2020

Impacts of a Movie's Rivals' Releasing Decisions on its Domestic Box Office Revenue

Yuanyuan Dong

IMPACTS OF A MOVIE'S RIVALS' RELEASING DECISIONS ON ITS DOMESTIC BOX OFFICE REVENUE

Yuanyuan Dong

Advisor : Randy Nelson

Second Reader: Lindsey Novak

Honor Thesis

Department of Economics

Colby College

May 2020

Abstract

This paper uses the OLS regression model to investigate and quantify the competition effects in the film industry, aiming to help film distributors in the making releasing decision. To do so, I define the movies that release within the same week as rivals and use the rivals' characteristics variables to capture the competition effects. The regression results show that a movie's rivals' total production budgets and the number of opening weekend's theater have significantly negative impacts on this movie's box office revenue. After adding control variables and indicator variables for seasonality, the competition effects become less obvious with less precision. This regression result, however, shows that the attributes of a movie explain the most variance in box office revenue. By interaction term of major distributors and rivals' characteristics variables, I find that major distributors are more vulnerable to the competition effects.

Acknowledgement

I would like to express my deep gratitude to Professor Randy Nelson, my thesis advisor, for his valuable suggestions during this research project. I also would like to thank my second reader, Professor Lindsey Novak, who helps me to construct my project. Finally, I would like to extend my thanks to Manny Gimond, a GIS and Quantitative Analysis Specialist, for helping me with data analysis.

I. Introduction

If you had invested \$1 in Netflix stock in February 2015, this \$1 would be worth approximately \$5 in January 2020. The dramatic increase in the stock price of Netflix exemplifies the development and growth of the streaming entertainment industry. While the emergence of Netflix, Hulu, and Amazon prime allows consumers to watch the films at home immediately after the release of the movie in the theater, this technological development has brought huge negative impacts on the global box office market. The emergence of this streaming industry is also reflected in the U.S box office market. The U.S. box office market had steadily increased since the late 1990s until 2009. After that, the U.S box office market has grown at a decreasing rate. According to Variety (Lang, 2019), the popularity of new platforms, such as Netflix and Hulu, reduces the revenue of exhibitors, commonly referred to as theaters. Besides exhibitors, the film industry consists of two other primary groups of companies: producers and distributors.

Distributors are companies or individuals in charge of marketing and financing a film. They negotiate with exhibitors about allocations of screens and decide the release dates. Does the decline in box-office revenue also reduce the total revenue to distributors? Box-office revenue is indeed a proxy for measuring the performance of a film, even though the revenue generated by new platforms, such as Hulu and Netflix, is not transparent. As Liran (2007) claims, “Maximize domestic box-office revenues seems like a reasonable approximation for the objective function of distributors.” In an attempt to increase box-office revenue, distributors devote a great deal of time and effort in determining when to release a film. The release strategy is vital to the distributors due to the nature of the movie. The movie has such a short life in theaters that the opening week revenue is crucial. Thus, even the major movie studios search for an ideal release

date (Krider and Weinberg, 1998). To increase the opening week's box office revenue, some film distributors even delay films' release dates to avoid potentially strong rivals. Thus, my research question is, "Does the competition effect present in the film industry impact the box office revenue of a film?" Through answering the research question, this paper aims to build a model that helps distributors to make releasing decisions.

Some literature evaluates the effects of competition in the motion picture industry by defining the competition by order of entry and submarket competition (Calantone et al., 2010). For example, films that are released within the same categories or related categories have negative impacts on the new launch of a film. By contrast, this paper defines rivals as movies that release within the same week, regardless of the genres or distributors of the movies. I use U.S. domestic box office revenue to measure the performance of a movie. In order to quantify the rivals' effects on the domestic box office revenue, I develop an OLS regression model that regresses the annual market share of a movie on the total number of rivals' theaters, number of rivals, and rivals' production budget, which capture the competition effect. Since a film is a highly differentiated product, I also add control variables, such as a movie's characteristics and a distributors' characteristics, into regression models. Considering the competition effect, I hypothesize that the number of rivals and the number of theaters of rival movies are negatively associated with domestic box office revenue of a movie. There is a limited number of screens in the theaters each week, and an increasing number of movies released in the same week will influence the screen allocations.

In the previous literature, the movie industry and box office revenue are fully examined. Einav (2007) devoted the whole paper discussing the seasonality of domestic revenue, concluding that numbers of movies that are released have a strong seasonal pattern and the

release decisions have impacts on the seasonality. By measuring theater elasticities of box-office revenue between different movie distributors, we could see the power and impacts of major distributors on the allocations of the number of screens in theaters (Prieto-Rodríguez et al., 2015).

My hypothesis is partially supported by Gutierrez-Navratil et al., (2014), who use the box-office revenues from 2000 to 2009 of five countries to measure and evaluate the competition effects among firms that have similar release dates. In doing so, the number of opening week's screens of rivals, used as a variable to capture competition, is included in their regression models. My paper, on the other hand, includes additional variables that are the number of rivals that release within the same week and the rivals' production budget.

There is also a considerable amount of literature on competition effects in the movie industry. There is a trade-off between "avoid the competition" and capture more revenue in the season (Krider and Weinberg, 1998). Here, the season refers to holidays such as New Year and Christmas. While more people go to cinemas during the season, there is also an increasing number of movies release simultaneously, and thus increases the competition as a result. The literature shows that the box office performance of a movie could be negatively influenced by the other concurrent movie releases that have the same genre and rating (Ainslie et al., 2005). But they also indicate that the traditional models overestimate the impacts of the number of opening week screens on a movie's market share. According to their new model, the opening week screens have an omittable variable influence on a movie's box-office revenue performance.

One major contribution of this paper is that it uses a new methodology to investigate the competition effects in the film market. As Gutietterz-Navaratil et al. (2014) indicate, most literature in the Economic field focuses on the explanatory power of films' characteristics

variables, such as genre, rating, and reviews rather than competition inside the market. Different from Gutierrez-Navratil et al., who use a more complicated system and longitudinal data to explore the temporal competition effects, this paper only uses three major rivals' characteristics variables to capture the competition effects. Thus, by analyzing the association between rivals' characteristics and movies' performance, this paper aims to contribute to the distributors' decision-making process.

By estimating competition effects with rivals' characteristics variables, I find that competition effects are present in the market and negatively impact a movie's box office revenue. After adding control variables and seasonality, the competition effects become less precise, and yet the market share of a movie is mostly explained by these characteristic variables. This result is also in line with the other literature on this topic. Surprisingly, my regression result shows that major distributors are more vulnerable to competition effects. And the competition effects, in fact, have different impacts in different genres.

This paper will be outlined as follows. Section II describes the sources of my dataset and the description of variables that I will use in my regression model. Section III has empirical framework of my regression model. The detailed regression results could be found in section IV, following a section about robustness check. Section VI is an extension on the definition of rivals, and Section VII is discussion on my regression results. The remaining two sections are appendix and reference.

II. Data and Data Description

The dataset used in this paper is collected by OpusData[3]. The initial dataset consists of more than 20,000 movies, including information on production year, running time, sequel, distributor names, opening weekend revenue, inflation-adjusted domestic box-office revenue, and so on. The advantage of using this dataset is that it has information on release dates. In my research, I focus on the movies that were released from January 1st, 2014 to December 31st, 2017. After filtering and dropping the observations with missing values for domestic box office revenue, I am left with 2590 observations(movies). Since the movie industry expands with a non-constant total box office revenue, I need to standardize all movies' box office revenue to assess and compare movies' performance in different years, and thus I construct a crucial variable called "Market Share", which is the dependent variable in the next section. Market Share is a value that is bounded between 0 and 1. In this context, the market share is movie *i*'s inflation-adjusted total domestic box office revenue at week *j*, normalized by the following 52 weeks' aggregate domestic box office revenue. The equation of computing Market Share is illustrated as below:

$$Market\ Share_{ij} = \frac{Box\ office\ revenue\ of\ movie\ i}{\sum_{t=j}^{j+52} aggregate\ box\ office\ revenue\ of\ all\ movies\ at\ week\ t} \quad (1)$$

Here is an example to better illustrate the equation. If a movie released on February 2, 2014, I sum up the box office revenue of movies that release between February 2, 2014, and February 2, 2015, and use it as the denominator of calculating market share.

Since I identify the movies that release within the same week as rivals, I also create three major explanatory variables: the number of rivals, the total number of opening week theaters of a

[3] The Numbers. https://m.the-numbers.com

movie's rivals, and the total production budgets of a movie's rivals. These three variables are the primary independent variables in my research because they capture the characteristics of rivals and rivals' releasing strategies. To better visualize the relationship between primary independent variables and market share, I create two plots (Figure 1 and Figure 2).

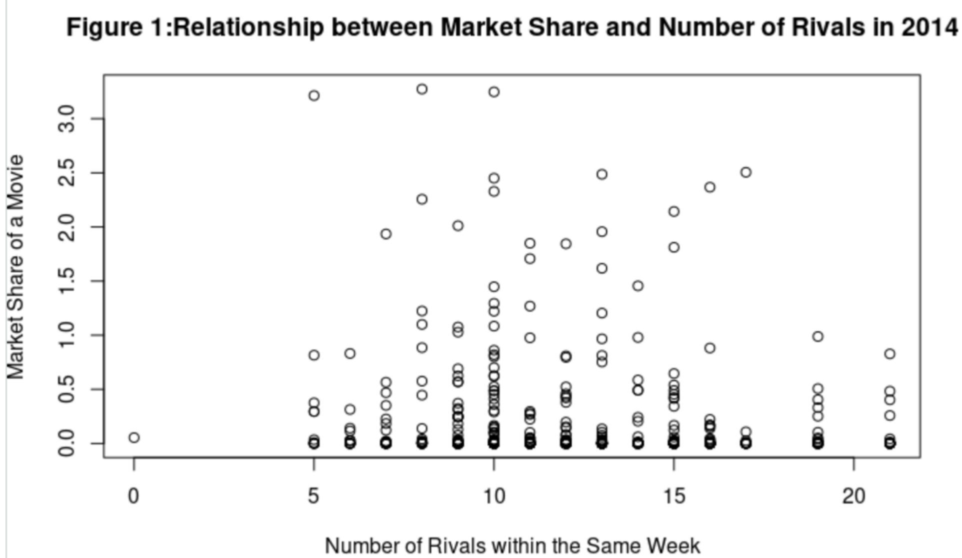

Figure 1. Visualization of relationship between variables. There are about ten or more rivals in most weeks. The movies with high market share only have fewer than ten rivals within the same week. The movies with more than 20 rivals do not have large market shares.

In the Figure 2, some films' total number or rivals' theaters is 0 because some movies are the only ones released during those weeks. Although figure 2 does not show a strong association, this provides preliminary evidence in favor of my hypothesis.

To control for the confounders, I include other dependent variables as well. X is a group of characteristic variables of a movie, such as genre, production budget, sequel, and the number of opening week screens. For genre, I create six indicator variables to capture the effects of the genre: Drama, Documentary, Comedy, Thriller, and Action (each is more than 8%). Considering the difference in the bargaining power of different distributors (Prieto-Rodríguez et al., 2015), I

also create a dummy variable called MajorDistributors, which is set to 1 if the distributors release more than 60 movies over these four years. The summary statistics are shown in Table 1.

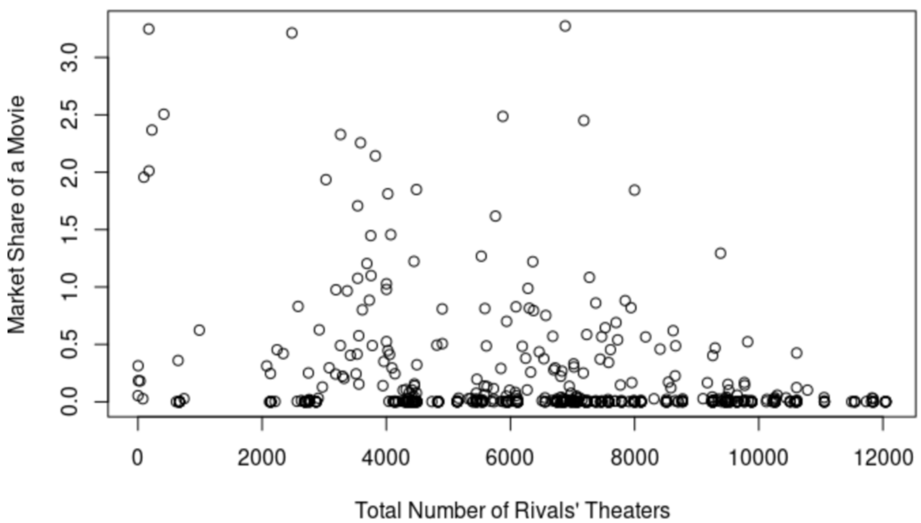

Figure 2. Visualization of the number of rivals' theater and market share in 2014. Total number of rival's theaters negatively associates with the market share of a movie. As the number of rival's theaters increases, the market share of a movie decreases. There are some movies with high market share when the total number of rivals' theaters approach 0.

Table 1: Descriptive Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Inflation Adjusted Domestic Box-Office Revenue	2,590	1.805e+07	5.888e+07	55	1.007e+09
Releasing Year	2,590	2,015	1.104	2,014	2,017
Total Box Office Revenue by Year($)	2,590	1.169e+10	3.061e+08	1.124e+10	1.201e+10
Market Share by Year	2,590	0.00154	0.00503	4.58e-09	0.0838
Total Box Office Revenue by Calendar Year ($)	2,590	1.188e+10	3.663e+08	1.096e+10	1.294e+10
Market Share by Calendar Year	2,590	0.00151	0.00487	4.40e-09	0.0778
Number of Rivals	2,590	12.55	3.612	0	21
Total Number of Opening Weekend Theaters of Rivals(thousands)	2,590	7.271	3.223	0	20.34
Production Budget($ millions)	2,590	12.58	35.99	0	330.6
Total Production Budget of Rivals($ millions)	2,590	146.5	104.0	0	619.5
Number of Opening Weekend Theaters	2,590	602.8	1,213	0	4,529
Sequel	2,590	0.0626	0.242	0	1
Running Time (mins)	2,590	101.9	26.72	0	334
Genre: Drama	2,590	0.3479	0.42	0	1
Documentary	2,590	0.186	0.390	0	1
Comedy	2,590	0.127	0.333	0	1
Thriller	2,590	0.0849	0.279	0	1
Action	2,590	0.0822	0.275	0	1
Others	2,590	0.172	0.378	0	1
Major Distributor (yes = 1, no =0)	2,590	0.419	0.494	0	1
Releasing Year: 2014	2,590	0.246	0.431	0	1
2015	2,590	0.255	0.436	0	1
2016	2,590	0.261	0.439	0	1
2017	2590	0.239	0.430	0	1

III. Empirical Framework

Using the data on the annual market share of a movie, I examine the impacts of rivals' characteristics and rivals' releasing strategy on a movie's box office revenue performance. Based on the previous literature, other variables also have impacts on the box office revenue performance, and thus I incorporate characteristics variables of a movie into the equation as well. I use equation 2 to estimate the competition effects,

$$Market\ Share_i = \alpha_0 + \alpha_1 number\ of\ Rivals_i + \alpha_2 Rivals\ Theaters_i + \alpha_3 Rivals' ProductionBudget_i + \alpha_4 X_i + \varepsilon_i \quad (2)$$

, where market share is a function of a movie i's characteristics, movie i's rivals' characteristics. X_i denotes a group of movie *i*'s characteristics variables. Then, I use an OLS regression model based on this equation to measure the association between competition effects and a movie's performance.

Equation 3 is the full model I use to run the regression. In this case, the main coefficients of interest are β_1, β_2, and β_3 because these three coefficients represent the rivals' major characteristics.

$$Market\ Share_i = \beta_0 + \beta_1 number\ of\ Rivals_i + \beta_2 Rivals\ Theaters_i + \beta_3 Rivals' ProductionBudget_i + \beta_4 I(MajorDistributor_i) + \beta_5\ I(Genre_i) + \beta_6 Opening\ Weekend\ Theaters_i + \beta_7 Production\ Budget_i + \beta_8 I(Sequel_i) + \varepsilon_i, \quad (3)$$

There are some concerns about my dataset and data interpretation: choice of the dependent variable, unobserved heterogeneity, and simultaneity. My dependent variable is used to measure and compare movies' performance. Thus, market share by a year is not the best proxy because of the seasonality of the movie industry. For instance, more consumers go to cinemas during the Thanksgiving break compared to the rest of the year (Einav, 2007). Then, it is not reasonable to standardize by a year's total box office revenue. Instead, I should use the monthly

total domestic box office revenue based on how long the movie is present in the theaters. And yet, my dataset only provides the annual domestic box office revenue of a movie. This measurement error may bias my regression results, and thus I establish the market share by another way in the robustness check section.

Another concern is unobserved heterogeneity because of the nature of the movie industry. The movie is such a highly differentiated and unique product (Gutierrez-Navratil el al., 2014) that my model does not capture all characteristics of a movie. For example, other literature emphasizes the important role star power, movie reviews and advertising (Basuroy et al., 2003) play in determining the box office revenue. None of them is present in my dataset, and thus I could not eliminate the possibility that my regression results are actually driven by these unobserved heterogeneities. These unobserved factors could influence the box-office revenue performance and bias the estimated coefficients of my interest. If a movie's distributor spends more on advertising to signal its competitors then this movie is a strong competitor, fewer distributors will choose to release within the same week, and the movie will earn a bigger share of the market. If so, my regression will bias the coefficient on the number of rivals upward toward zero. This would make the estimated coefficient appear closer to zero than it actually is. And yet this result is caused by the advertising instead of competition effects. To deal with the heterogeneity issues, I create and add dummy variables and interaction terms to my regression models.

Simultaneity is another potential problem, which may lead to bias. Although this paper expects to observe the impacts of competition on market share, there is a possibility that the causality between my dependent variable and primary independent variables is two-way. Notice that the movie distributors may move around the release dates if they think the competition effect

within a particular week is too strong. Then, the box office revenue would not reflect the competition effects and the results may be biased.

Based on my concern and my topic, my ideal dataset will be a movie's monthly domestic box office revenue, an indicator showing the star power, movie reviews, and advertising costs for over ten years. This ideal dataset will help me to create the most approximate variable for measuring the movie's performance and control for the omitted variables.

IV. Results

Table 2 presents the regression results with primary explanatory variables only. I ran the regression with each primary explanatory variable separately and report the results in Column 1, Column 2, and Column 3 of Table 2. From these three columns, the three estimated coefficients are statistically significant with negative signs. An additional rival movie within the same week relates to a 0.00995% decrease in the market share. A 1000 theater increase in the opening weekend theaters of rivals associates with a 0.0251% decrease in the market share of the movie. And a one million dollar increase in the total rivals' budgets relates to a 0.000398% reduction in the market share of a movie. The magnitudes of the estimated coefficients seem to be small, and

Table 2: Primary Independent Variables Results

Dependent Variable: Market Share					
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Rivals Within a Week	-9.95e-05***			-1.86e-05	-7.39e-07
	(2.75e-05)			(2.84e-05)	(2.87e-05)
Total # Opening Weekend Theaters of Rivals(thousands)		-0.000251***		-0.000260***	-0.000276***
		(4.24e-05)		(4.27e-05)	(4.34e-05)
Total Rival's Budget($millions)			-3.98e-06***	8.30e-07	-1.32e-05***
			(1.08e-06)	(8.60e-07)	(2.55e-06)
Total Rival's Budget^2					3.36e-08***
					(6.04e-09)
Constant	0.00276***	0.00334***	0.00209***	0.00351***	0.00437***
	(0.000387)	(0.000358)	(0.000208)	(0.000456)	(0.000522)
Observations	2,590	2,590	2,590	2,590	2,590
R-squared	0.005	0.028	0.007	0.028	0.043

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

yet the result becomes meaningful when I convert the percentage into dollars. As mentioned in the introduction section, the U.S box office market generated $11.9 billion in 2018. Then, an additional rival relates to $11.9 billion· 0.00995% =$1184050 reduction in the box office revenue of a film. Moreover, considering that the average market share from Table 1 is 0.154%, the magnitudes of estimated coefficients are relatively large.

When I run these three variables together, only the total number of opening weekend theaters of rivals is statistically significant (Column 4 of Table 2). Total Rivals' Production Budget even flips the sign, becoming a positive coefficient but is insignificant. This unexpected sign is explained after plotting the relationship between market share and rivals' total production budgets.

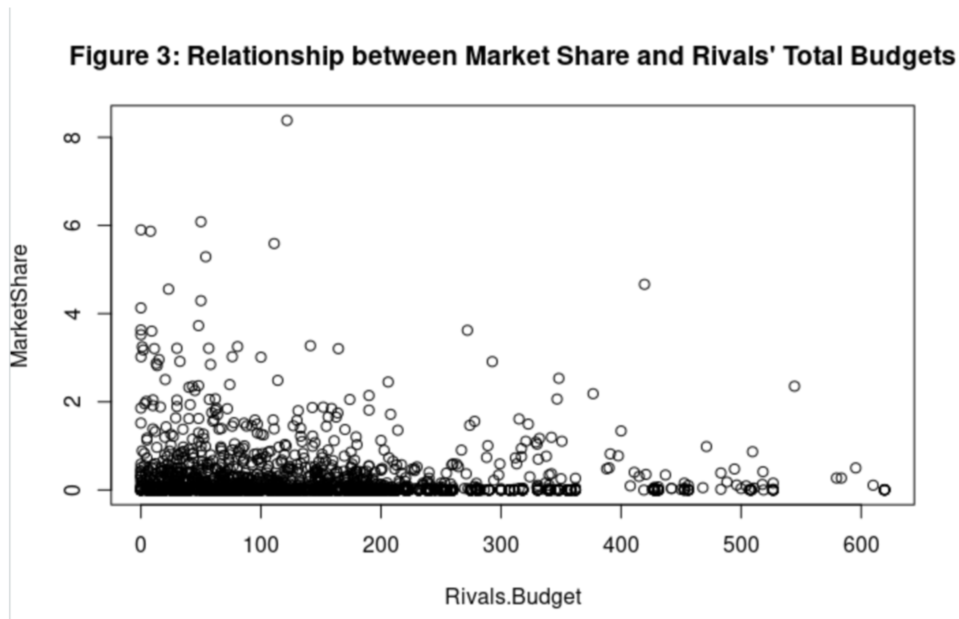

Figure 3. A plot of rivals' total production budgets and market share. There is a negative quadratic relationship between market share and rivals' total production budgets.

Figure 3 shows a quadratic relationship between rivals' budgets and a film's box office revenue, and thus I include a quadratic term of rivals' total production budgets. The result is reported in Column 5 of Table 2. As shown, the primary explanatory variables have negative signs, and two of them are statistically significant. This result demonstrates that the competition effects present in the film industry and shows that this competition has negative impacts on the box office revenue of a movie. The quadratic term of total rivals' production budget is statistically significant with a positive sign, meaning that the total rivals' production budget

negatively impacts the market share at a decreasing rate. The positive value of this quadratic term is reasonable since as the budget of a movie increases, the quality will depend on other factors as well, such as the director and actors.

The results presented in Table 2 support my hypothesis that competition effect presented in the movie industry negatively impact a movie's box office revenue. Since a film is a highly differentiated, these significant results may be due to the difference between movies. Moreover, seasonality plays an important role in determining box office revenue (Einav, 2007). To control for the seasonality effects and heterogeneity, I add movie characteristics and holiday dummy variables to the model. The holiday dummy variables are Memorial Day and Winter Holiday, which include movies that were released between Thanksgiving and New Year.

Table 3 shows that the significant results of Table 2 are heterogeneous across movie type. The first column shows that the total number of opening weekend theaters of rivals and total rivals' production budget stay significant, and genre matters in explaining the market share of a movie. The baseline category here is drama movies. The significant result of other genre variables suggest that the competition effects may differ in different genres; This issue is explored in greater detail in the Extensions section. By contrast, Column 2 shows that when more attributes of a movie are accounted for, the estimate of competition effects in the market becomes less precise. With the exception of the total number of rivals in the theaters, other two primary independent variables now both flip their signs and are not statistically significant. The total number of opening weekend theaters of rivals still has a significant result, but the magnitude of competition effects deceases. And the estimation becomes less precise because the standard error of the estimated coefficient increases from 4×10^{-5} to 2.18×10^{-5}. Notice that a movie's opening weekend's number of theaters has a positive and significant estimated

coefficient. Since a movie's opening weekend theaters is closely related to its rivals' total opening weekend theaters, multicollinearity probably leads to the imprecision.

Table 3: Competition Effects with Attributes of a Film

	Dependent Variable:Market Share		
VARIABLES	Model 1	Model 2	Model 3
Number of Rivals Within a Week	6.61e-06	3.28e-06	1.66e-05
	(2.73e-05)	(1.55e-05)	(1.60e-05)
Total # Opening Weekend Theaters of Rivals(thousands)	-0.000238***	-3.61e-05*	-2.42e-05
	(4.00e-05)	(2.18e-05)	(2.52e-05)
Total Rival's Budget($millions)	-1.03e-05***	7.85e-07	2.54e-06
	(2.27e-06)	(1.42e-06)	(2.00e-06)
Total Rival's Budget^2	2.75e-08***	1.02e-09	-4.71e-09
	(5.42e-09)	(3.32e-09)	(5.23e-09)
Genre: Drama			
Documentary	-0.000523***	9.96e-05*	0.000105*
	(8.06e-05)	(5.67e-05)	(5.67e-05)
Comedy	0.000655***	9.20e-05	6.53e-05
	(0.000171)	(0.000109)	(0.000112)
Thriller	0.000651***	-0.000289*	-0.000274*
	(0.000246)	(0.000166)	(0.000165)
Action	0.00362***	-0.000763**	-0.000707**
	(0.000574)	(0.000370)	(0.000355)
Other	0.00275***	0.000136	0.000112
	(0.000383)	(0.000184)	(0.000183)
Major Distributor(yes=1, no=0)		-0.000168	-0.000183
		(0.000127)	(0.000128)
Running Time(mins)		2.43e-06*	2.12e-06
		(1.33e-06)	(1.33e-06)
Opening Weekend Theaters		7.45e-07***	7.75e-07***
		(1.67e-07)	(1.62e-07)
Production Budget		8.90e-05***	8.83e-05***
		(1.03e-05)	(1.01e-05)
Sequel (yes = 1, no=0)		0.000665	0.000644
		(0.000487)	(0.000483)
Memorial Day =1			0.000139
			(0.000601)
Winterbreak =1			0.000774**
			(0.000391)
Constant	0.00296***	-0.000172	-0.000549
	(0.000437)	(0.000278)	(0.000393)
Observations	2,590	2,590	2,590
R-squared	0.120	0.657	0.658

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Column 3 demonstrates that seasonality plays an important role in explaining the market share of a movie. A movie that releases within winter break realizes a 0.0774% increase in its market share. And yet, the rivals' characteristics variables' estimated coefficients are not statistically significant anymore. Observe that including movie characteristics variables in the model dramatically increases the R-squared from 0.043 in Column 4 of Table 2 to 0.658 in Column 3 of Table 3. That means that the observed movie characteristics help to explain about 65.7% of variation in the market share. Although Column 3 of Table 3 does not support my hypothesis and gives opposite answers from Table 2, the explanatory power of these characteristics variables is shown. And this result agrees with other literature that discusses the impacts of attributes of a movie on its market share.

Table 4: Competition Effects by Major Distributors

	Dependent Variable: Market Share			
VARIABLES	Model 1	Model 2	Model 3	Model 4
Number of Rivals Within a Week	5.09e-06	3.14e-05	1.99e-06	3.58e-06
	(2.83e-05)	(3.43e-05)	(2.83e-05)	(2.84e-05)
Total # Opening Weekend Theaters of Rivals (thousands)	-0.000264***	-0.000264***	-0.000181***	-0.000262***
	(4.27e-05)	(4.27e-05)	(5.14e-05)	(4.29e-05)
Total Rival's Budget($millions)	-1.23e-05***	-1.24e-05***	-1.21e-05***	-1.15e-05***
	(2.50e-06)	(2.51e-06)	(2.51e-06)	(2.58e-06)
Total Rival's Budget^2	3.16e-08***	3.17e-08***	3.14e-08***	3.16e-08***
	(5.93e-09)	(5.93e-09)	(5.99e-09)	(5.95e-09)
Major Distributor (yes =1, no=0)	0.00154***	0.00236***	0.00295***	0.00181***
	(0.000194)	(0.000784)	(0.000711)	(0.000410)
Number of Rivals Within a Week		-6.60e-05		
*MajorDistributor		(5.63e-05)		
Total # Opening Weekend Theaters of Rivals			-0.000195**	
*MajorDistributor			(8.48e-05)	
Total Rival's Budget($millions)				-1.84e-06
*MajorDistributor				(2.17e-06)
Constant	0.00350***	0.00318***	0.00290***	0.00339***
	(0.000525)	(0.000571)	(0.000579)	(0.000537)
Observations	2,590	2,590	2,590	2,590
R-squared	0.067	0.068	0.071	0.068

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

One objective of this paper is to help distributors to choose a release strategy. Since major distributors, such as Walt Disney and Warner Bros, have larger bargaining power in deciding the allocation of the opening week's screens, I include interaction terms between Major Distributor and the primary independent variables to examine whether the small distributors should act differently from major distributors. Table 4 shows that the competition effects are different for major distributors. Column 3 of Table 4 shows that the total number of opening weekend theaters of rivals' impact on the market share does depend on market power of distributors. Surprisingly, this estimated coefficient is negative, meaning that if the distributor of this movie is a major distributor, increasing the total number of opening weekend theaters will have a bigger impact on the movie's market share. This result contradicts my hypothesis and the previous literature, which claims that a major distributor would be less vulnerable to the competition effects. One explanation for this unexpected result is that small distributors has already adjusted their release dates after they know major distributors are going to release within the same week. By doing so, the small distributors already avoid the competition.

V. Robustness Check

As I mention in empirical framework section, there are some concerns about the choice of dependent variable. To check my choice of dependent variable, I use another approach, market share by calendar year, to calculate market share and see how it differs from my original definition of market share. For market share by calendar year, the market share is a movie's inflation-adjusted total domestic box office revenue, normalized by the calendar year's total

domestic box office revenue. The equation of computing Calendar Market Share is illustrated as below:

$$Calendar\ Market\ Share_{it} = \frac{Box\ Office\ Revenue\ of\ Movie\ i\ in\ Calender\ Year\ t}{Aggregate\ Annual\ Box\ Office\ Revenue\ in\ Calender\ Year\ t} \quad (4)$$

I then run the same regressions as before with the calendar market share as the dependent variable and report the results in Table 5. From Table 5, an additional rival relates to $11.9 billion· 0.0105% =$1249500 reduction in the box office revenue of a film, and a one million dollar increase in the total rivals' budget is associated with a $11.9 billion· 0.0260% =$3094000 reduction in the box office revenue of a film.

Regression results in Table 5 and Table 2 are similar. The estimated coefficients of the primary independent variables have the same direction and significance, although the magnitude of the estimated coefficients may differ. The regression results shown in Table 5 suggests that even though there is a data limitation, my definition of market share is the most appropriate given the available data.

Table 5: Compeition Effects with Calendar Market Share

	Dependent Variable: Calendar Market Share				
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Rivals Within a Week	-0.000105***			-2.12e-05	-3.12e-06
	(2.85e-05)			(2.94e-05)	(2.97e-05)
Total # Opening Weekend Theaters of Rivals (Thousands)		-0.000260***		-0.000267***	-0.000283***
		(4.33e-05)		(4.38e-05)	(4.45e-05)
Total Rival's Budget($millions)			-4.12e-06***	8.29e-07	-1.34e-05***
			(1.10e-06)	(8.72e-07)	(2.60e-06)
Total Rival's Budget^2					3.40e-08***
					(6.12e-09)
Constant	0.00286***	0.00343***	0.00215***	0.00363***	0.00450***
	(0.000402)	(0.000367)	(0.000213)	(0.000472)	(0.000539)
Observations	2,590	2,590	2,590	2,590	2,590
R-squared	0.006	0.028	0.007	0.028	0.043

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VI. Extension

In the previous sections, I define the rivals as the movies that release within the same week regardless of genre. Intuitively, the movies within the same genre compete with each other. For instance, an animation that targets children will not compete with a thriller that targets adults because they have different target consumers. It is evident in Column 2 of Table 3 as well, where other types of movies are significantly different from dramas. Thus, it is reasonable to study subsamples of different genres and to compare the regression results to that of the total sample. Table 6 shows the competition effects within drama movies. Table 7 (Appendix) and Table 8 (Appendix) demonstrate the competition effects within Documentary and Comedy, respectively. The choice for these three types of movies is that other genres do not have sufficient sample size to study.

Table 6 : Competition Effects in Drama Movies

	Dependent Variable: Market Share				
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Rivals Within a Week	-4.76e-05**			-2.07e-05	-1.74e-05
	(2.12e-05)			(2.44e-05)	(2.49e-05)
Total # Opening Weekend Theaters of Rivals(thousands)		-6.76e-05***		-8.80e-05***	-9.41e-05***
		(2.49e-05)		(3.12e-05)	(3.13e-05)
Total Rival's Budget($millions)			-3.20e-08	1.55e-06**	-1.63e-06
			(6.31e-07)	(6.81e-07)	(1.48e-06)
Total Rival's Budget^2					7.45e-09**
					(3.44e-09)
Constant	0.00125***	0.00116***	0.000657***	0.00134***	0.00157***
	(0.000298)	(0.000221)	(0.000121)	(0.000307)	(0.000291)
Observations	899	899	899	899	899
R-squared	0.007	0.011	0.000	0.017	0.021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For the drama films that release within the same week, we can tell that the number of total opening weekend theaters of rivals significantly impacts on the market share from Column 5 of Table 6. And yet, documentary films do not show any competition effects (Table 7 in

Appendix). The estimated coefficients of the primary interests do not exhibit any significance. In contrast, the estimated coefficient of the total number of opening weekend theaters of rivals is statistically significant for comedies (Table 8 in Appendix). For thrillers, however, the number of rivals within a week and total rival's budget have a significant impact on a movie's market share. The implication is that competition effects may be present within the same genre, such as drama and thrillers. But the competition effects may present in different forms. Therefore, if distributors observe the same genre movie release within the same week, they should be more careful about their releasing strategy.

VII. Discussion and Conclusion

In this paper, I show how competition effects present in the film industry impacts a movie's box office revenue. By applying the OLS regression model with controlled variables, I find that the total number of opening weekends' theaters of rivals contributes most to the competition effects. In general, competition effects present in the film industry negatively impact the market share of a movie. Adding the characteristics variables of a movie explains the most variation in the market share of a movie. From Table 4, we could conclude that, major distributors are more vulnerable to the competition effects compared to other distributors.

One advantage of my construction of market share is that it is annual. However, I have mentioned that the ideal dataset will be a weekly dataset with the duration of the movies. The weekly dataset will be ideal for academic pursuits. And yet, for distributors who care more about the total box office revenue, the method of building market share is suitable and reasonable.

Moreover, my approach to estimating competition effects is that it is easy for distributors to simulate, and thus they could make decisions regarding releasing dates immediately. And yet the simplicity of my model could also be a limitation. First, it will be easy for all distributors to model without any expenses and adjust their release strategies according to their results. Thus, it will become meaningless to use this model. Second, this model does not explain the endogeneity of the competition effects and the possible simultaneity. If distributors intentionally avoid the competition because they are aware of the competition effects, then these competition effects will not be able to be detected by this model. This also possibly explains the insignificant result of primary independent variables after adding controlled variables.

A small sample size of the subsamples in my extension section is another limitation of my research. There are 899 observations within drama movies, ranging from 2014 to 2017. That means there are about four dramas released within the same week on average. By my definition of rivals, there are three rivals for each movie to study. Thus, it probably not appropriate to drive to a conclusion about how distributors should behave in different genres.

Another limitation is that this model does not take previous week's movies and future week's movies into consideration. Although a film is a short-life product, it still lasts in the theaters for about three weeks. Thus, the future release of a movie and previous week's movies should also have competition effects on the box office revenue.

One direction for future research is to use another way to define the rivals, possibly by ratings. In my study, I do not include ratings. By identifying the competitors by ratings, the subsamples will have more observations because there are only four different ratings. Moreover, I will come up with another way to capture the competition effects instead of using rivals' characteristics variables.

VIII. Appendix

Table 7 : Competition Effects in Documentary

	Dependent Variable: Market Share				
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Rivals Within a Week	-7.88e-07			1.92e-07	8.00e-08
	(2.05e-06)			(2.49e-06)	(2.44e-06)
Total # Opening Weekend Theaters of Rivals(thousands)		-3.33e-06		-2.78e-06	-2.66e-06
		(2.03e-06)		(3.66e-06)	(3.63e-06)
Total Rival's Budget($millions)			-8.27e-08	-3.87e-08	5.00e-08
			(5.19e-08)	(9.26e-08)	(1.61e-07)
Total Rival's Budget^2					-2.21e-10
					(2.59e-10)
Constant	5.01e-05*	6.52e-05***	5.26e-05***	6.46e-05**	5.88e-05*
	(2.70e-05)	(1.98e-05)	(1.25e-05)	(2.94e-05)	(3.23e-05)
Observations	483	483	483	483	483
R-squared	0.000	0.004	0.002	0.004	0.005

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 : Competition Effects in Comedy Films

	Dependent Variable: Market Share				
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Rivals Within a Week	-7.18e-05			-1.48e-05	-9.85e-06
	(4.47e-05)			(5.06e-05)	(4.96e-05)
Total # Opening Weekend Theaters of Rivals(thousands)		-0.000154***		-0.000196***	-0.000199***
		(4.75e-05)		(6.43e-05)	(6.46e-05)
Total Rival's Budget($millions)			-6.30e-07	2.81e-06	1.53e-09
			(1.57e-06)	(1.95e-06)	(4.00e-06)
Total Rival's Budget^2					6.75e-09
					(8.11e-09)
Constant	0.00219***	0.00244***	0.00140***	0.00249***	0.00265***
	(0.000601)	(0.000440)	(0.000292)	(0.000643)	(0.000729)
Observations	329	329	329	329	329
R-squared	0.008	0.031	0.001	0.039	0.041

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 : Competition Effects in Thriller Films

	Dependent Variable: Market Share				
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Rivals Within a Week	6.22e-05			0.000112**	0.000148***
	(5.79e-05)			(5.33e-05)	(5.33e-05)
Total # Opening Weekend Theaters of Rivals(thousands)		-0.000125		-0.000146	-0.000188
		(0.000121)		(0.000142)	(0.000151)
Total Rival's Budget($millions)			-3.28e-06	-4.45e-07	-1.65e-05***
			(2.74e-06)	(2.16e-06)	(6.03e-06)
Total Rival's Budget^2					3.52e-08**
					(1.41e-08)
Constant	0.000615	0.00232**	0.00189***	0.00112	0.00210
	(0.000796)	(0.000969)	(0.000509)	(0.00101)	(0.00128)
Observations	220	220	220	220	220
R-squared	0.003	0.015	0.011	0.024	0.070

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

IX. Reference

Ainslie, A., Drèze, X., Zufryden, F., Dreze, X., & Zufryden, F. (2012). *Modeling Movie Life Cycles and Market Share*. *24*(3), 508–517. https://doi.org/10.1287/mksc.l040.0106

Basuroy, S., Chatterjee, S., & Abraham Ravid, S. (2003). How Critical are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets. *Journal of Marketing*, *67*(4), 103–117. https://doi.org/10.1509/jmkg.67.4.103.18692

Calantone, R. J., Yeniyurt, S., Townsend, J. D., & Schmidt, J. B. (2010). The effects of competition in short product life-cycle markets: The case of motion pictures. *Journal of Product Innovation Management*, *27*(3), 349–361. https://doi.org/10.1111/j.1540-5885.2010.00721.x

Chen, X., Chen, Y., & Weinberg, C. B. (2013). Learning about movies: The impact of movie release types on the nationwide box office. *Journal of Cultural Economics*, *37*(3), 359–386. https://doi.org/10.1007/s10824-012-9189-z

Chisholm, D. C., Fernández-Blanco, V., Abraham Ravid, S., & David Walls, W. (2015). Economics of motion pictures: the state of the art. *Journal of Cultural Economics*, Vol. 39. https://doi.org/10.1007/s10824-014-9234-1

Einav, L. (2007). Seasonality in the U.S. motion picture industry. *The RAND Journal of Economics*, *38*(1), 127–145. https://doi.org/10.1111/j.1756-2171.2007.tb00048.x

Gutierrez-Navratil, F., Fernandez-Blanco, V., Orea, L., & Prieto-Rodriguez, J. (2014). How do your rivals' releasing dates affect your box office? *Journal of Cultural Economics*, *38*(1), 71–84. https://doi.org/10.1007/s10824-012-9188-0

Hennig-Thurau, T., Houston, M. B., & Walsh, G. (2006, October). The differing roles of success drivers across sequential channels: An application to the motion picture industry. *Journal of the Academy of Marketing Science*, Vol. 34, pp. 559–575. https://doi.org/10.1177/0092070306286935

Krider, R. E., & Weinberg, C. B. (1998). Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing. In *Source: Journal of Marketing Research* (Vol. 35).

Lang, B. (2019, March 21). *Global box office flat in 2018, Netflix and subscription services rise in popularity.* Variety. https://variety.com/2019/film/news/box-office-2018-netflix-black-panther-1203168974/

McKenzie, J. (2010). How do theatrical box office revenues affect DVD retail sales? Australian empirical evidence. *Journal of Cultural Economics*, *34*(3), 159–179. https://doi.org/10.1007/s10824-010-9119-x

Prieto-Rodriguez, J., Gutierrez-Navratil, F., & Ateca-Amestoy, V. (2015). Theatre allocation as a distributor's strategic variable over movie runs. *Journal of Cultural Economics*, *39*(1), 65–83. https://doi.org/10.1007/s10824-014-9220-7