies, Advertising Budgets, Advertising Competition.

Key Contributions to Academe and Practitioners

For contributions to academe, this research contributes to the academic marketing discipline by empirically demonstrating the significant impact of prelaunch advertising on movie demand, providing quantitative evidence on its effectiveness compared to post-release advertising. It advances econometric modeling in the context of movie marketing through the development of a logit diffusion model that accounts for consumer heterogeneity and competition. Additionally, the study introduces novel structural models to explain how studios allocate advertising budgets at the slate level, enhancing the understanding of advertising strategy in the highly competitive movie industry and expanding the application of marketing theory to entertainment sectors.

For contributions to practitioners, non-academic stakeholders such as film studios, marketing agencies, and advertising firms would find significant value in this research. Film studios can use the findings to optimize their prelaunch advertising strategies, allocate budgets more effectively across movie slates, and enhance the overall profitability of their releases. The study's focus on maximizing the effectiveness of prelaunch advertising, rather than spending on individual movies, provides practical insights into improving marketing ROI. Advertising agencies could benefit from understanding how advertising elasticity varies across different stages of a movie's lifecycle, allowing them to tailor campaigns more effectively. Additionally, market analysts and industry consultants could use these insights to predict the financial outcomes of different advertising strategies and guide studios in their decision-making processes. Moreover, governmental agencies focused on entertainment regulation might use the study's insights to better understand industry dynamics and the role of marketing in economic outcomes.

In summary, this paper contributes valuable theoretical advancements and practical strategies for both academics studying consumer behavior and advertising in the entertainment sector, and for practitioners seeking to optimize their advertising decisions and maximize profitability in an increasingly competitive market.

Introduction

This research explores the impact of pre-release advertising on movie demand and how studios allocate advertising budgets. Over the past few decades, numerous studies have examined factors driving box-office sales, highlighting the economic significance of the movie industry. In 2022, the U.S. box office grossed $7.5 billion, with 819 million tickets sold, and employed over 451,000 people (NATO, BLS). Despite the central role of advertising in the film industry—spending $839 million on movie advertising in 2015 (PwC)—its strategic role has not been sufficiently explored, particularly from the supply side. While previous studies have analyzed release timing, revenue-sharing contracts, and other factors, the strategic role of pre-release advertising remains underexplored.

This study addresses this gap by focusing on pre-release advertising expenditures, which typically account for 80-90% of a film's advertising budget. These budgets are determined by studios not only after production but also after release dates are set. Research by Elberse and Anand (2007) and Joshi and Hanssens (2009) suggests that pre-release advertising influences both a movie's box-office performance and the studio's stock price. Our goal is to understand how studios determine these budgets, specifically whether they follow a "movie profit maximization" approach (treating each movie as a separate profit center) or a "movie line profit maximization" approach (maximizing profit across a studio's entire slate). We hypothesize that the latter approach, which accounts for the potential cannibalization between movies released at the same time, would lead to lower advertising expenditures for individual films.

We examine various advertising strategies, including both approaches mentioned above, to determine which best fits observed data on pre-release advertising expenditures. The implications of this analysis are important for studios like Disney, which can optimize advertising budgets by anticipating competitor strategies. The "Big Six" studios—Buena Vista, Warner Brothers, 20th Century Fox, Universal, Sony/Columbia, and Paramount—dominate the box office, accounting for 80% of the revenue in 2016 (Box Office Mojo). Our study focuses on these major studios, as well as “Mini-Major” studios like Lions Gate and MGM, exploring whether pre-release advertising reflects movie-level competition or studio-level competition.

Using a structural model of advertising competition, we estimate a multiplier reflecting the benefit (box-office revenue) relative to the cost (advertising expenditure) of pre-release advertising. A multiplier greater than 1 indicates that studios value long-term revenue streams (e.g., merchandising, DVD sales) beyond box-office returns. We expect larger studios with better revenue-sharing terms to exhibit higher multipliers, particularly for franchise films.

We propose three structural econometric models of pre-release advertising, with one treating each movie as a separate profit center and the other two treating the studio’s entire slate as a profit center. Using data on box-office revenues and advertising spending from January 2009 to June 2012, we estimate these models using a logit diffusion model to account for the impact of various factors, including advertising, on movie demand. We find that pre-release advertising is better explained by studio-level profit maximization, with studios planning over a yearly horizon rather than a quarterly one.

Policy experiments suggest that if studios treated each movie as a separate profit center, advertising spending would increase by 4.89%, but profits would decrease by 2.75%. Additionally, if advertising effectiveness were to improve by 10%, industry-wide advertising spending would rise by 51.18%, with major studios driving the increase. A specialization strategy for Disney focusing exclusively on animated films could increase total profit by 4.44%.

This paper proceeds by detailing the data and methodology used, presenting estimation results, and discussing the managerial implications based on policy experiments. We conclude by offering directions for future research.

Data

Our dataset consists of 1,276 movies released in U.S. theaters from January 2009 to July 2012. It combines data from multiple sources: weekly box office revenues from BoxOfficeMojo.com, weekly advertising spending from Kantar Media’s Ad Spender database, and movie characteristics such as studio, production budget, genre, MPAA rating, and critical rating from IMDB. The first three years of data (2009–2012) are used as the estimation sample, while the last six months serve as the holdout sample, leaving 1,104 movies in the estimation set.

The dataset reveals some key patterns in movie revenue and advertising spending. Notably, box office revenues show a spike during the summer and the Thanksgiving-Christmas holiday seasons. Based on these observations, we created two season indicator variables: SEASON1 for the summer (weeks 21-33 in 2009) and SEASON2 for the Christmas season (weeks 46-52 in 2009).

The six major studios—Warner Brothers, Paramount, 20th Century Fox, Sony/Columbia, Disney, and Universal—dominate the market, accounting for over 80% of both box office revenues and advertising spending. Warner Brothers leads with 18.43% of box office revenues and 20.57% of advertising spending. Pre-launch advertising typically makes up 80-90% of the total advertising expenditure for most studios, signaling a clear emphasis on preparing for a successful release. Advertising spending relative to box office revenues ranges from 23% to 42% for major studios, a notably high percentage when compared to other highly advertised sectors like personal care products.

Our analysis also highlights the variability in box office performance across studios. Even the least successful movies from major studios like Disney and Paramount outperform the most successful movies from mini-major studios. Paramount, in particular, shows the highest median and maximum revenues, though its revenue outcomes are more variable, possibly due to a broader range of movie types in its portfolio.

When it comes to pre-release advertising, Warner Brothers stands out with the highest median and maximum expenditures, though its spending is also the most consistent across movies. This is in contrast to smaller studios, where the spread in pre-release advertising is more variable. In terms of profits, mini-major studios, despite lower revenues, show comparable profitability to major studios, likely due to a focus on niche markets with guaranteed returns. Disney, however, exhibits the highest profit spread, which may reflect the unpredictable nature of the children's market it targets.

Ticket prices in U.S./Canada theaters have steadily increased from $7.50 in 2009 to $7.93 in 2011, and these prices are used to calculate proxies for movie demand. For example, weekly box office revenues are divided by the average ticket price to estimate the number of consumers attending a movie each week.

Finally, we observe notable trends in the types of movies distributed by each studio. For example, 60% of Disney's movies are animated or family films, while Sony/Columbia distributes a more diverse range of genres. Additionally, Disney's movies have the highest production budgets on average, while Paramount films feature the highest star value.

Econometric Model of Movie Demand

Let U_{hjt} denote the (indirect) utility of consumer h for movie j during week t. We assume that we can express this utility as a function of movie covariates, (AD_{jt}, PA_j, $\boldsymbol{X_j}$), as well as the movie's intrinsic attractiveness, which is assumed to decay over time, as follows.

$$U_{hjt} = \beta_{1h} * AD_{jt} + \beta_{2h} * PA_j + \mathbf{X_j} * \boldsymbol{\beta}_{\mathbf{3h}} + \ln\left(\tau_{jt}^{\frac{a_j}{b_j}} e^{\frac{1-\tau_{jt}}{b_j}} \right) + \varepsilon_{hjt}, \quad (1)$$

Let U_{h0t} denote the (indirect) utility of consumer h for the no-purchase option (also called "outside good") 0 at shopping trip t. We assume that we can express this utility as follows.

$$U_{h0t} = \delta_1 * SEASON_1 + \delta_2 * SEASON_2 + \varepsilon_{h0t}, \quad (2)$$

The multinomial outcome y_{ht} is determined by the principle of maximum utility. We observe $y_{ht} = j$ when the utility of the j^{th} movie to the consumer exceeds that of the remaining movies. This yields the following probabilistic model for movie choice,

$$\Pr\left(y_{ht} = j\right) = \Pr_{hjt} = \Pr\left(U_{hjt} = \max\left\{U_{h1t}, ..., U_{hJt}, U_{h0t}\right\}\right), \quad (3)$$

which reduces to

$$\Pr_{hjt} = \frac{e^{\beta_{1h}*AD_{jt}+\beta_{2h}*PA_j+\mathbf{X_j}*\boldsymbol{\beta}_{\mathbf{3h}}+\ln\left(\tau_{jt}^{\frac{a_j}{b_j}} e^{\frac{1-\tau_{jt}}{b_j}}\right)}}{e^{\delta_1*SEASON_1+\delta_2*SEASON_2} + \sum_{k=1}^{J_t} e^{\beta_{1h}*AD_{kt}+\beta_{2h}*PA_k+\mathbf{X_j}*\boldsymbol{\beta}_{\mathbf{3h}}+\ln\left(\tau_{kt}^{\frac{a_j}{b_j}} e^{\frac{1-\tau_{kt}}{b_j}}\right)}}, \qquad (4)$$

Following the latent class approach of Heckman and Singer (1984), we assume that consumers belong to M segments. We estimate the utility parameters for each of M segments, as well as the associated segment sizes, using data on aggregate weekly box office revenues of movies. This is done by maximizing the following sample log-likelihood function.

$$\ln L = \sum_{t=1}^{T}\sum_{j=0}^{J_t} N_{jt} * \left[\sum_{m=1}^{M} \pi_m * \Pr_{mjt}\right], \qquad (5)$$

We then subtract the observed demand for all movies in a given week, i.e., $\sum_{j=1}^{J_t} N_{jt}$, from this market potential, MP, to construct the demand for the outside good that week. This is explained in the equation below, and is the procedure also followed by Ainslie, Dreze and Zufryden (2005).

$$N_{0t} = MP - \sum_{j=1}^{J_t} N_{jt}, \qquad (6)$$

One more issue deserves mention here. In the generalized gamma hazard function, as shown in equation (1), the parameters a_j and b_j have j subscripts and are, therefore, movie-specific. While it is indeed important to represent the empirical reality that movie attractiveness typically decays over time, it is clearly wasteful to estimate a movie-specific decay process, which yields a total of 1104*2 = 2208 additional parameters for estimation. Therefore, we use the following hierarchical specification to parsimoniously capture heterogeneity in the hazard function across movies.

$$\begin{aligned} a_j &= \alpha_a + \mathbf{X'}_{\mathbf{j}}\boldsymbol{\chi}_a, \\ b_j &= \alpha \ + \mathbf{X'}_{\mathbf{j}}\boldsymbol{\chi}_b, \end{aligned} \qquad (7)$$

Econometric Model of Movie Pre-Release Advertising

To develop a structural econometric model of pre-release advertising for movies, we recognize that each movie j is associated with a pre-release advertising budget PA_j in the data. Since there are 1104 movies in the data, we have 1104 pre-release advertising outcomes in the data. Our econometric approach models these continuous outcomes PA_j ($j = 1, \ldots, 1104$) using structural foundations. We present a menu of three structural models below. They differ in terms of the objective function that is being maximized by each studio to set pre-release advertising budgets for its movies. All of these models require a predictive model of movie demand, which depends (among other things) on pre-release advertising, as an input. We assume that the studio predicts movie sales for movie j in week t, Q_{jt}, in week t as follows:

$$Q_{jt} = MP * \left[\sum_{m=1}^{M} \pi_m * \left\{ \Pr^m \left(y_{ht} = j \right) \right\} \right], \tag{8}$$

and, therefore, the studio can predict total movie sales for movie j over its entire run as follows.

$$Q_j = \sum_{t=\tau_{jr}}^{\tau_{je}} Q_{jt}, \tag{9}$$

<u>Pre-Release Advertising Model 1 (PAM1): Profit Maximization at the Movie Level</u>

Under this model, the assumption is that each movie studio manages each of its movies as a separate profit center. In other words, if a studio has two upcoming movies A and B, John Doe may be managing movie A, while Jane Doe may be managing movie B, with the profit-based monetary compensation for each manager being tied to the profit of their own movie and not to the profit of the other movie. Under this scenario, we specify the profit function of movie j, which is assumed to be maximized by the studio distributing the movie, as follows.

$$\Pi_j = P_j * Q_j * \delta_j - PA_j - B_j, \tag{10}$$

The first-order condition for profit maximization for movie j reduces to the following.

$$\delta_j * MP * \sum_{m=1}^{M} \pi_m \sum_{t=\tau_{jr}}^{\tau_{je}} P_j * \frac{d \Pr_{jt}^m}{dPA_j} = 1, \tag{11}$$

which can be algebraically derived to be as follows.

$$\beta_2 * \delta_j * MP * \sum_{m=1}^{M} \pi_m \sum_{t=\tau_{jr}}^{\tau_{je}} P_j * \Pr_{jt}^m * (1 - \Pr_{jt}^m) - PA_j = 1, \tag{12}$$

where β_2 is the consumer utility parameter associated with prelaunch advertising in equations (1) and (4).

Pre-Release Advertising Model 2 (PAM2): Quarterly Profit Maximization at the Studio Level

Under this model, the assumption is that each movie studio manages the entire slate of its scheduled movies over each quarter – Q1: (Jan – Mar), Q2: (Apr – Jun), Q3: (Jul – Sep), Q4: (Oct – Dec) -- as a collective profit center for the studio. In other words, if a studio has three scheduled movies A, B and C for Q1 of a given year, studio manager Jane Doe may be jointly managing movies A, B and C. Under this scenario, we specify the profit function of a studio, which is assumed to be maximized by the studio manager, as follows.

$$\Pi_{q\tau} = \sum_{k=1}^{N_{q\tau}} \Pi_k = \sum_{k=1}^{N_{q\tau}} \left(P_k * Q_k * \delta_k - PA_k - B_k \right), \tag{13}$$

The first-order condition for profit maximization for movie j reduces to the following.

$$\sum_{k=1}^{N_{q\tau}} P_k * \frac{d\,\mathrm{Pr}_k}{dPA_j} * \delta_k = 1, \tag{14}$$

which can be rewritten as follows.

$$MP * \sum_{k=1}^{N_{q\tau}} \delta_k \sum_{m=1}^{M} \pi_m \sum_{t=\tau_{kr}}^{\tau_{ke}} \left(P_{kt} * \frac{d\,\mathrm{Pr}_{kt}^m}{dPA_j} \right) = 1, \tag{15}$$

where it can be algebraically shown that

$$\frac{d\,\mathrm{Pr}_{kt}^m}{dPA_j} = \begin{cases} \dfrac{\beta_2}{PA_j + 1} * \mathrm{Pr}_{jt}^m * \left(1 - \mathrm{Pr}_{jt}^m\right) \text{ if } \mathrm{k} = \mathrm{j} \\ -\dfrac{\beta_2}{PA_j + 1} * \mathrm{Pr}_{jt}^m * \mathrm{Pr}_{kt}^m \text{ if } \mathrm{k} \neq \mathrm{j} \end{cases}. \tag{16}$$

Pre-Release Advertising Model 3 (PAM3): Annual Profit Maximization at the Studio Level

Under this model, the assumption is that each movie studio manages the entire slate of its scheduled movies over each calendar year as a collective profit center for the studio. This model is similar to PAM2 except for the assumption of the time horizon over which the studio constructs the portfolio of movies whose profits are collectively maximized. The first-order conditions will be similar to equations (15) and (16), except for the time horizon and, therefore, resulting portfolio of movies.

Model Estimation

We first calculate movie-specific δ_j using the derived first-order conditions (i.e., equation (12) or (15), depending on which model one is testing) for all movies $j = 1,\ldots, 1104$. These values are then taken as outcomes for the following observational model.

$$\ln\left(\delta_j\right) \sim N\left(\lambda_j, \sigma^2\right), \tag{17}$$

Empirical Results

Estimation Results for Movie Demand Model

Table 1 present the estimates of our movie demand model under the 5-support latent class heterogeneity specification for the coefficients associated with the indicator variables for genre and MPAA ratings.

In order to understand the estimated diffusion parameters (a_j and b_j in the generalized gamma function) of movies, we plot the temporal revenue pattern for a movie of "average" (based on the data) movie characteristics, making different assumptions about the studio distributing the movie (assuming a competitive movie set of unvarying attractiveness). These plots are reported in Figure 1.

In order to illustrate the substantive implication of this coefficient, we plot the temporal revenue pattern for a movie of average movie characteristics (as in Figure 2), additionally assuming that the studio distributing the movie is Warner Brothers (the highest revenue studio in our data).

In Figure 3, we plot the temporal revenue pattern for a movie of average movie characteristics, separately for a non-sequel versus a sequel. This explains why studios are increasingly viewing sequels to existing "movie franchises" (such as X-Men), rather than movies based on new scripts, as the cash cow in their new product pipeline.

We plot the temporal revenue pattern for a movie with minimum (4.1) critical rating, as well as a movie with maximum (9) critical rating in Figure 4. We find that the opening week revenue for a movie can be higher as much as $7.3m (48%), and the total revenue can be higher by $54.4m (125%), if it had the highest, rather than, lowest critical rating.

<u>Estimation Results for Movie Pre-Release Advertising Model</u>

Table 2 presents the results of the Vuong test based on the three different movie pre-release advertising models, i.e., PAM1, PAM2 and PAM3. The models can be ranked as follows: PAM3 > PAM2 > PAM1. The best-fitting model is PAM3, which is based on annual studio-level profit maximization.

Table 3 present the estimates of the three different movie pre-release advertising models, i.e., PAM1, PAM2 and PAM2.

We present the top movies in terms of DVD sales for 2014 in Table 4.

Managerial Implications

We conduct three policy experiments, based on the estimation results, in this section to examine the managerial implications of our pre-release advertising model, PAM3. Under these policy experiments, we allow the studio's advertising objective to change, or one or more parameters of demand and/or supply to change, and then compute, using PAM3, the new equilibrium characterizing pre-lease advertising for all movies in the data. In other words, new optimal values of pre-release advertising, under the changed circumstances, are calculated and compared to the current values of pre-release advertising in the data. These differences have implications for potential profit changes for studios.

Conclusions

Advertising is a key marketing tool in the film industry, with pre-release advertising expenditures accounting for 80-90% of movie advertising budgets. This study focuses on how studios determine these pre-release expenditures, comparing three strategies: maximizing predicted movie profit as a separate profit center (PAM1), maximizing total predicted profit across a studio's slate for the upcoming quarter (PAM2), and maximizing profit over the next year (PAM3). We use structural models of advertising competition to estimate the multiplier assigned to the benefit (box office revenue) relative to the cost (advertising outlay) for each movie.

To test these models, we first estimate a demand model using a logit diffusion approach that includes movie characteristics such as pre-release advertising. We also refine this model to account for unobserved consumer heterogeneity. We then compare the maximized likelihood values across the three models to determine which best explains observed pre-release advertising decisions.

Results show that studios maximize profit over the long term (annually) at the studio level, rather than for individual movies. Policy experiments suggest that if movies were treated as separate profit centers, advertising spending would increase by 4.89%, but profits would decrease by 2.75%. Additionally, more effective advertising would boost industry profits by 37.85%. Specializing in animation would increase Disney's profit by 4.44%. This study's findings offer insights into strategic advertising decisions in the movie industry.

Tables and Figures

TABLE 1: ESTIMATION RESULTS – MOVIE DEMAND MODEL

First week										
			Seg 1	Seg 2	Seg 3	Seg 4	Seg 5		Peak	Speed
AMC	2.221	Intercept	-13.781	-11.473	-12.100	-18.105	-14.405	AMC	-1.345	-0.152
Anchor Bay	-1.020	Dra_Per_Rom	0.668	-5.716	-2.263	3.603	-0.682	Anchor Bay	1.383	-0.001
CBS	0.305	Com	-5.157	0.316	-0.438	3.794	-0.122	CBS	-0.274	0.000
Disney	0.593	Thr_Act_Hor_Cri	-4.310	0.691	0.661	0.154	0.390	Disney	-0.181	-0.090
20th Century Fox	0.637	Ani_Fam_Fan_Sci_Adv	1.539	-8.102	0.179	-2.310	-0.675	20th Century Fox	0.044	-0.009
Lions Gate	0.690	Mpaa-G	0.411	4.401	-2.926	-2.653	-2.487	Lions Gate	-0.350	-0.003
MGM	0.583	Mpaa-PG	-0.802	0.260	1.210	2.803	-0.221	MGM	-0.672	-0.001
Miramax	-0.035	Mpaa-PG13	-0.040	-6.812	-0.119	2.470	5.214	Miramax	-0.558	-0.001
Paramount	0.642	Mpaa-R	-0.329	0.446	-0.400	2.503	4.903	Paramount	-0.067	0.005
Sony	0.580	Size	0.483	0.023	0.171	0.198	0.125	Sony	-0.272	0.001
Summit	0.669							Summit	-0.199	-0.001
Universal	0.343							Universal	-0.155	-0.002
Warner Brothers	0.477							Time Warner	-0.081	0.007
Weinstein	0.218							Weinstein	-0.171	0.000
Star Value	0.013							Star Value	-0.005	-0.125
Star Value Square	0.001							Star Value Square	0.000	-0.429
Sequel	0.798							Sequel	-0.308	-0.011
Critical Rating	0.090							Critical Rating	0.115	-1.343
Budget	0.128							Budget	-0.053	-0.439
Screens	0.081							Screens	-0.173	-0.920
Pre-launch Advertising	0.420							Intercept	0.866	1.328
Advertising	0.127									
Outside Good: Season 1	-0.497									
Outside Good: Season 2	-0.319									

TABLE 2: ESTIMATION RESULTS – MOVIE PRE-RELEASE ADVERTISING MODEL: VUONG TEST

	Movie Profit Maximization	Studio Profit Maximization-Quarterly	Studio Profit Maximization-Yearly
Movie Profit Maximization	NaN	-5.77	-6.14
Studio Profit Maximization-Quarterly	5.77	NaN	-4.18
Studio Profit Maximization-Yearly	6.14	4.18	NaN

TABLE 3: ESTIMATION RESULTS – MOVIE PRE-RELEASE ADVERTISING MODEL: ESTIMATES

	Movie Profit Maximization	Studio Profit Maximization-Quarterly	Studio Profit Maximization-Yearly
Loglikelihood	-1225.39	-1163.46	-1153.61
Mini Majors	**0.34**	**0.38**	**0.39**
Majors	**0.74**	**0.97**	**1.02**
Dra_Per_Rom	**0.27**	0.19	0.16
Com	**0.94**	**0.81**	**0.78**
Thr_Act_Hor_Cri	**1.21**	**1.08**	**1.05**
Ani_Fam_Fan_Sci_Adv	**0.96**	**0.77**	**0.73**
mpaa-G	0.07	0.02	0.03
mpaa-PG	**0.44**	**0.43**	**0.43**
mpaa-PG13	0.18	**0.23**	0.23
mpaa-R	-0.16	-0.07	-0.05
Constant	**-2.69**	**-2.67**	**-2.66**
S.D.	**1.11**	**1.03**	**1.01**

TABLE 4: TOP SELLING DVDS IN 2014 (STATISTA)

	Genre	Mpaa	Dvd Sales (in Million US Dollars)	Box office (in Million US Dollars)
Frozen	Animation, Adventure, Comedy	PG	185.2	400.7
The Hunger Games: Catching fire	Action, Adventure, Sci-Fi	PG13	54.94	424.6
The Lego Movies	Animation, Adventure, Comedy	PG	44.78	257.8
Despicable Me 2	Animation, Comedy, Family	PG	34.89	368.0
The Hobbit: The Desolation of Smaug	Adventure, Fantasy	PG-13	34.77	258.4
Guardians of the Galaxy	Action, Adventure, Sci-Fi	PG-13	31.42	333.1
Maleficient	Action, Adventure, Family	PG	30.17	241.4
Divergent	Adventure, Mystery, Sci-Fi	PG-13	27.65	150.8
Thor: the dark world	Action, Adventure, Fantasy	PG-13	27.38	206.4
How to Train Your Dragon 2	Animation, Action, Adventure	PG	27.3	177.0
Teenage Mutant Ninja Turtles	Action, Adventure, Comedy	PG-13	25.97	190.9
Rio 2	Animation, Adventure, Comedy	G	25.71	131.5
Gravity	Sci-Fi, Thriller	PG-13	24.51	274.1
Heaven is for Real	Drama	PG	24.28	91.4
Lee Daniels' the Butler	Biography, Drama	PG-13	23.83	116.6

FIGURE 1: ESTIMATED STUDIO-SPECIFIC BASELINE DIFFUSION PATTERNS

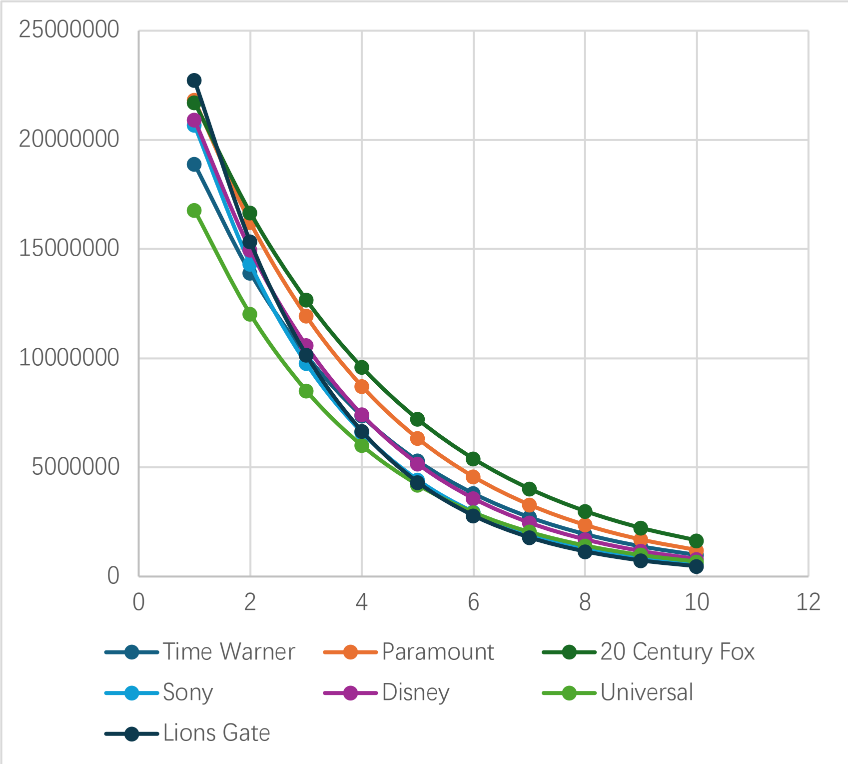


FIGURE 2: ESTIMATED EFFECT OF STAR VALUE ON MOVIE REVENUE

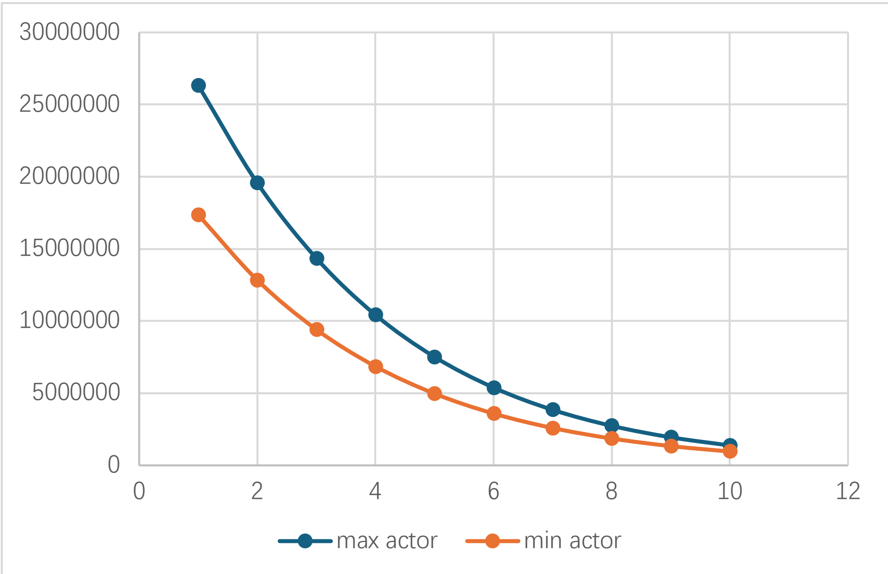


FIGURE 3: ESTIMATED EFFECT OF SEQUEL ON MOVIE REVENUE

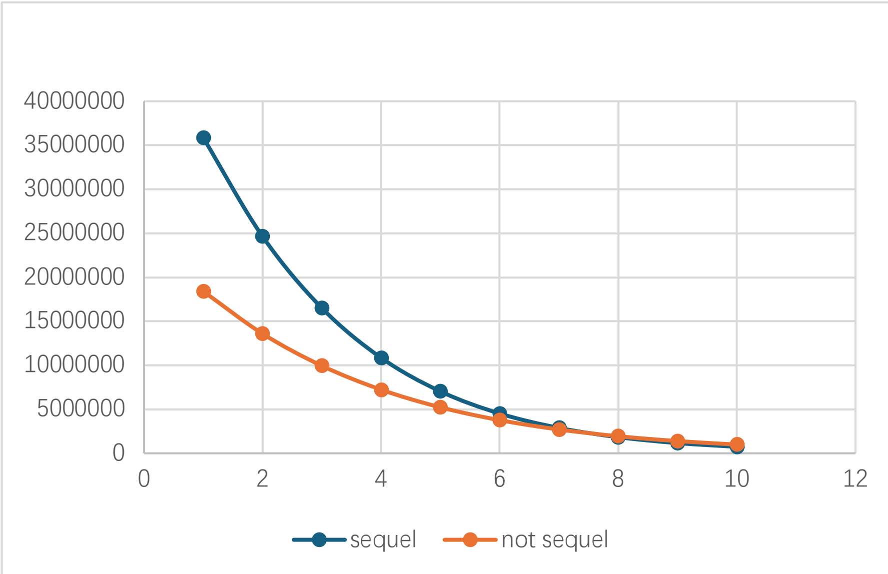
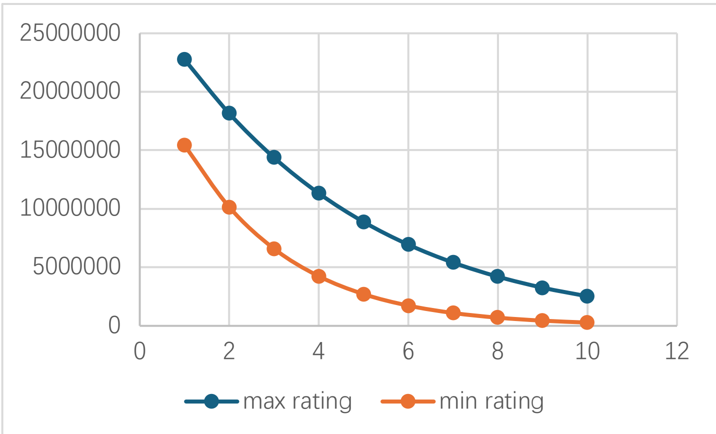


FIGURE 4: ESTIMATED EFFECT OF RATING ON MOVIE REVENUE



Selected References

Ainslie, A., Dreze, X., Zufryden, F. (2005), "Modeling Movie Life Cycles and Market Share," *Marketing Science*, 24, 3, 508-517.

Duan, W., Gu, B., Whinston, A. B. (2008), "Do Online Reviews Matter? An Empirical Investigation of Panel Data," *Decision Support Systems*, 45, 4, 1007-1016.

Einav, L. (2007), "Seasonality in the U.S. Motion Picture Industry," *The RAND Journal of Economics*, 38, 1, 127-145.

Elberse, A. (2007), “The Power of Stars: Do Star Actors Drive the Success of Movies?, ” *Journal of Marketing*, 71, 4, 102-120.

Elberse, A., Anand, B. (2007), “The Effectiveness of Pre-Release Advertising for Motion Pictures: An Empirical Investigation Using a Simulated Market,” *Information Economics and Policy*, 19, 1, 319- 343.

Elberse, A., Eliashberg, J. (2003), “Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures,” *Marketing Science*, 22, 3, 329-354.

Eliashberg, J., Sawhney, M. S. (1994), “Modeling Goes to Hollywood: Predicting Individual Differences in Movie Enjoyment,” *Management Science*, 40, 9, 1151-1173.

Eliashberg, J., Elberse, A., Leenders, M. A. A. M. (2006), “The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions,” *Marketing Science,* 25, 6, 638-661.

Filson, D., Switzer, D., Besocke, P. (2005), “At the Movies: The Economics of Exhibition Contracts,” *Economic Inquiry*, 43, 2, 354-369.

Gordon, B. R., Hartmann, W. (2016), “Advertising Competition in Presidential Elections,” *Quantitative Marketing and Economics*, 14, 1, 1-40.

Heckman, J., Singer, B. (1984), “A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data,” *Econometrica*, 52, 3, 271-318.

Joshi, A. M., Hanssens, D. M. (2009), “Movie Advertising and the Stock Market Valuation of Studios: A Case of “Great Expectations”?,” *Marketing Science*, 28, 2, 239-250.

Krider, R. E., Weinberg, C. B. (1998), “Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game,” *Journal of Marketing Research*, 35, 1, 1-15.

Moul, C. (2007), "Measuring Word of Mouth's Impact on Theatrical Movie Admissions," *Journal of Economics and Management Strategy*, 16, 4, 859-892.

Neelamegham, R., Chintagunta, P. K. (1999), "A Bayesian Model to Forecast New Product Performance in Domestic and International Markets," *Marketing Science*, 18, 2, 115-136.

Prag, J., Casavant, J. (1994), "An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry," *Journal of Cultural Economics*, 18, 1, 217-235.

Radas, S., Shugan, S. M. (1998), "Seasonal Marketing and Timing New Product Introductions," *Journal of Marketing Research*, 35, 3, 296-315.

Raut, S., Swami, S., Lee, E., Weinberg, C. B. (2008), "How Complex Do Movie Channel Contracts Need to Be?," *Marketing Science*, 27, 4, 627-641.

Sawhney, M. S., Eliashberg, J. (1996), "A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures," *Marketing Science*, 15, 2, 113-131.

Sudhir, K. (2001), "Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer," *Marketing Science*, 20, 3, 244-264.

Swami, S., Eliashberg, J., Weinberg, C. B. (1999), "SilverScreener: A Modeling Approach to Movie Screens Management," *Marketing Science*, 18, 3, 352-372.

Zufryden, F. (2000), "New Film Website Promotion and Box Office Performance," *Journal of Advertising Research,* 40, 1, 55-64.