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Niklas S. Dürr, Benjamin Engelstätter,
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Zentrum für Europäische
Wirtschaftsforschung GmbH

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Abstract: We investigate how competition in product niches affects the timing of product release for experience goods using data on motion pictures in the United States. Additionally, we attempt to estimate the ultimate gain of this timing. We identify product niches that movies occupy along three different product dimensions: common actor, director, and genre. We estimate the drivers for a motion picture´s weekly sales based on the variation in the level of competition in these particular niches over the movie's run in cinema. We start by showing that release dates of motion pictures are more likely to be rescheduled when there is more competition during the initially proposed release week. Next, we find that competition from movies by the same director or within the same movie genre decreases motion picture's box office revenue most. Finally, we compare a movie's actual sales to estimated sales at the originally planned release date. Rescheduled movies generate about $5.4 million more revenue as they would have at their originally proposed release date.

Keywords: Non-price competition, Niche competition, Strategic timing of entry, Movie market

JEL Class: D22, L21, L82, M31

[♣]Competition and Regulation Research Group, ZEW Centre for European Economic Research, MaCCI Mannheim Centre for Competition and Innovation, Address: P.O. Box 10 34 43, D-68034 Mannheim, Germany, E-mail: duerr@zew.de.

[†] Darmstadt Business School, University of Applied Sciences Darmstadt, Address: Haardtring 100 D-64295 Darmstadt, Germany, Email:benjamin.engelstaetter@h-da.de and ZEW Centre for European Economic Research, Germany

[‡] University of Texas at Arlington, 701 S. West St., Arlington, TX, United States 76019, and ZEW Centre for European Economic Research, Germany.

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”We’ve been waiting six months for DreamWorks to change the date, and they weren’t going to do it,” said one person involved in “Gangs [of New York].” “Everyone talked some sense into Harvey [Weinstein]. We said, ‘We’re not going up against their movie because they will win.’”[1]

1 Introduction

Movies compete for audience attention during a theatrical run of typically 8-10 weeks. When competing movies are too similar, such as sharing the same star cast member, it can be profitable to abandon a proposed release date and opt for later, second-best date. This was the case when two movies starring Leonardo DiCaprio were slated to open Christmas Day 2002. This episode highlights the strategic use of product release date to enter markets when competition is expected to be lighter. This movie strategic ’microscheduling‘ was first proposed in Eliashberg et al. (2006). We investigate movie studios’ choices of the timing of product entry as a potential non-price strategy and answer the research question of how profitable this ’microscheduling‘ can be.

The strategic choice of product release dates is a concern in many industries. The relevant conditions can be characterized as a constant flow of new, limited-lifespan products being released into an uncertain competitive environment. In particular, this describes entertainment industries, such as music, books, video games, or motion pictures. The determination of the appropriate release date for a product must counterbalance two countervailing forces. On the one hand, producers want to publish when demand is especially high, usually during peak seasons. On the other hand, producers wish to avoid the possibly heavy competition from rival products during these periods of high demand. It could be optimal to select an off-peak release date if this means competing against fewer substitutes.

[1] Laura Holson, New York Times, pg. C1, October 11, 2002 (http://www.nytimes.com/2002/10/11/business/miramax-blinks-and-a-double-dicaprio-vanishes.html)

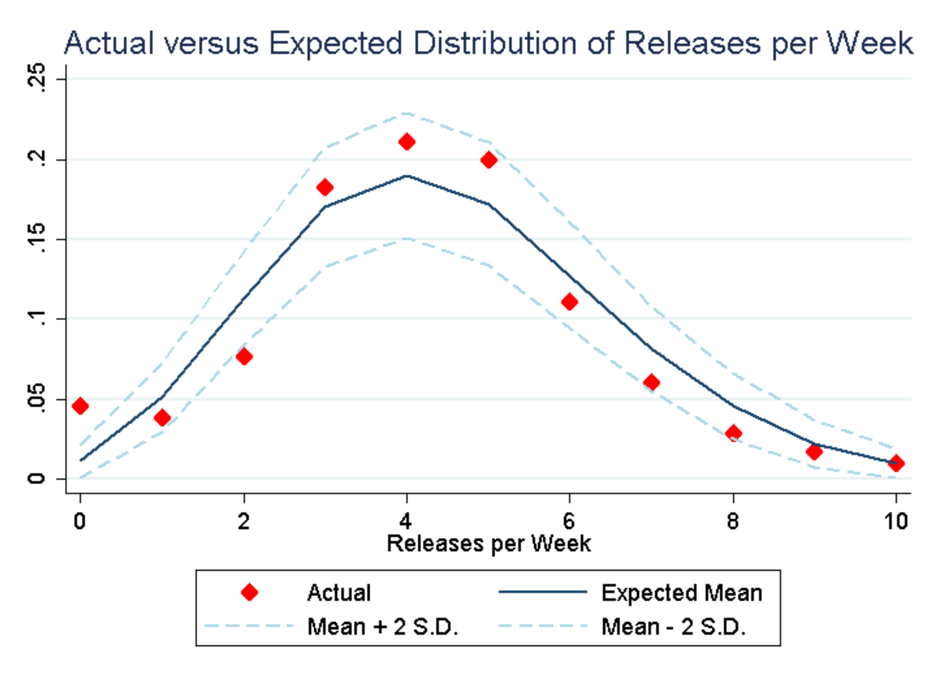
Strategic planning of the release dates is especially prominent in the motion picture industry. Multiple movies are released every week and they have a short window of time to compete for customers. After this lifespan the movie is cycled out of the market and replaced with a new one. In other settings, reducing prices could be used as a mechanism to increase demand of a product at the end of their lifecycle. In the motion picture industry, however, cinemas tend to charge uniform prices regardless of the movie quality or time in theaters (Orbach & Einav, 2007). With such short product life cycles and no price competition, the release date becomes one of the few strategic variables available to the studio. Accordingly, there may be room for additional profitability improvement by the 'microscheduling' of movies.

The pattern of movie releases per week motivates our analysis. How does the pattern of releases per week compare to the pattern if weeks were chosen randomly? If a movie's release date was chosen without reference to other movies' release dates then the number of releases on any week should follow a binomial distribution.[2] In the sample described below, 4.5 movies were released each week on average. We simulated the distribution of movie releases each week under this independence assumption from 500 replications. Figure 1 compares the expected number of movie releases each week to the actual number. The solid line represents the expected distribution while the dashed lines represent two standard deviations above or below the mean. The diamonds represent the actual distribution from our sample.[3] Relative to what would be expected if release date decisions were independent of each other, it appears that the actual distribution puts less weight on weeks with 6 or more simultaneous movie releases and puts more weight on weeks with 3, 4, or 5 simultaneous releases. This is suggestive evidence of movie studio release date decisions being coordinated so as to avoid "too many" competing

[2] In the data below, we cannot reject the hypothesis that the number of releases is constant over the weeks of the year.
[3] We describe our sample in Section 4.

movies opening simultaneously rather than the decisions being independent of each other. Moreover, it suggests that studios coordinate so as to avoid the fiercest competition. Our further analysis tries to confirm this regularity.

Figure 1: Actual versus Expected Distribution of Releases per Week



One complication with the exercise above is that not all movies are equal alternatives to one another. Our approach addresses this issue with a model that features both vertical and horizontal differentiation. Movie reviews, e.g. metacritic[4], provide a proxy for perceived quality while product niches are based on movies with a common genre, common sets of actors, or a common director. In this model, consumers prefer higher quality movies and consider movies within the same niche to be closer substitutes. When considering alternatives to a specific movie choice, consumers may be willing to trade off product quality for product closeness. Thus, movies face most of their competition from higher quality movies within their niche.

[4] See www.metacritc.com

We exploit data on both the characteristics and sales of recent movies and, for a subset of these movies, information on both an initially proposed release date and an actual release date. We hypothesize that, if the competitive landscape looks too daunting on the initially proposed release date, studios will abandon it in favor of another release date. A Probit estimation of initial release date abandonment as a function of expected competition largely confirms this hypothesis. Further, movie ticket sales are adversely affected by greater niche competition.

We then estimate how much changing the release date is worth to the studio. This is simulated for rescheduled movies by comparing the expected sales between the initially proposed release date and the actual release date. To achieve this, we estimate a demand function for movies based on their own characteristics and the characteristics of other currently available competing movies. Since the characteristics of competing movies tend to be more favorable at the new date, the decision to change date tends to increase sales by about $5.4 million.

Our analysis offers three main contributions to the field of product entry decisions in markets with short product life cycles and non-price competition. First, we confirm and quantify the additional profitability by ‘microscheduling’ product releases as conjectured by Eliashberg et al. (2006). Second, we explore drivers for product release date changes with the aid of hypothetical competitive situations. Third, we add to the modelling of competition by establishing niche variables along horizontal product differentiation to model the competitive environment.

The remainder of this paper is organized as follows. Section 2 goes through literature previously published in this field. In Section 3 we provide the description of our model and econometrical approach, followed by a detailed description of the data we utilize in this approach in section 4. In section 5 we present our results and discuss them carefully. Finally, we conclude and point out directions further research in section 6.

2 Previous Literature

The basic assumption in non-price competition applications is that prices are taken as a parameter by each player. So, in order to maximize profits, firms can only adjust the quality of their products or the associated advertising level (Archibald, 1964). Yet, competing in a market characterized by non-price competition is difficult as marginal costs of advertising and quality are higher than marginal cost of production (Stigler, 1968). The reasons for non-price competition are different, for example no price discrimination by regulation or in the case of the movie industry due to an implicit agreement between exhibitor and customer. In an application like this, instead of prices, quality and variety are drivers for demand (Calantone et al., 2010, Hatfield et al., 2012). Non-price competition has been studied in several entertainment industries including video games (Zhu & Zhang, 2010, Engelstätter & Ward, 2013) and books (Chevalier & Mayzlin, 2006, Clay et al., 2002). Other non-entertainment industries where non-price competition has been investigated are (regulated) airline markets (Douglas & Miller, 1974), hospitals (Joskow, 1980), dry cleaners (Plott, 1965), and food retail (Richards & Hamilton, 2006).

Entertainment goods, like movies, are classified as experience goods since their quality cannot be assessed a priori and only usage can reveal their actual quality (Elberse & Eliashberg, 2003). Therefore, critic´s reviews are very important as quality indicators and decision supporters because moviegoers want to decrease uncertainty and want to make sure not to attend a motion picture that does not meet their expectations. Basuroy et al. (2003) observes a dual role of critic´s reviews since they are influencers and as well predictors of revenues.

The market for motion pictures is also subject to strong seasonal fluctuations. Einav (2007) identifies two peak seasons within one year, summer time and Christmas. He observes that the strongest movies are released during peak seasons. Accordingly, seasonality reflects both a deviation in the underlying demand pattern but also a change in the movies´ quality. The underlying differences in demand are exogenous to firms’ decisions while the systematic differences in quality over the year result from firm decisions. Einav (2007) observes that one third of the seasonality can be attributed to quality differences. This result, and the lack of price competition, imply that choosing the appropriate release date is important to profitability (Einav, 2007).

This tradeoff is studied in detail by Weinberg & Krider (1998) in their motion picture timing game. The authors also distinguish two high seasons, Christmas and the summer holidays and most blockbusters are released in either one of these peaks. The authors show that at least one movie should open at the beginning of the peak season. Considering two competing movies, it has to be the stronger one which should claim the earlier release date. Furthermore, the authors suggest that strong movies should compete head to head during peak seasons in order to capture as much of the demand rather than to shy away from each other. Belleflamme & Paolini (2015) build upon Weinberg & Krider’s approach by establishing a first stage to their model where producers can invest into a movie’s attractiveness. What follows is a two-stage game with staggered releases due to asymmetric investments in the first stage. The firm investigating less would then delay the release. This is in line with the finding that there is a negative interaction effect between order of entry and market share (Kalyanaram et al., 1995). On average, earlier entrants obtain a higher market share. This finding is also supported by Szymanski et al. (1995). Finally, Einav (2010) finds that movies are clustered too heavily around peak seasons and distributors could increase sales by spreading their releases. Our work attempts to estimate what actually has been gained by refraining from the initially planned release date.

3 Empirical methodology

The aim of our empirical approach is threefold. First in section 3.1, we identify drivers for release date changes with the help of the hypothetical release date. In section 3.2, we identify drivers for weekly sales. Here we show the impact of the competition a movie is facing and establish the direction of correlation of the covariates. As a final step in section 3.3, we perform a simulation in which we assess a hypothetical scenario that can be seen as a counterfactual and allows us to estimate the value of changing the release date.

3.1 Abandoning a Scheduled Release Date

We hypothesize that a studio is more likely to reschedule the release of a movie if it learns that the competition on the proposed date would be stronger. We are able to test this because we observe an initially proposed release date and an actual release date for a subset of movies. Our tests center on estimating how the likelihood of abandoning an initial release date is affected by measures related to the expected competition on that date. Our competition measures exploit both the horizontal and vertical nature of product differentiation by focusing on competing movies that have to have higher quality and share product characteristics with the focal movie.

We use the Probit estimator to model movie rescheduling due to expected competition. The independent regressors include the characteristics of the focal film as well as measures related to the expected quality of movies with similar characteristics of the focal film. The variables measuring competition are all constructed for the initially proposed release date. Specifically, our estimating equation is the following:

$$\text{(1)} \quad Resched_i \sim \Phi(\alpha_1 AllQual_i + \alpha_2 RecentQual_i + \alpha_3 ActorQual_i + \alpha_4 DirQual_i + \alpha_5 GenreQual_i + \alpha_6 FocalQual_i + \alpha_7 FocalBudget_i + \delta X_i)$$

Our measure of an individual movie's expected quality is an aggregation of online reviews. We aggregate these into $AllQual_i$ for all movies in theaters for the week that the focal movie is initially scheduled to be released. Because ticket sales decline quickly, we allow for a larger competitive effect from recent movie releases. Consequently, we construct $RecentQual_i$ as the average quality of movies released within four week prior to movie *i*'s initially proposed release date. We construct $ActorQual_i$, $DirQual_i$, and $GenreQual_i$ as the average quality of all movies in theaters the week that movie i was released that overlap with the focal movie's principal cast members, director, and genre. Essentially, we interact movie quality with an indicator variable for each type of overlap before calculating the average. Our tests of hypothesis is that each of α_1 through α_5 are positive. Since stronger movies are less likely to reschedule (Weinberg & Krider, 1998) we include the quality and budget of the focal movie ($FocalQual_i$ and $FocalBudget_i$) to allow for more scheduling commitment for bigger movies (Fudenberg & Tirole, 1984). Finally, we include dummy variables X_i to control for seasonality and indicator variables for interactions. It would be preferred to include the characteristics of the movie at the time the rescheduling decision takes place. However, these characteristics are only observed by the econometrician at the time of actual movie release as revealed in publicly available data. It is likely that the players in this 'microscheduling' game are aware of both the characteristics of their own productions and their rivals' projects at the time of the rescheduling. Under the assumption that rescheduled movie characteristics do not change much, the characteristics revealed later are a good proxy for the information available to the game participants.

3.2 Descriptive sales estimation

The above analysis tests whether movies are rescheduled for competitive reasons. Here in turn, we attempt to estimate how much such a rescheduling might earn a movie studio. To accomplish this, we estimate movie ticket sales as a function of both movie characteristics and the competitive strength of alternative movies in theaters at the same time. For this analysis, we use the actual release dates whether the movie was rescheduled or not. We then use these parameter estimates to forecast what a rescheduled movie's sales would have been, had it not been rescheduled. Comparing the forecasts for the actual and these hypothetical release dates generates a change in sales due to rescheduling.

Our specification for estimating the effect of competition on movie sales uses the competition measures described above. However, now we observe multiple observations for each movie representing sales for the different weeks of its theatrical run. While the focal movie's characteristics do not vary over the theatrical run, the effect of competition does as new movies are released and others finish their runs. This change in competition across the different weeks during a movie's run allows us to identify the competition parameters. Similar to above, we hypothesize that greater competition from higher quality movies that share product characteristics will depress sales. Our estimating equation is:

$$\begin{aligned} Ln(Sales_{it}) = \quad & \beta_1 AllQual_{it} + \beta_2 RecentQual_{it} + \\ & \beta_3 ActorQual_{it} + \beta_4 DirQual_{it} + \beta_5 GenreQual_{it} + \\ & \beta_6 FocalQual_i + \beta_7 FocalBudget_i + \gamma X_{it} + \varepsilon_{it}. \end{aligned} \tag{2}$$

The natural logarithm of weekly sales for movie i in week t is regressed against the same variables as above. However, our control variables X_{it} now also include time trends for the number of weeks on the market. In order to allow for a non-linearity decay in sales over the theatrical run, the time trend also enters as a quadratic.[5] Analogous to above, tests of our hypothesis is that $\beta_1$through β_5 should be negative.

Note that we do not refer to equation (2) as a structural demand function. First, the specification allows for factors that shift demand but not for reactions to price changes. We do not include a price variable mainly because there is almost no variation in prices across movies or over the theatrical run. Second, the omission of price does not mean that the estimates are bias free. This is because, if 'microscheduling' is important, movies will not be released during weeks when the expected competition is strongest. Instead, they will be rescheduled to a week with less overlap with competing movies. This could imply that we will observe higher sales occurring in periods with less competition by construction. Thus, the error term is correlated with the regressors which can lead to biased coefficient estimates.

It may be possible to address another potential source of estimation bias due to endogeneity in our model. Movies with larger production budgets tend to have higher quality production inputs. These could be better or well-known actors that draw larger audiences, more and better special effects, or more spectacular images from filming on location. At the same time however, for movies that are expected to draw larger audiences, the marginal value of these inputs might be higher. If so, the causality could be reversed with higher expected sales being correlated with both higher actual sales and higher budgets.

We address this form of potential endogeneity with a Two-Stage Least Squares (2SLS) model, relying on binomial estimation. In the first stage, we include distributor location dummies as instrumental variables for $FocalBudget_i$.[6] Movie production largely takes

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[5] In unreported specifications, we also included dummies for the playing week. The estimates for the competition variables are virtually unchanged.

[6] In most cases, the distributor is also the production company. To be a valid IV, the distributor location dummies need only to be correlated with a movie's budget. So long as they are not "weak" any mismeasurement does not bias the results.

advantage of locally sourced inputs including the technical crafts, e.g. wardrobe, makeup, set production, lighting, and sound and service industries e.g., catering, transportation. The state in which a distributor primarily operates impacts the budget available through clusters and connections, but should have virtually no impact on the sales of a particular movie in the second stage. Hence, our first-stage regression becomes:

$$FocalBudget_i = \gamma_1 AllQual_{it} + \gamma_2 RecentQual_{it} + \gamma_3 ActorQual_{it} + \gamma_4 DirQual_{it} + \gamma_5 GenreQual_{it} + \gamma_6 FocalQual_i + \sum_s \phi_s state_i^s + \theta X_{it} + \mu_{it}. \tag{3}$$

We modify equation (2) to add the $Control\_Function$ which are the predicted residuals from the first stage.

$$Sales_{it} \sim exp(\beta_1 AllQual_{it} + \beta_2 RecentQual_{it} + \beta_3 ActorQual_{it} + \beta_4 DirQual_{it} + \beta_5 GenreQual_{it} + \beta_6 FocalQual_i + \beta_7 FocalBudget_i + \lambda X_{it} + \beta_8 Control\_Function_i). \tag{4}$$

Estimates from Equation (4) should contain less bias than those from the specification represented by Equation (2). Ultimately, we are not primarily interested in identifying the coefficients exactly but rather want to find a model that fits the data best to make meaningful predictions in our counterfactual analysis we describe in the next section. Therefore, and due to the lack of better identification strategies, we can only accept coefficients that are meaningful in direction and size.

3.3 Prediction

We use our estimates of how competition affects sales from Equation (4) to estimate the effect that rescheduling movie releases had on sales. Under the assumption that distributors who reschedule their movie are comparable to “price takers” (Einav 2007) in a sense that they take the un-rescheduled movies as given, we hypothesize that rescheduling the release date increases sales. We also abstract from distributors managing several movies at each point in time and assume that the distributors optimize the sales of each movie individually. For rescheduled movies, we can compare the sales predicted by Equation (4) on the actual release date with the sales predicted on the initially proposed release date. One would see an increase in sales if variables measuring the competitive threat are more favorable on the new date than the abandoned date. It would further confirm that, not only was the competitive threat higher than normal on the initial date, but also that the studio sought out a week with a smaller competitive threat.

Our test of hypothesis is that predicted sales of rescheduled movies increase because of the rescheduling. This is accomplished by replacing the values of the competition variables from the actual week of release with the values from the initially proposed week. If rescheduling was motivated by seeking a more favorable competition situation, then the sales for rescheduled movies should be greater on the actual release date than on the initially proposed release date.[7]

4 Data and variables

Our analysis makes use of a unique micro-level dataset created by merging three different data sources. The basis is the Internet Movie Database (IMDb)[8] from which we obtained for each movie: weekly revenues, movies' budget, the sets of actors, director, and the movies' genres. We merge these data with quality ratings from Metacritic, an online review aggregator.[9] Metacritic reports different ratings by professional reviewers from online and offline sources into a single cardinal value, where 100 represents the best and 0 the worst possible outcome. An important point to mention is that professional reviewers give all these

[7] Because our dependent variable is in logarithms, we adjust the predicted values by its variance (Cameron & Trivedi, 2009)
[8] http://www.imdb.com/ (last accessed on 19 December 2017)
[9] http://www.metacritic.com/ (last accessed on 19 December 2017)

reviews in advance, so that we do not face any problems of reverse causality due to better reviews stemming from higher selling movies. Finally, we add release date information from Box Office Mojo[10]. Box Office Mojo lists initially planned and finally realized movie release dates. This allows us to identify which movies' release dates were rescheduled and to distinguish both the initially proposed and actual release dates. Please note that we consider a movie only as rescheduled if the initially planned and actual release dates are exactly known. For example if only a month or a season like 'October' or 'Fall' is listed as initial release date, we do not consider this eligible for a change in the release date. We make this assumption because an imprecise initial release date does not reflect as strong of a commitment to a particular date. At the point in time when only a season or month is mentioned, expectations are not firm. Additionally, as a practical matter, in such cases we cannot attribute hypothetical competition to a specific date. We also ignore possible dates that might be posted between the first and final release date. We hypothesize that these are intermediate stages between the first (random) and the equilibrium outcome. Accordingly, when testing for gains with these intermediate dates, these should be between zero and the maximum under the equilibrium outcome.

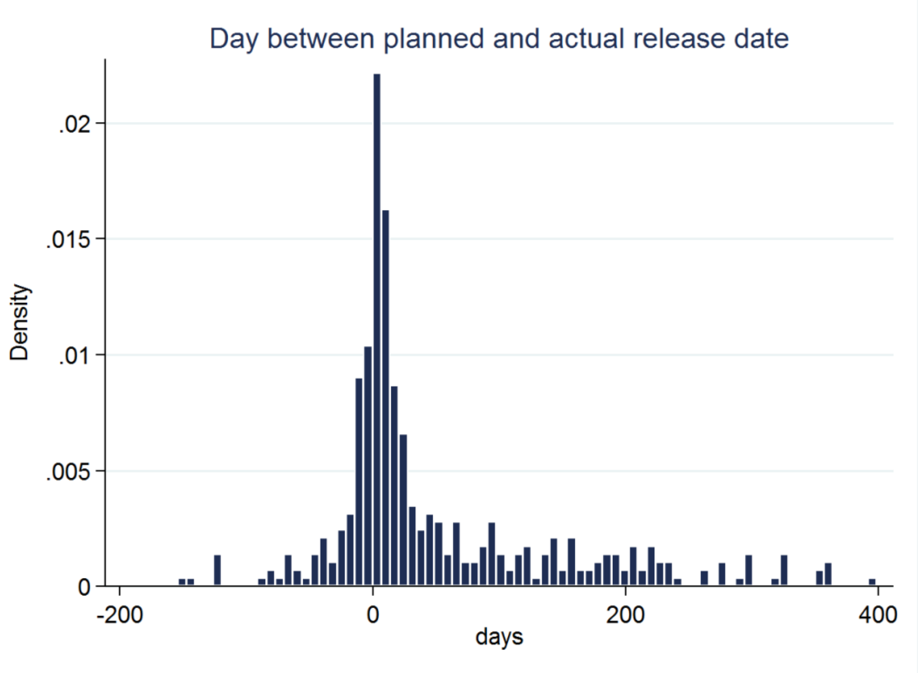
Our data represents a panel spanning January 1, 2006 to January 17, 2014 and is restricted to the U.S. market. Our starting point is a sample of 2,732 movies from IMDb which received a Metacritic Rating. Usually, movies with small sales tend to not receive a Metacritic Rating. Box Office Mojo reported release date information for 2,567 of these movies and movie budget information was reported for 1,653 of these movies. The information from Box Office Mojo is crucial for our analysis as we need to know the release date changes. Movie ticket sales information is available for each movie so that these 1,653 movies generate an unbalanced panel

[10] http://www.boxofficemojo.com/ (last accessed on 19 December 2017)

of 17,932 movie by week observations. We restricted the time in cinema to half a year, i.e. 26 weeks, resulting in 17,764 weekly observations for our final sample.[11]

For some analyses, we restrict the sample to exclude movies whose release was postponed. Rescheduling a movie's release could be for non-strategic reasons. For example, unforeseen delays in the production schedule could make it impossible for a producer to meet the initially proposed release date. In such cases, postponing could be for either strategic or production delay reasons. However, it is less likely that an unanticipated hastening of production causes a movie to be released prior to its initially proposed release date. Thus, a sample that excludes postponed rescheduled releases will contain a large fraction of movies that were rescheduled for strategic reasons. Figure 2 indicates that most rescheduling is toward later release dates where each bar represents one week. The sample excluding postponed movies features 282 movies and 3,203 movie by week observations.

Figure 2: Days between planned and actual release date (excluding non-rescheduled movies)



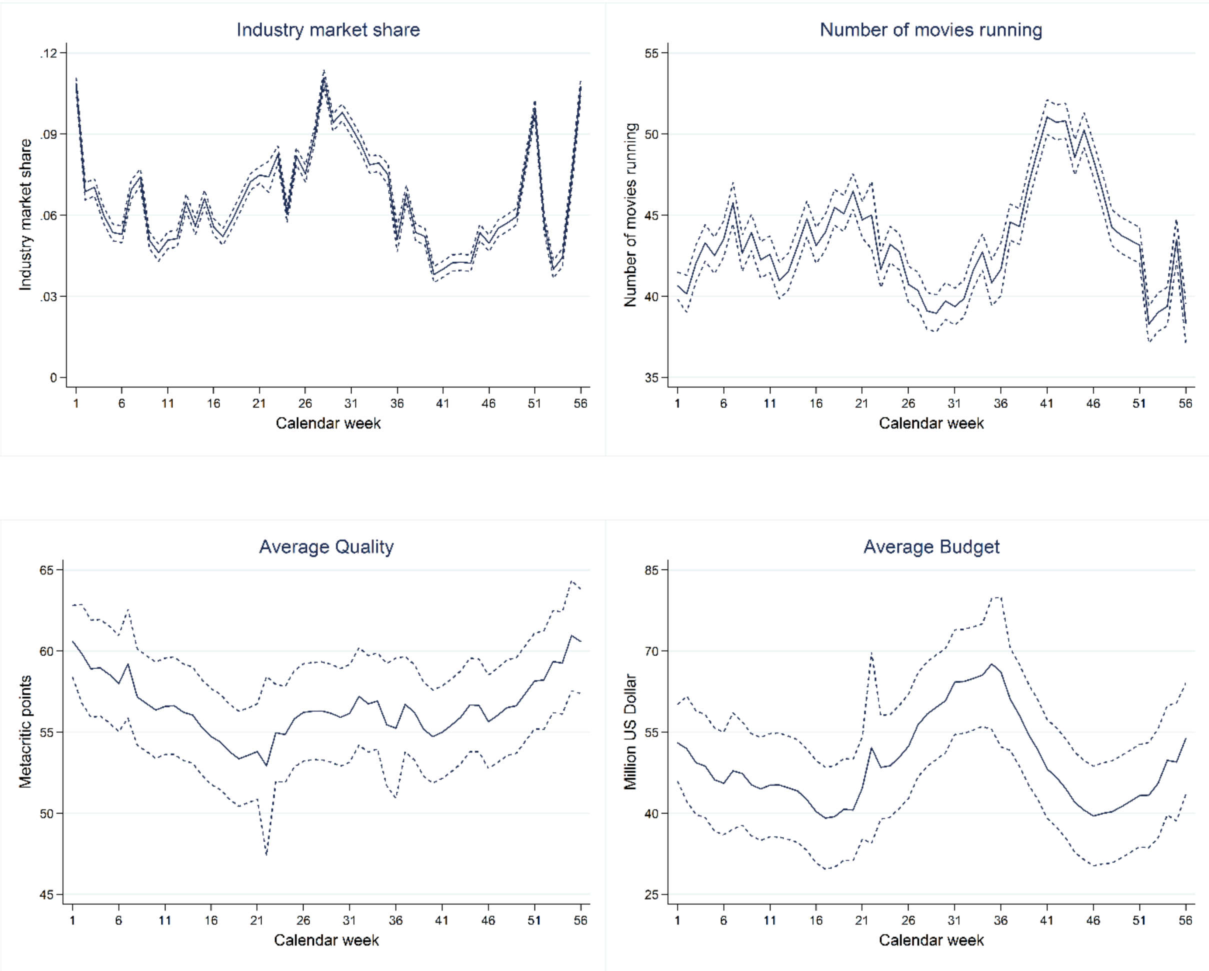
[11] Only 2 percent of all movie releases have theatrical runs of more than 26 weeks. These tend to be children's (animation) movies and even they receive the bulk of their sales during the first few weeks.

Each movie observed is described by four variables key to our analysis. The dependent variable in Equation (1), $Resched_i$, equals one for movie *i* if Box Office Mojo indicates the movie was released on a date different from its initially proposed release date and zero otherwise. We also set this to zero for the 60 movies with no information on an initially proposed release date. The dependent variable in Equations (2) and (4) is the weekly revenues in millions of US dollars for a movie in all US movie theaters. We identify $FocalQual_i$ with the movie's Metacritic rating and $FocalBudget_i$ with the movie's overall budget in millions of US dollars.

In addition, we construct five variables to measure the competition the focal movie would face. The variable $AllQual_{it}$ is the average quality (i.e., Metacritic rating) of all movies currently showing in theaters in week *t* and $RecentQual_{it}$ is the average quality of movies released on week *t* or within four week prior to *t*. We construct three variables to capture competition from more similar movies. The variable $ActorQual_{it}$ is the average quality of movies showing at time *t* that share a common principle cast member as movie *i*. We define this principle cast members as the actors listed as 'stars' on IMDB as those represent the relevant 'brand' differentiating a movie from its competitors. Similarly, $DirQual_{it}$ is the average quality of movies showing at time *t* that were directed by the same director as movie *i* and $GenreQual_{it}$ is the average quality of movies showing at time *t* that share a common genre designation as movie *i*, e.g. comedy, action or horror. Our data sometimes features no shared actor or director. To indicate these cases we construct an overlap dummy that is one if there is an overlap and zero otherwise.

The different analyses require control variables, X_{it}. We account for general seasonality in both the demand and supply with week-of-year dummy variables. Figure 3 provides an overview of this seasonality. The upper left hand side graph shows the average industry market share in the US. Industry market share peaks on July 4th, Thanksgiving and Christmas. In order to make sure that these major holidays fall into the same calendar week each year, we inserted buffer weeks when needed. Hence, there are 56 weeks reported in Figure 3. This approach follows Einav (2007). The following three graphs show comparable patterns, however the numbers are not as sharply distinguished from week to week as the industry market share because movies tend to stay in theatres for several weeks.

Figure 3: Seasonality*



* The solid line is the average for the week and the dotted lines are the 95 percent confidence intervals.

Table 1 summarizes the sales data. The average movie had $4.49 million in sales on an average week. The maximum of $218 million was for the opening weekend of 'Transformers: Revenge of the Fallen' in 2009. One-quarter of all movies were rescheduled. Metacritic ratings, which can take on values between 0 and 100, had an average of 56 with a maximum of 96 (‘Ratatouille’ 2007, ‘Gravity’ 2013) and a minimum of 7 (‘Miss March’ 2009).

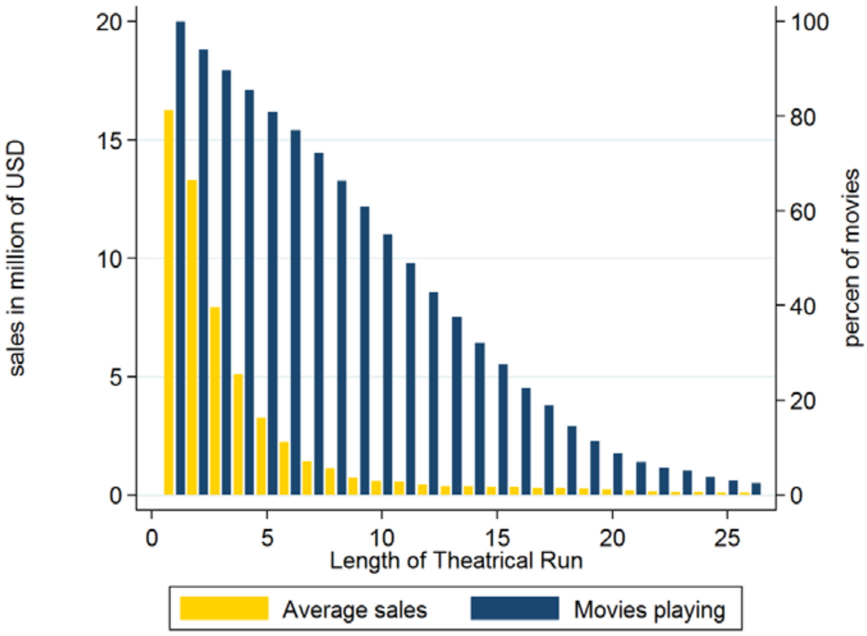
Table 1: Summary Statistics

	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
	Entire sample 17,764 Obs.				Exclude Postponed Releases 14,561 Obs.			
Weekly sales in millions	4.49	12.81	0.00	218.00	4.37	12.60	0.00	189.00
Rescheduled release date	0.27	0.44	0.00	1.00	0.11	0.31	0.00	1.00
Quality	56.38	17.58	7.00	96.00	56.85	17.41	7.00	96.00
Budget in millions	49.41	57.99	0.00	339.00	47.50	57.09	0.00	339.00
Week since release	7.70	5.37	1.00	26.00	7.69	5.39	1.00	26.00
Quality of recent releases	55.88	4.27	0.00	96.00	55.89	4.19	0.00	96.00
Quality all concurrent movies	59.14	2.24	43.77	74.00	59.11	2.24	43.77	74.00
Quality same actor	24.95	30.47	0.00	97.00	22.78	29.95	0.00	97.00
Overlap same actor	0.43	0.50	0.00	1.00	0.39	0.49	0.00	1.00
Quality same director	10.34	23.76	0.00	95.00	6.99	20.29	0.00	95.00
Overlap same director	0.17	0.38	0.00	1.00	0.11	0.32	0.00	1.00
Quality same genre	57.28	4.61	0.00	83.00	57.18	4.63	0.00	83.00

Recent releases had a smaller average quality than all competing movies which is consistent with better movies having longer theatrical runs. Quality actor niche and quality director niche have with 24.94 and 10.34 points a smaller average as quality genre niche with 57.28. This is due to the fact that competition is less frequently observed in these niches and then set to zero. The maximum of the actor niche is with 97 points higher as the quality itself. The reason for this peculiarity is that we first calculated the average niche competition before excluding movies without the entire range of information thereby using as much information as possible in the econometrical analysis.

In the sales estimations, we also account for the decay in movie sales over the theatrical run with a variable measuring weeks since release and its square. Average movie sales fall precipitously over its theatrical run. Typically, a movie generates most of its sales in its release week with a steady decline in the following weeks. As sales taper off, some theaters stop showing the movie. The blue bars in Figure 4 show the distribution of the length of theatrical runs. The percentage of movies with ever longer theatrical runs declines steadily with no more than 2 percent having runs longer than 26 weeks. The yellow bars in Figure 4 display average weekly dollar sales. Average sales fall per week not only because fewer movies have long theatrical runs, but also because sales per week decline conditional on the movie still being shown in theaters.

Figure 4: Average sales & number of movies over theatrical run



5 Estimation results

In the following three subsections we present the respective results of the estimations and the simulation laid out in section 3. To summarize, we find that rescheduling is related to stronger competition, that sales fall with stronger competition, and that rescheduling results in a 7 percent increase in sales.

5.1 Rescheduling

In Table 2, we report the coefficient estimates for the release date rescheduling analysis following equation 1. The first three columns include all movies while the next three exclude movies with postponed rescheduled release dates. Recall that postponed releases are more likely to have been caused by production delays as described earlier. Thus, we expect stronger strategic effects to be present in columns (d) through (f). Indeed, we see stronger strategic effects in the larger and more significant coefficients for the competition variables.. In addition, columns (b) and (e) exclude the focal movie's budget and columns (c) and (e) include dummy variables for the different movie distributors to control for some studios being better at movie production. In columns (c) and (f) we also include the aforementioned overlap dummies for actor and director.

The coefficient for quality is negative, meaning that the higher the quality of a movie, the less likely it is to be rescheduled by the distributor. This coefficient shows that the distributors know the quality of their movies very well and can judge whether to release as planned or find another releasing date. This finding is consistent with distributors' strong movies competing head to head while weaker movies being more likely to delay their release as proposed by Weinberg & Krider (1998).

Table 2: Probability of release date change

Probit	(a)	(b) All Movies	(c)	(d)	(e) Postponed movies excluded	(f)
Quality	-0.0094***	-0.0099***	-0.0007	-0.0209***	-0.0210***	0.0054
	(0.0024)	(0.0025)	(0.0029)	(0.0056)	(0.0056)	(0.0070)
Budget		0.0029***	0.0013		0.0014	-0.0012
		(0.0008)	(0.0012)		(0.0018)	(0.0029)
Quality young comp.	-0.0269**	-0.0306***	-0.0466***	0.0165	0.0138	0.0237
	(0.0112)	(0.0115)	(0.0131)	(0.0429)	(0.0426)	(0.0512)
Quality all comp.	0.0034	0.0090	-0.0066	-0.0609	-0.0565	-0.1686***
	(0.0242)	(0.0240)	(0.0244)	(0.0516)	(0.0501)	(0.0584)
Quality Actor Niche	0.0030**	0.0025*	-0.0051	0.0077***	0.0074**	-0.0246**
	(0.0015)	(0.0015)	(0.0051)	(0.0029)	(0.0029)	(0.0104)
Overlap Actor niche			0.3750			1.9625***
			(0.3002)			(0.6284)
Quality Director Niche	0.0293***	0.0289***	-0.0060	0.0530***	0.0527***	-0.0146
	(0.0026)	(0.0027)	(0.0079)	(0.0051)	(0.0050)	(0.0141)
Overlap Director Niche			2.1758***			4.8056***
			(0.4680)			(0.8571)
Quality Genre Niche	0.0335***	0.0422***	0.1070***	0.0694***	0.0724***	0.2071***
	(0.0097)	(0.0102)	(0.0147)	(0.0212)	(0.0221)	(0.0417)
Week & year dummies	yes	yes	yes	yes	yes	yes
Distributor, Genre & MPAA Dummies	no	no	yes	no	No	yes
Pseudo R^2	0.2418	0.2479	0.3331	0.6199	0.6206	0.7579
# Obs.	1,653	1,653	1,653	1,370	1,370	1,370

Dummies are included for director, actor, and genre, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The variables representing competition from the most similar movies all have the expected sign and are largely significant. This indicates that movies, which would face higher quality close substitutes, are more likely to reschedule. These effects are larger for genre and director similarity. These results indicate that distributors anticipate how the competitive landscape is shaping up and act according to this anticipation to insure more favorable competition for their movie. This shows that the competition from overlapping movies is important to distributors when deciding to reschedule the release date. The marginal effect at the mean for the actor, director and genre niche when the quality increases by one percentage point and the overlap dummy is held constant is 0.56 (significant at the 5 percent level), 3.98 and 11.86 (both significant at the 5 percent level) percent respectively. If the quality in the actor or director niche increases by one standard deviation, the probability that a movie is rescheduled increases by 8.39 and 66.87 percent. In contrast if there is one standard deviation change in the quality of movies in the genre niche, the probability of rescheduling increases by 47.42 percent. This indicates that director and genre similarity are more important drivers for a change in the release date than an actor overlap. Overall, these results indicate that our measures of competition seem to capture the differential effects of more similar movies for this strategic decision.

5.2 Descriptive sales estimation

Analogously to Table 2, Table 3 shows the results of the sales estimation following equation 2. In column (a) the budget and distributor dummies are not included. In column (b) the budget is added, and in column (c) the distributor dummies are added. As expected the coefficient for quality shows a positive impact on sales. As the weekly sales are estimated in logarithms, an increase of one quality point (which take on values between 0 and 100) results in a 1.6 to 2.2 percent increase in weekly sales depending on the specification. A movie's budget also impacts sales positively. Increasing the budget by one million dollars increases weekly sales by 1.8 respectively 1.2 percent. The coefficients for the movie's age and age squared indicate that sales decline with time in the theaters but at a declining rate. This can be seen in a plot of the predicted values in Figure 9 in the Annex. While there is no impact from the average of more recent competing movies, there is positive impact from the average quality of all competitors. The coefficient for all movies can be interpreted as the effect of movies that are not close substitutes. One possibility is that these qualitatively stronger movies are more likely to be sold out, causing some patrons to choose the focal movie as a second-best alternative. This covariate will include the seasonality in quality of available movies as it has been described by Einav (2007). He argues that not only does consumer demand exhibit seasonality, but that producers' releases also exhibit seasonality in both the number and quality of movies released.

Distributors tend to release movies of higher quality in periods of high demand. The weekly dummies will capture demander-side seasonality while the covariate *All Quality* will include seasonality on the side of suppliers. Focusing on the niches, it turns out that the niches for director and genre are harmful for a movies success in terms of sales. The coefficients of the genre and the director niche are negative indicating that high competition in these two niches impacts weekly sales negatively. However, this just provides a rough descriptive estimation of the model. The results of our final model are provided in section 5.3.

Table 3: Sales estimation

OLS	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
		All Movies			**Postponed Movies Excluded**	
Quality	0.0172*** (0.0030)	0.0163*** (0.0025)	0.0216*** (0.0027)	0.0198*** (0.0033)	0.0178*** (0.0029)	0.0226*** (0.0030)
Budget		0.0176*** (0.0008)	0.0118*** (0.0010)		0.0183*** (0.0010)	0.0122*** (0.0011)
Age	-0.4044*** (0.0147)	-0.4377*** (0.0142)	-0.4578*** (0.0136)	-0.3871*** (0.0164)	-0.4248*** (0.0159)	-0.4495*** (0.0151)
Age squared	0.0087*** (0.0007)	0.0091*** (0.0007)	0.0094*** (0.0007)	0.0081*** (0.0008)	0.0088*** (0.0008)	0.0093*** (0.0008)
Quality recent comp.	-0.0039 (0.0075)	-0.0048 (0.0065)	0.0014 (0.0056)	-0.0108 (0.0088)	-0.0110 (0.0075)	-0.0038 (0.0064)
Quality all comp.	0.1031*** (0.0220)	0.0735*** (0.0197)	0.0199 (0.0174)	0.1136*** (0.0253)	0.0768*** (0.0227)	0.0186 (0.0201)
Quality Actor Niche	0.0098*** (0.0014)	0.0067*** (0.0012)	-0.0079** (0.0031)	0.0109*** (0.0015)	0.0076*** (0.0014)	-0.0077** (0.0036)
Overlap Actor Niche			0.6435*** (0.1916)			0.6578*** (0.2201)
Quality Director Niche	-0.0065*** (0.0025)	-0.0093*** (0.0022)	0.0114 (0.0078)	-0.0079*** (0.0029)	-0.0102*** (0.0025)	0.0130 (0.0094)
Overlap Director Niche			-1.2873** (0.5201)			-1.4690** (0.6394)
Quality Genre Niche	-0.1938*** (0.0138)	-0.1223*** (0.0119)	-0.0524*** (0.0121)	-0.2038*** (0.0152)	-0.1296*** (0.0131)	-0.0507*** (0.0131)
Week & year dummies	yes	yes	yes	Yes	Yes	yes
Distributor, Genre & MPAA Dummies	no	no	yes	No	No	yes
R^2	0.324	0.454	0.557	0.319	0.449	0.559
# Obs.	17,764	17,764	17,764	14,561	14,561	14,561

Standard errors are clustered at the movie level. Dummies are included for director, actor, and genre, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Prediction

The final step in our methodology is to simulate the change in movies sales due to rescheduling. As already mentioned in equation 4 in section 3.3, we use a nonlinear model. We have two reasons for doing so. The first one is that by estimating a non-linear model we avoid the problem of retransformation. This means that when we predict fitted values with this model, we directly receive actual dollar values in comparison to the natural logs we would receive using standard IV with logged dependent variable. Secondly, the predicted values show a much better fit with the actual data in comparison to a standard IV with logged dependent variable. Especially when compared to a linear model the fit is 350 fold better.[12] Following the approach from Cameron & Trivedi (2009) we first estimate a Poisson regression. However, according to the test of over-dispersion our data show variation that is greater than the mean, a violation of the assumptions of the Poisson model.[13] Therefore, we adopt the more general negative binomial regression (Cameron & Trivedi, 2009). Additionally, one might argue that the budget is not exogenous as it is probably correlated with the (expected) sales. As described in section 3.2, we address this objection by estimating the budget on the first stage with the help of the distributors' locations as instrumental variables and adding the control function for budget in the second stage. We use state dummies of distributors' locations as instruments as they are highly correlated with the budget a distributor can expend for a movie but are not correlated with the sales in the second stage. A list with all the states is included in Table 9 in the Annex.

[12] The square root of the mean squared error is 3.8 million USD for the negative binomial estimator and 1,360 million USD for ordinary least squares.

[13] We have to reject the hypothesis that the data is not over dispersed ($t-value = 5.33$). We conclude that we have over dispersed data.

Table 4: Negative binomial estimation

Negative binomial 2nd stage of IV	All movies	Postponed Movies Excluded
Quality	0.0224***	0.0264***
	(0.0030)	(0.0030)
Budget	0.0128***	0.0122***
	(0.0011)	(0.0010)
Age	-0.5617***	-0.5730***
	(0.0184)	(0.0224)
Age squared	0.0144***	0.0148***
	(0.0010)	(0.0012)
Quality recent comp.	-0.0121*	-0.0139*
	(0.0070)	(0.0078)
Quality all comp.	-0.0017	-0.0051
	(0.0241)	(0.0248)
Quality Actor Niche	-0.0048	-0.0043
	(0.0034)	(0.0034)
Overlap Actor Niche	0.3455	0.3709*
	(0.2101)	(0.0685)
Quality Director Niche	-0.0009	0.0004
	(0.0099)	(0.0165)
Overlap Director Niche	-0.2809	-0.2902
	(0.7073)	(0.8820)
Quality Genre Niche	-0.0331*	-0.0320
	(0.0174)	(0.0220)
Control function	-0.0048***	-0.0055***
	(0.0006)	(0.0008)
Week & year dummies	yes	yes
Distributor, Genre & MPAA Dummies	yes	yes
LR χ^2	24,102.19	7,524.09
$p>\chi^2$	0.0000	0.0000
# Clusters	1,653	1,370
# Obs.	17,764	14,561

Standard errors in parentheses clustered at movie level and are bootstrapped from 4,763/5000 replications. Dummies included for week and year, distributor, actor, and genre * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

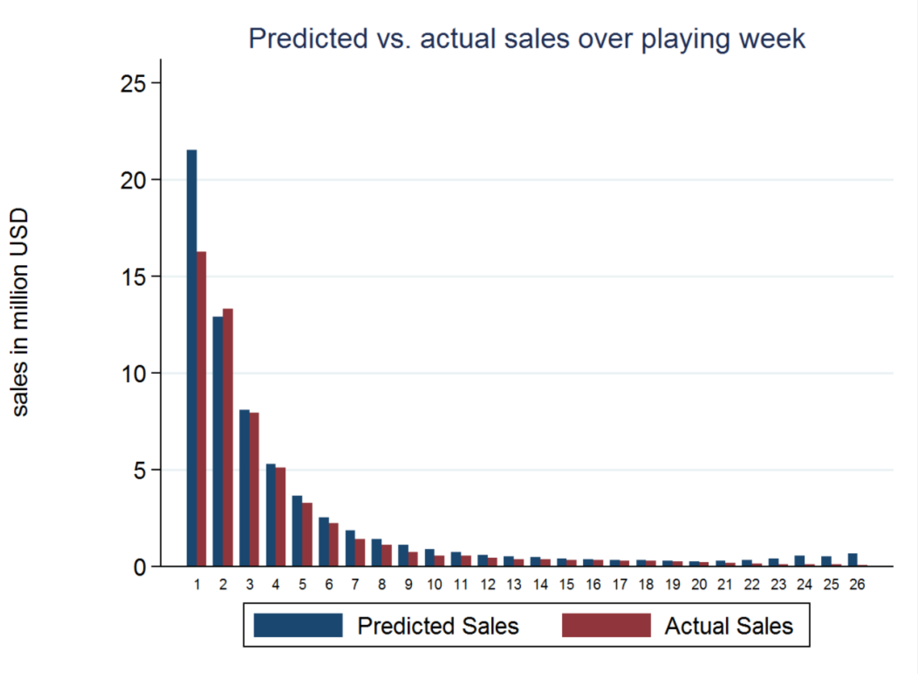
To test whether the budget is endogenous we performed a robust Durbin-Wu-Hausman test of endogeneity. It generated an F-statistic of 108.17 with 26 degrees of freedom for a P-value of 0.000 rejecting the hypothesis that Budget_i is exogenous, thereby verifying our IV approach. Additionally, we can reject the hypothesis that we have weak instruments as the test of joint significance on the first stage for all instruments revealed an F-statistic of 21.94. Table

4 shows the outcome for the second stage in the two stage least squares model[14]. The marginal effect at the mean for the actor and director niche when quality increases by one standard deviation and the overlap dummy is held constant is 1.89 (with p-value of 0.102) and -5.07 (with p-value of 0.034) respectively. Hence, if the quality in the director niche increases by one standard deviation, sales will decrease by about 5 percent if quality in the director niche increases by one standard deviation. The marginal effect at the mean for the genre niche is -8.558 (with p-value of 0.107). So, an increase in quality of one standard deviation in the genre niche implies a reduction of sales by about 9 percent. The coefficients in Table 4 are less biased estimates of the true parameters compared to the coefficients obtained in Table 3 due to the identification strategy based on instruments.

Overall the fit is quite good as shown in Figure 5 which compares the actual weekly sales to the sales predicted by the model over the playing weeks. The week sales are slightly under-predicted except for weeks two and three which end up slightly over-predicted.

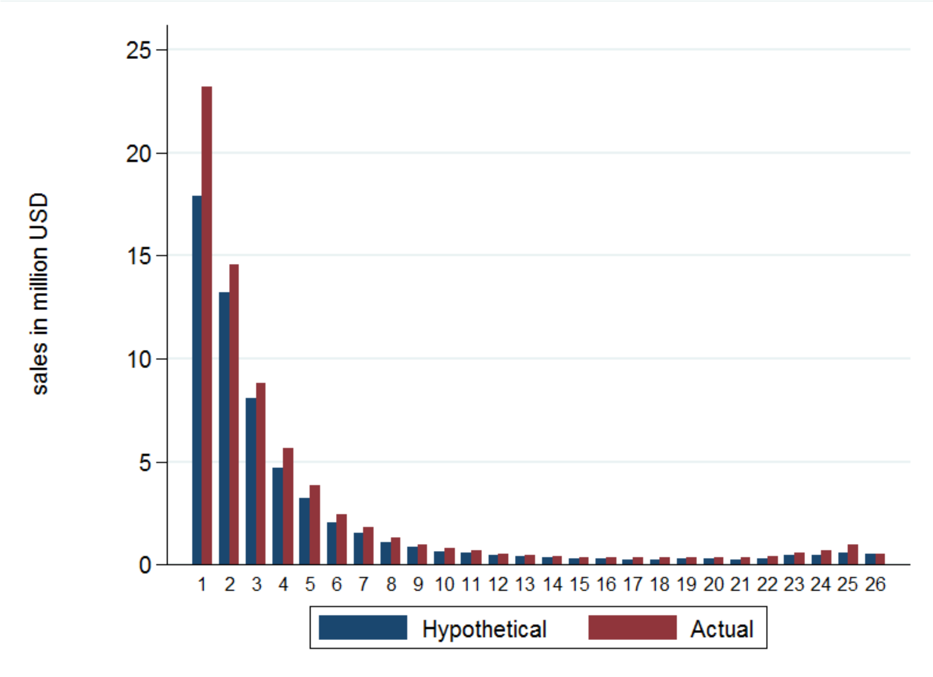
[14] The first stage of the model is reported in the Annex.

Figure 5: Predicted vs. actual weekly sales



Multiplying the coefficients from Table 4 with the respective independent variables at the hypothetical release date generates our estimate of the unobserved hypothetical sales. In short, this simply entails substituting the values of the competition variables for the week in question. In Figure 6, we compare these simulated hypothetical sales to predicted actual sales. Again, we present this result over the theatrical run, but the first few weeks dominate overall sales and the estimated difference in sales. For nearly every week, the simulated hypothetical sales stay below the predicted actual sales indicating that at the initially planned point in time the distributors would have made fewer sales as they did at the actual release date. On average this sums up to $5.40 million additional revenue per movie. This is an equivalent of about 6 percent additional sales per rescheduled movie.

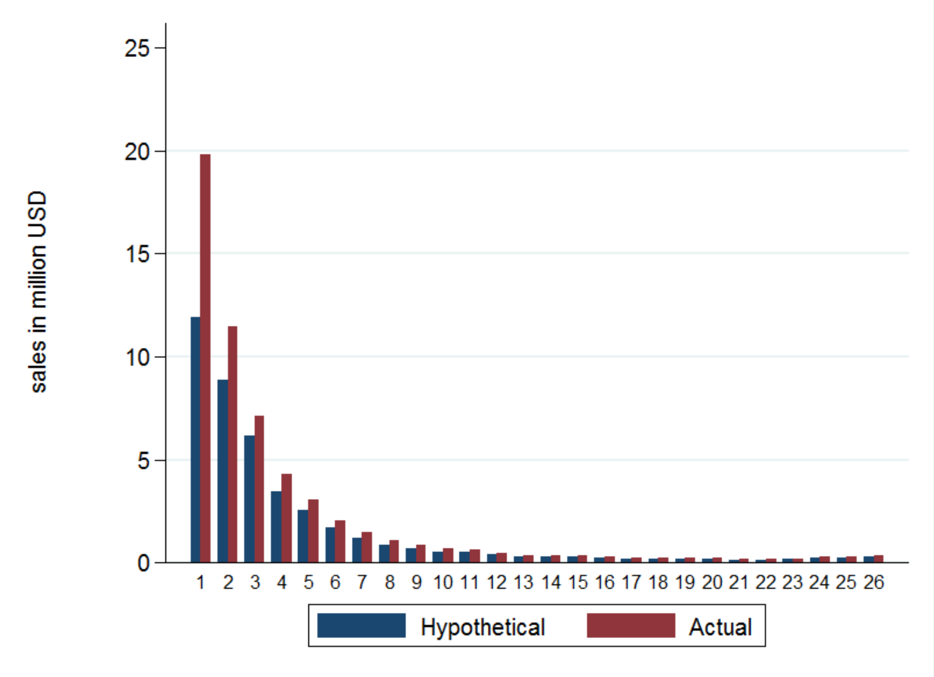
Figure 6: Comparison hypothetical to actual sales



Whether the change in movie date is profitable depends on whether the additional revenue exceeds any costs incurred due to the change. These costs are likely to be associated with any sunk marketing costs that are specific to the initial date. If the movie release is rescheduled soon enough, these could be minimal. We do not have any information on marketing expenses but a rule of thumb could be that a movie's marketing costs are about 50 percent of the production budget or averaging about $25 million in our sample.[15] However, it is likely that only a small fraction of this will be specific to the initial date. So long as this sunken portion is less than the aforementioned 6 percent, changing the release date is profitable on average.

[15] See http://entertainment.howstuffworks.com/movie-cost1.htm and http://articles.latimes.com/2008/mar/06/business/fi-boxoffice6. (last accessed on 19 December 2017)

Figure 7: Comparison hypothetical to actual sales excluding postponed movies



In Figure 7, we restrict the sample to movies without postponed rescheduling. In this case, the difference between actual and hypothetical release date becomes even bigger. This finding can be attributed to the strictly strategic reasons of rescheduling in this subsample as argued before. Here the additional revenue sums up to $6.79 million, an equivalent of even 7.6 percent.

We now turn to movies that stayed and did not change to another release date, given that the changers stayed at their initially announced date. Figure 8 shows their revenues in the two different cases, first the changers moved out of their initially planned release date (actual) and second changers stayed at their initially announced date (hypothetical). It is striking that the largest difference occurs in the first week. This might be due to the fact that this first week is the best one to plan for the players and generates the highest sales.

Figure 8: Comparison hypothetical to actual sales non-rescheduled movies

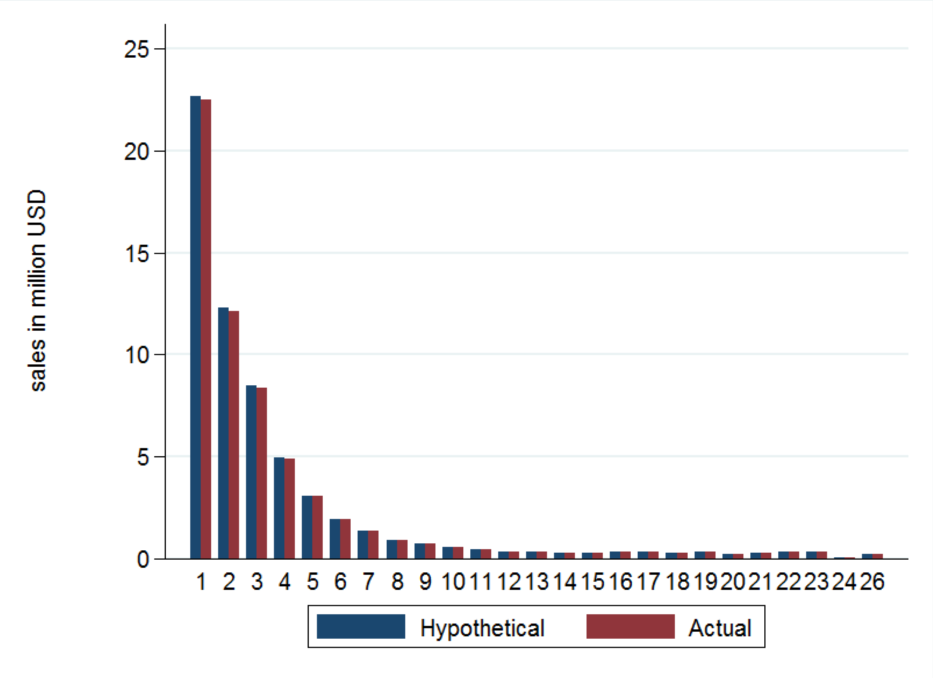


Table 5 shows that overall, the group of movies, that stayed, performed a little worse, on average $228K per movie. Compared to the $5.40 million for the movies with a release date change this is a small number even if multiplied with the number of respective movies. Multiplying the $228K losses with 1,240 (the number of unchanged movies) results in $283 million. Multiplying $5.4 million with 413 (the number of rescheduled movies) results in $ 2.230 billion. Accordingly, the additional overall industry profit is close to $2 billion for the observation period. This is equal to $243 million per year on average.

Table 5: Comparison of different types of rescheduling behavior

	Number of Movies	Difference in overall sales per movie (actual - hypothetical)	Number of movies × Difference
Rescheduled movies	413	5,397,734***	2,229,264,142
Preponed (strategic)	130	6,788,747***	882,537,110
Postponed	283	4,758,753***	1,346,727,099
Non-rescheduled movies	1,240	-227,504***	-282,104,960
Strategic ENTERING	1,085	-259,495***	-284,966,570
No strategic ENTERING	244	-41,738**	-10,184,072
Strategic LEAVING	1,087	-258,881***	-281,403,647
No strategic LEAVING	153	-4,590***	-702,270

Column 1 in Table 6 documents the results of a simple OLS estimation that regresses the predicted sales on the number of movies entering into a movie's run window and controls. We find that that the predicted sales decrease by $205K with every movie entering the playing window, an equivalent of 4 percent of the average weekly sales. In Column 2, the same regression is performed just with the number of movies leaving instead of the number of movies entering. However, the coefficient is not significant for the number of movies leaving, indicating that leavers are far less relevant for sales compared to entering competitors.

Table 6: OLS regression of predicted sales on number of movies entering / leaving

	(1) Predicted sales	(2) Predicted sales
# movies entering	-204,897.01***	
	(78949.48)	
# movies leaving		-54,318.51
		(86418.30)
Controls for age, quality, and seasonality	yes	yes
R^2	0.1316	0.1312
# Obs.	13,019	13,019

Standard errors in parentheses. Control variables: Seasonality age and quality
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4 Discussion of empirical results

The variables capturing the competitive situation are potentially endogenous as they are affected by the very presence of the focal movie itself. Yet, we observe a movie over its entire run and measure its weekly sales. Variation enters via different sets of competitors and seasonality over the movie's run. Looking at the number of weekly playing movies over the year, we might still observe a distribution flatter than a random distribution. This would tend to bias our coefficients downward, which in turn would lead to conservative predictions. The fundamental challenge of this work is to make a statement of how much sales were increased by the movies that were rescheduled. Unfortunately, we can observe a movie only once, i.e. at the time when it finally played on screens. We do not observe its performance at the hypothetical date as we only know the date itself. Under the assumption of the non-rescheduled movies being fixed, we can conduct an empirical counter-factual experiment, that shifts the rescheduled movies to their initially planned release date and see how they would have performed.

If a movie had stayed at its initially scheduled release date, it could have potentially induced other movies to reschedule which would lead them to face less competition than assumed. Hence, the estimated 7.6 percent is the upper bound of what could be gained due to rescheduling. If all release dates would not have been changed, sales would be 7.6 percent lower. In other words, the entire process of 'microscheduling' increases sales in the market for motion pictures by 7.6 percent. This result is driven by distributers changing their release dates, as they act surely more strategic, even more so if we look at preponed movies only, compared to movies that stay. Some of the movies that do not change their release date might choose to commit to the date also for strategic reasons or they may remain simply due to inertia in the planning process, i.e. the costs of switching dates are too high. Since costs are unobservable, we cannot distinguish between the two.

6 Conclusion and Future Work

There are several strategic actions firms can take to increase profitability, with one of these being the timing of new product entry. The movie industry provides a fertile setting to study this because, as the release date nears, few other strategic actions, such as adjusting price or content, are employed. We show that 'microscheduling' new product releases can increase revenue significantly. In an empirical experiment, we exploit those cases when distributors change the product's release date to show that 1) releases are rescheduled when competition is expected to be stronger, 2) that sales decline when competition is stronger, and 3) that the revenues increase by 6-8 percent on average due to weaker competition at the rescheduled date. The costs incurred with such a change are likely small enough making these changes overall profitable. Moreover, it is likely that the expected level of competition at the release date is considered by the distributors even for movies that were not rescheduled making observing the competitive landscape even more crucial to generate revenue in this industry.

We expect this strategic importance of the release date to hold for other entertainment markets as well. In these markets, content and production decisions are important overall but, as with movies, are sunk well before the product is marketed. Advertising and promotion are largely tied to budget or quality although there is first evidence for movies that these are adjusted based on viewer reactions (Lampe, 2015). At least for movies and video games, other features of these industries render price to be of little use as a strategic variable (Orbach & Einav, 2007, Engelstätter & Ward, 2013). Therefore, once the entertainment product becomes marketable, there are few other strategic variables besides release date left.

Our work opens up several directions for future research. Given the limitations of our work we pointed out, further research questions focusing on the competitive landscape suggest themselves. Given appropriate data a confirmation of our results in other entertainment industries, like, e.g., video games, music or books, is desirable. Also, a model describing how a distributor should choose the optimal release date might yield insights into how firms balance between several dimensions of competition and consumer demand.

Annex

Table 7: Summary statistics cross section

	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
	Whole sample 1,653 Obs.				Exclude Postponed Releases 1,370 Obs.			
Overall sales	16.28	27.51	0.00	218.00	15.76	27.34	0.00	189.00
Rescheduled release date	0.25	0.43	0.00	1.00	0.09	0.29	0.00	1.00
Quality	52.73	17.03	7.00	96.00	52.96	16.97	7.00	96.00
Budget in millions	39.24	49.99	0.00	339.00	37.27	49.06	0.00	339.00
Week since release	1.00	0.00	1.00	1.00	1.00	0.00	1.00	1.00
Quality of recent releases	55.95	4.54	0.00	80.67	56.00	4.36	0.00	80.67
Quality all concurrent movies	59.13	2.41	43.77	74.00	59.09	2.35	43.77	74.00
Quality same actor	20.59	28.89	0.00	97.00	20.30	28.80	0.00	97.00
Overlap same actor	0.36	0.48	0.00	1.00	0.36	0.48	0.00	1.00
Quality same director	6.41	18.90	0.00	95.00	6.10	18.51	0.00	95.00
Overlap same director	0.11	0.32	0.00	1.00	0.11	0.31	0.00	1.00
Quality same genre	57.35	4.64	38.00	73.00	57.26	4.64	38.25	73.00

Figure 9: Age Digression Effect

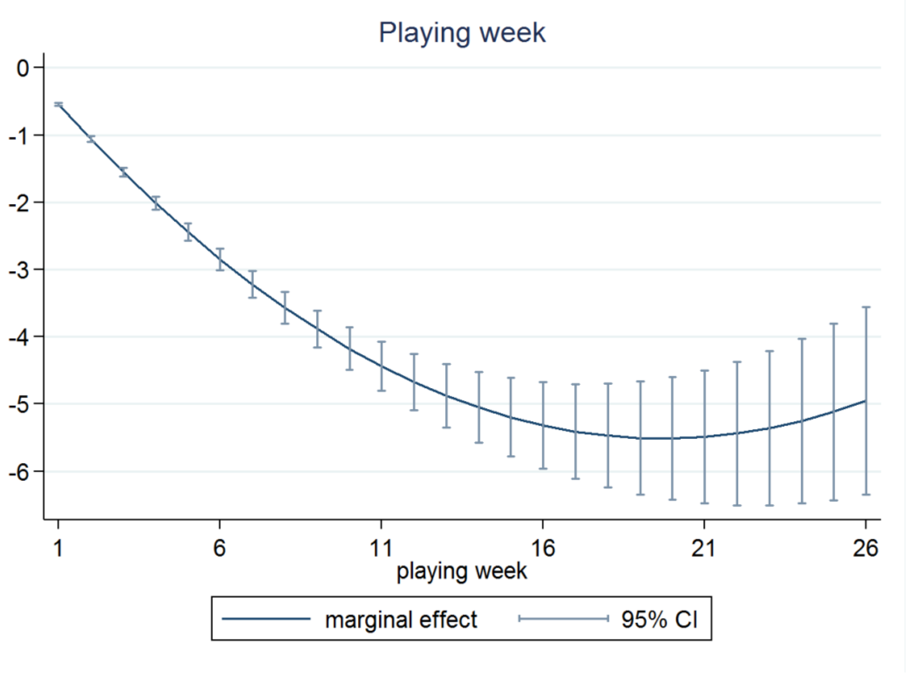


Table 8: First stage of IV

OLS first stage of IV	(1) Budget
Quality	0.3071***
	(0.0859)
Age	0.8282***
	(0.2418)
Age squared	-0.0137
	(0.0147)
Quality recent comp.	0.0705
	(0.1194)
Quality all comp.	0.3852
	(0.4376)
Quality Actor Niche	0.2238*
	(0.1256)
Overlap Actor Niche	-6.1925
	(6.8769)
Quality Director Niche	0.1513
	(0.2228)
Overlap Director Niche	-5.4202
	(12.1667)
Quality Genre Niche	-1.4771***
	(0.3312)
# Clusters	1,653
#Obs.	17,764

Standard errors in parentheses clustered at movie level. Dummies included for week and year, distributor, genre, and state * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Filming locations used as instruments

Number	State	Number	F-Test	Chi2
1	Australia	47	10.32	0.0013
2	California	1,244	33.83	0.0000
3	Canada	3	4.71	0.0301
4	Colorado	1	11.57	0.0007
5	Connecticut	1	1.65	0.1989
6	Florida	2	26.43	0.0000
7	France	2	49.28	0.0000
8	Georgia	1	4.32	0.0378
9	Germany	2	33.40	0.0000
10	Hungary	1	0.20	0.6553
11	Illinois	5	1.86	0.1729
12	India	9	3.39	0.0657
13	Ireland	1	6.15	0.0133
14	Maine	2	1.54	0.2152
15	Malaysia	1	7.34	0.0068
16	Massachusetts	2	12.94	0.0003
17	New Jersey	2	31.52	0.0000
18	New York	293	9.57	0.0020
19	Ohio	1	2.02	0.1559
20	Oklahoma	1	-	-
21	Ontario	4	14.09	0.0002
22	Pennsylvania	3	9.09	0.0026
23	Texas	7	1.86	0.1727
24	United Kingdom	9	4.53	0.0335
25	Utah	7	4.79	0.0287
26	Washington	1	11.13	0.0009

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