THE ROLE OF COMMITMENT IN THE U.S. MOVIE INDUSTRY

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Abstract

This paper studies the release timing game played by movie distributors. When deciding on release dates for movies, studios trade-off between releasing in high demand periods and facing milder competition from the movies of competitors. The estimation results suggest that this trade-off explains a substantial part of the variation in observed release dates. I also find that prerelease announcements play an important role in the game of releases. Announced release plans have a considerable effect on final release decisions of studios, and are not likely to be cheap talk. In addition, observed behavior of market participants is consistent with the idea that certain studios are using announcements as a way to pre-commit to particular release dates. As a whole, the results support the main predictions of the endogenous commitment theory recently proposed in the theoretical literature.

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1 Introduction

One of the most important ideas in game theory is the value of commitment, the idea that in many situations players can benefit from the opportunity to make binding promises to play in certain ways. In economic models commitment is typically introduced by assuming that certain players have a possibility to make binding actions at the beginning of a game. However, recent theoretical studies suggest that commitment power may arise endogenously from the fundamentals of the model (Caruana & Einav, 2008b; Quint & Einav, 2005; Lipman & Wang, 2000). For example, firms can make public announcements of their future plans with respect to production quantities or entry to different markets. To the extent that changing plans is costly, firms may behave strategically and use announcements as a commitment device (Caruana & Einav, 2008a). Empirical validation of this theory is interesting, as the new approach tends to deliver very different predictions from the ones in standard game theoretic models. A substantial part of this paper is an attempt to discuss the nature of commitment in the context of one particular industry and check whether behavior of firms is consistent with the idea of endogenous commitment.

This paper addresses two main questions in the context of the U.S. movie industry. The first part of the paper analyzes how studios choose release dates for their movies. Demand for movies varies substantially over the course of the year, so certain time periods are more profitable for movie releases. At the same time, studios tend to release better movies in the weeks that have higher underlying demand, so high demand periods are characterized by more intense competition among movies (Einav, 2007). I argue that when studios decide on theatrical release dates, they trade-off between releasing films in high demand periods and facing milder competition from other movies. The estimation results for the static release timing game suggest that a trade-off between seasonal effects and competition explains a substantial part of the variation in the observed release dates of movies.

The second part of the paper explores the role of commitment in the industry. One interesting feature of the market is that ahead of time studios make public announcements of their release plans. At around the same time they start a large scale marketing campaign, which aims to promote the movies and inform consumers about forthcoming releases. Studios typically need to book advertising slots and negotiate a proper amount of screens with the owners of movie theaters. Given that any adjustments of the marketing campaign are potentially costly (one has to shift advertising slots and renegotiate contracts with theaters), studios could use announcements as a way to make credible commitments. For example, one strategy would be to make an early announcement with the hope that it will deter competitors from choosing the same release date. This could help a studio to capture rents from the large mass of moviegoers without facing too intense competition from the movies of other distributors.

To study the role of prerelease announcements I use a unique dataset on the history of scheduled release dates. The data suggests that different studios tend to behave differently with respect to the announcements of their release plans. In particular, Universal Pictures and Paramount Pictures tend to announce their final release dates much earlier than other distributors do. These two studios also rarely change their release dates in response to the announcements of competitors. I also show that studios holding ex ante more successful movies tend to announce the final release dates earlier. I then explore the data on box-office revenues and show that such strategies of early announcements are associated with significantly higher realized profits. Together these observations suggest that studios may be using prerelease announcements as a commitment device.

Further discussion in the paper suggests that the best way to explain the observed configuration of release dates would be to analyze a sequential game of announcements. This is not feasible both computationally and due to the data limitations. Instead, I study a modification of the static game that allows to analyze the role of prerelease announcements in a simple way. The estimation of this extended model shows that studios are often reluctant to adjust previously announced release dates, even when adjustment promises higher box-office revenues. The observed behavior can be rationalized by the presence of adjustment costs that a studio needs to pay every time it switches to another release date. This finding suggests that prerelease announcements indeed have a binding nature, and thus may have a substantial effect on the outcome of release timing game.

The model proposed in this paper is a discrete-choice model that captures the main incentives of studios with respect to release decisions. The proposed structure falls down into the category of structural entry models (Bresnahan & Reiss, 1990; Berry, 1992). Specifically, the model considered here is a static game with asymmetric information in the spirit of the location-choice model in Seim (2006). However, in Seim's model all potential entrants are ex ante identical. This symmetry assumption is too restrictive in my application as all players are ex ante different along observable dimensions. The model I propose allows for observable heterogeneity of entrants, and can therefore be viewed as an extension of the framework proposed by Seim.

Another paper that analyzes release decisions of distributors is Einav (2010). In the paper Einav assumes that observed release dates are the outcome of a sequential move game with private information. He estimates the model and finds that release dates of movies are too clustered around big national holiday weekends. The analysis I propose here is different from his paper in two dimensions. First, his main focus is on the optimality of release decisions, whereas the main purpose of my analysis is to study the role of commitment in a release timing game. Second, in his structural model players move in a prespecified exogenous order. This assumption complicates the discussion of commitment related issues, as commitment is assumed exogenously. Instead, the model proposed here assumes that studios choose release dates simultaneously. The resulting structure is quiet flexible and allows to explicitly analyze the effect of prerelease announcements on the final release decisions of distributors.

Multiplicity of equilibria is an important issue in the analyzed release timing game. The presence of multiple equilibria makes predictions of the model ambiguous, which creates a challenge for the estimation of parameters. Different ways were proposed in the literature to deal with this problem. Several authors (Bresnahan & Reiss, 1990; Berry, 1992) propose to set up a model that does not provide uniqueness, but provides the econometrician with a coarser partition of the empirical model that satisfies uniqueness. This approach imposes strong symmetry assumptions on the structure of the model. Given that in my application players are ex ante different, these assumptions seem too restrictive.

Two alternative approaches to deal with multiplicity have been proposed recently in the literature. First, several papers (Andrews et al., 2004; Ciliberto & Tamer, 2009) show that in the presence of multiple equilibria, an econometrician can place bounds on the parameters rather than obtain point estimates for them. The potential of these methods in the models, in which players are heterogeneous in their observable characteristics, has yet to be fully realized. A second approach (Aguirregabiria & Mira, 2007; Pakes et al.,

2007) uses a two-step estimation strategy to get around the multiplicity problem. This approach assumes that despite multiplicity of equilibria in the model, only one equilibrium is played in the data. The method relies on accurate nonparametric estimation of the policy functions, which are then used to back out the structural parameters. A two-step approach has an advantage of being computationally simple, and at the same time flexible enough to allow for heterogeneity of players. Thus, in my application I use a two-step method as a primary estimation technique.

The paper is organized as follows. Section 2 describes the main features of the movie industry. Section 3 presents two datasets used in the empirical analysis. Section 4 contains the detailed description of the demand models and the results of its estimation. Section 5 sets up a release timing game, and Section 6 describes estimation techniques used to back out parameters of interest. Section 7 documents interesting announcement patterns of studios and provides discussion of the main findings in the spirit of endogenous commitment theory. Section 8 contains final remarks, and Section 9 concludes the paper.

2 Industry

The movie industry comprises of three main players: producers, distributors, and exhibitors. Producers take care of all production aspects of a movie starting from the choice of a script and finishing with a final montage of film scenes. Distributors are responsible for the nationwide distribution of movies that are already produced, and exhibitors own the movie theaters. The U.S. motion picture industry is dominated by six major companies that combine production and distribution: Walt Disney Pictures, Paramount Pictures, Columbia Pictures, Universal Pictures, Warner Brothers, and 20th Century Fox. There are also several studios that distribute their own movies as well as films of small producers. Those are, among others, MGM, DreamWorks, and Lionsgate Films. By historical reasons, distribution and exhibition are vertically separated. Distributors routinely make profit-sharing contracts with the theater owners in order to show their movies to the wide audience.

Studios make several important decisions with respect to the distribution of movies. The choice of a release date is one of the most important decisions. Release date matters because an average movie earns around 40% of its final box-office revenues during the opening week (See Figure 1). According to the common wisdom on the industry, successful opening also gives a movie good publicity, which makes a film more successful in the later stages of distribution, e.g. when it is released in the DVD format. When deciding on release dates, studios face two important considerations. One is that demand in the industry is highly seasonal. Certain time periods (e.g. summertime or winter holidays) tend to be more popular among moviegoers, which makes those periods more favorable for movie releases. Another consideration is potential competition. All studios want to release their movies on the attractive holiday weekends and at the same time deter competitors from doing the same. In order to do so, distributors try to release their best movies during these high demand periods, as big blockbusters have higher deterrence potential. This leads to tougher competition among movies in the near-holiday weeks and milder competition during the rest of the year. Distributors should take this effect into account, when they decide on release dates. Therefore, the problem they face is a trade-off between seasonal and competition effects.

An interesting feature of the industry is that studios tend to make public announcements about their future release plans. The first announcements are made as early as

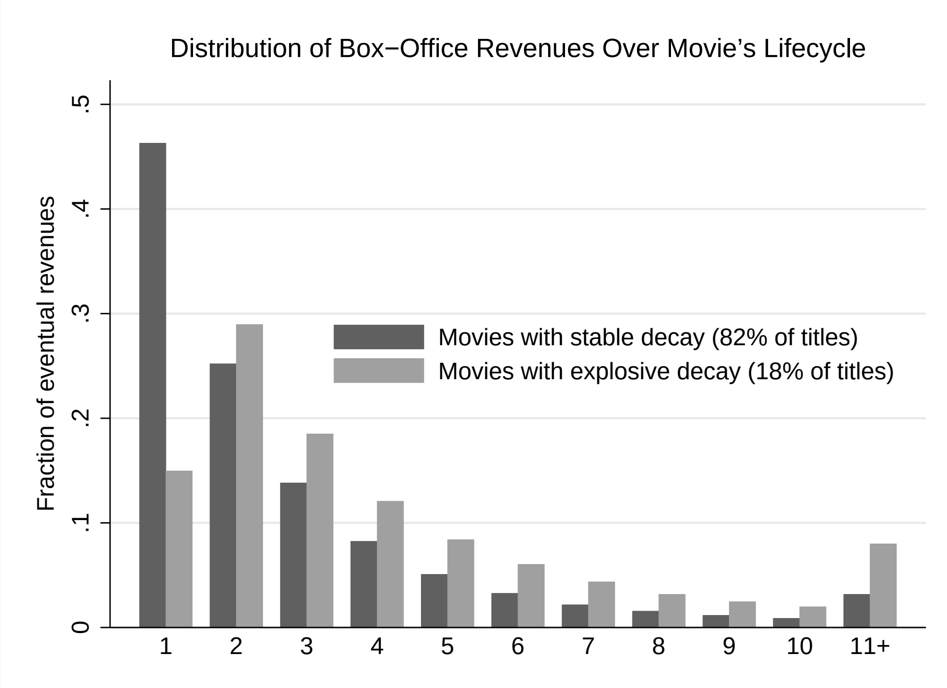

Figure 1: Distribution of box-office revenues over the lifetime of a movie.

one–two years before the actual release of a movie. At around the same time, studios start to prepare for the opening week. Typical preparation comprises of booking advertising slots and negotiation of screens with the owners of theaters. Distributors are free to adjust their preliminary plans later on. However, any consequent changes of a release date are costly as studios have to reoptimize the national advertising campaign of a movie and renegotiate contracts with exhibitors. Such adjustments of release dates become even more costly over time, because it is hard to find a large amount of spare screens and alter the marketing campaign shortly before the scheduled opening week. Given the costly nature of adjustments, studios could use announcements strategically.

One potential commitment strategy for a studio is to make an early announcement with the hope that it will deter competitors from choosing the same release date. Such preemptive action may eventually help to extract more rents from the weeks characterized by high demand. This strategy would not work if all studios face the same adjustment costs, as then all players have equal commitment power. However, there are two reasons to believe that there exist substantial asymmetries in switching costs. The first reason is a repeated nature of the game. Since the same studios interact with each other for decades, reputation may play an important role in the strategic game of releases. Some distributors may have reputation of being tough competitors. For them changing an announced release date can be associated with higher reputational costs. The second reason is heterogeneity of movies. Blockbusters are typically released on thousands of screens all over the country and require massive national advertising campaign. Adjusting such a large scale marketing campaign can be extremely costly. By this reason, adjusting release dates for big budget movies can be more expensive than shifting release dates of lower budget films. The presence of asymmetric adjustment costs makes it possible for commitment strategies to arise in this market.

Table 1: Movie Industry Trends

Period	Wide Releases	Avg Ticket Price	Total Box-Office Revenues	Admissions (per Capita)
1983-1986	435	7.98	22.4	2.89
1987-1990	480	8.01	26.6	3.29
1991-1994	519	7.03	27.8	3.76
1995-1998	520	6.93	30.9	4.04
1999-2002	707	7.68	42.8	4.84
2003-2006	783	7.89	44.9	4.74
2007-2010	835	8.28	44.5	4.35
2011-2014	838	8.31	43.3	4.07

Ticket prices and revenues are in December 2014 U.S. dollars. Wide release is defined as a movie that was played in more than 100 theaters at some point in the sample. Total box-office revenues are in billions of dollars.

3 Data

Dataset 1: Panel Data on Box-Office Revenues

The first dataset covers all movies released nationwide in the United States between January 1, 1983 and December 31, 2014. For each movie the data includes the official release date, total box-office revenues, estimated budget, the distributor, the genre, and the MPAA rating[1]. In addition, for the weeks following the official release date, the dataset includes weekly box-office revenues and weekly amount of theaters in which a movie was run. The data were obtained from *IMDb database*, except for the data on the estimated production costs, which were obtained from *Nash Information Services*.

Because the sample spans a long period of time, I deflate box-office revenues to accommodate trends in the average ticket price and the total market size. I obtain yearly data on the average ticket price from National Association of Theater Owners. Weekly average ticket prices are then interpolated from annual figures under the assumption that prices grow linearly throughout the year. The total market size is taken as the whole population of the United States. I take the annual population figures from the U.S. Census Bureau. Weekly figures for the population are interpolated in the same way as average ticket prices. Weekly market shares for each movie are computed by dividing weekly box-office revenues by the weekly ticket price and by the weekly population size.

The initial sample includes 11,621 movie titles and 105,051 weekly observations. I restrict my attention only to the nationwide releases, which I define as movies that were shown in more than 100 theaters at some point after the official release. For those movies I do not include in the final sample, the average peak number of theaters is 15 and the average budget is lower than $7 million. Those are relatively small movies competing in a different segment of the market. Sometimes a movie is first released in a limited number of theaters, and only after a few weeks it is brought to the theaters all over the country. In this cases I consider the actual release date to be the first week in which a number of theaters is high enough.[2] The percentage of those limited releases in the data

[1] The data on production costs (budgets) covers only 50% of movies, and the data on genres is available for 85% of titles.

[2] Operationally, the actual release of a movie is the first week, in which it is shown in more than 50 theaters.

Table 2: Summary Statistics

Total Box-Office Revenues, millions			Total share, %		
Mean		53.4	Mean		2.4
Median		24.5	Median		1.4
Standard deviation		69.4	Standard deviation		3.1
Titles		5117	Titles		5117
Highest	Avatar	766	Highest	Titanic	31.3
2nd highest	The Avengers	642	2nd highest	Avatar	28.4
3rd highest	Titanic	604	3rd highest	Star Wars ('99)	27.3
4th highest	The Dark Knight	579	4th highest	Jurassic Park	27.1
5th highest	Star Wars ('99)	577	5th highest	Star Wars ('83)	25.7
First-Week Revenues, millions			Maximum Theater Count		
Mean		18.2	Mean		1767
Median		11	Median		1702
Standard deviation		23.8	Standard deviation		1068
Titles		5117	Titles		5117
Highest	The Avengers	283	Highest	The Twilight Saga ('10)	4468
2nd highest	The Dark Knight	265	2nd highest	Harry Potter ('09)	4455
3rd highest	Harry Potter ('11)	243	3rd highest	The Dark Knight Rises	4404
4th highest	The Dark Knight Rises	236	4th highest	Iron Man 2	4390
5th highest	Pirates of the Caribbean ('06)	234	5th highest	Shrek Forever After	4386
Budget, millions			Profit, %		
Mean		52.8	Mean		120
Median		37	Median		13
Standard deviation		49.8	Standard deviation		800
Titles		2812	Titles		2812
Highest	Avatar	469	Highest	Paranormal Activity	23523
2nd highest	Pirates of the Caribbean ('07)	348	2nd highest	The Blair Witch Project	21908
3rd highest	Spider-Man 3	300	3rd highest	Super Size Me	15250
4th highest	Titanic	297	4th highest	The Brothers McMullen	12458
5th highest	John Carter	289	5th highest	Facing the Giants	9691

Revenues and budgets are in December 2014 U.S. dollars. Total share is computed as total box-office revenues divided by the average ticket price and U.S. population. Both revenues and total shares are based only on the first ten weeks. Profit is the difference between the total box-office revenues and movie's budget divided by the budget.

is less than 15%. Throughout the analysis I restrict the sample only to the first 10 weeks after the release of a movie. During this time an average movie earns over 97% of its total box-office revenues.

The final dataset contains 5,117 movie titles and 37,001 weekly observations. On average, I observe slightly more than 7 weekly observations per title. This is well below the maximum of 10 because the exhibition of some movies had been terminated by the owners of theaters several weeks after the official release. Later in the demand estimation part of the paper I show that the main results are not sensitive to truncation issue.

The movie industry in the U.S. works on a weekly schedule. Around 70% of movies in the sample were released on Friday, and additional 15% were released on Wednesday. The main competition is for consumers who watch movies during the weekend, which accounts for almost 80% of revenues.[3] Because of these reasons, I tabulate the release dates at the weekly level, where the definition of a week is a 7-day period from Friday to Thursday of the next calendar week.

National holidays play an important role in shaping seasonality of the industry. Major American holidays can appear on different weeks in different years, and it is important to adjust for such calendar differences. I change the labels of weeks so that national holidays always correspond to the same weekly dummies. For example, in different years there may be 5 or 6 weeks between Memorial Day and Independence Day. I insert an additional week between them in the years, where these two holidays stand 5 weeks apart. As a result, Memorial Day and Independence Day are always assigned to the same weekly dummies (22 and 28 relatively). The total number of weekly dummies is 56. Weeks 1, 14, 24, 33, 42, and 51 are the ones that do not appear in all years.

Table 1 provides some description of the industry trends. The industry share (admissions over U.S. population) was growing until the late 1990s and reached its peak at around 2000. Since that time, admissions per capita declined steadily. This downward trend can be explained by an increasing popularity of home video reflected in a rapid growth of the market for DVDs and video-on-demand services.

Table 2 reports summary statistics for the final sample of movies. The mean and standard deviation of the total box-office revenues are \$53 million and \$70 million, respectively. The median is only \$25 million, which implies that distribution is highly skewed. The peak number of theaters for an average movie was 1800, whereas the same figure for the most successful blockbusters was almost 4500 (for comparison, there were overall 6000 theaters in U.S. during the observation period). A median movie earned only 13% with respect to its estimated production cost. This figure largely overestimates domestic profits as it ignores advertising expenses, which are sometimes as large as the budget of a movie. On the other hand, reported figures may underestimate overall profitability of the business as the profits reported in Table 2 do not include revenues from other sources, e.g. from theatrical distribution in other countries or DVD sales.

Finally, one interesting feature of the data is apparent seasonal patterns in industry sales, which are depicted in Figure 2. It is very common to see the discussion of this graph in popular media. Industry practitioners typically discuss four different periods within a year: winter-spring (January to Early May), summer (Late May to August), fall (September and October), and winter holidays (November and December). Summertime and winter holidays are usually considered as peak-demand periods because of vacations and school breaks, whereas spring and fall are described as low demand "dump months".

[3]The figure of 80% is obtained from the daily data on box-office revenues for the period from January 2000 to December 2014. The data were obtained from IMDb database.

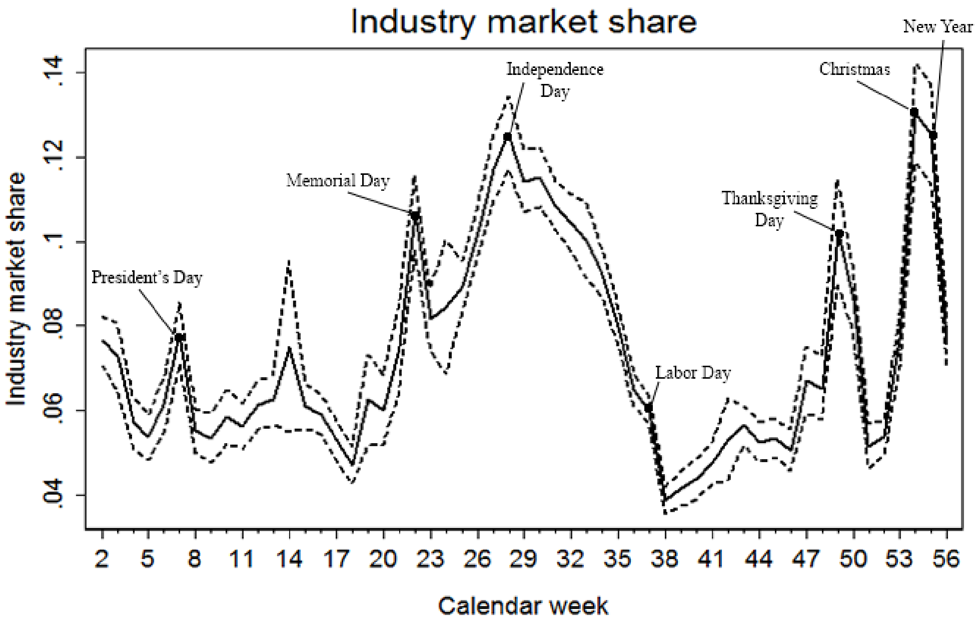

Figure 2: Seasonality of total industry share. Dashed lines represent lower and upper bounds of the 95% confidence interval.

Keeping this seasonal demand variation in mind, distributors try to release their tent-pole blockbusters in the beginning of high demand periods, as reflected in Figure 3. All other movies are usually released during the periods with lower demand to avoid competition from successful high-quality films.

Dataset 2: Prerelease Announcements

The second part of the data is the unique dataset that contains prerelease information about scheduled release dates. It covers 2,427 movies that were eventually released nationwide between January 1, 1985 and December 31, 1999. For each movie the data contains the whole history of scheduled release dates. The dataset contains 23,358 observations, around 10 observations per one movie title. The source of the data is the *Feature Release Schedule*, industry magazine published monthly by *Exhibitor Relations Inc.*

During the first days of each month, a magazine publishes the updated release schedule of all movies that have started the production process but have not been released yet. An average movie is first listed in publication around 10-12 months before its observed release date. Typically, at the beginning studios disclose their general release plans. At this point they do not provide a specific date, but schedule a release for a wide time interval. The announcements of this type vary from completely general ("Coming in 2000") to more specific ones ("July 2000").

As scheduled release date approaches, normally around 5-6 months before the observed release date, studios start to refine their release plans and announce particular dates ("4th July 2000"). Around 75% of all observations in the data are announcements with a specified release date, and the remaining 25% of observations contain information about general release plans of studios.

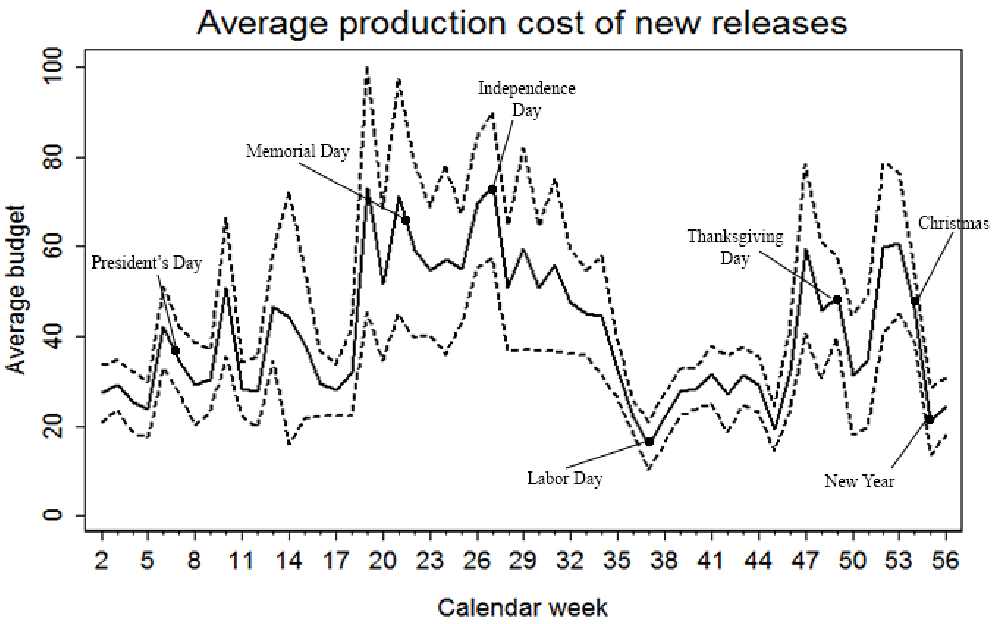

Figure 3: Average budget of new releases. Dashed lines represent lower and upper bounds of the 95% confidence interval.

The main feature of the data is the high frequency of changes in scheduled release dates. Over 50% of movies switched release dates at least once. This is a surprising finding given the costly nature of release date adjustments. As discussed earlier, adjustment costs arise because studios have to reoptimize the advertising campaign and renegotiate contracts with exhibitors. Such adjustment costs increase over time, as it is very hard to find a large amount of spare screens and alter the marketing campaign shortly before the scheduled release date. Supporting this idea, I observe less movies changing their release dates closer to the scheduled opening week.

Across all movies and observations, around 20% of the monthly announcements are changes in relation to the most recent announcement of the same movie. The distribution of the magnitude of these changes is described in Figure 4. This distribution has larger right tail because of switches caused by production delays. However, the central part of the distribution is roughly symmetric, and 70% of switches do not shift release dates by more than one month. This observation suggests that switches are often made for strategic reasons not related to the exogenous production shocks. Figure 5 also shows that the amount and average magnitude of switches decreases as a scheduled release date becomes closer. This is consistent with the idea that over time it becomes more costly to adjust the previously announced release dates.

4 Demand

A. Benchmark Model

The purpose of this section is to setup a structural demand model that would allow to capture both seasonal and strategic incentives of distributors with respect to movie releases. In principle, we could proceed without a model and measure profitability of

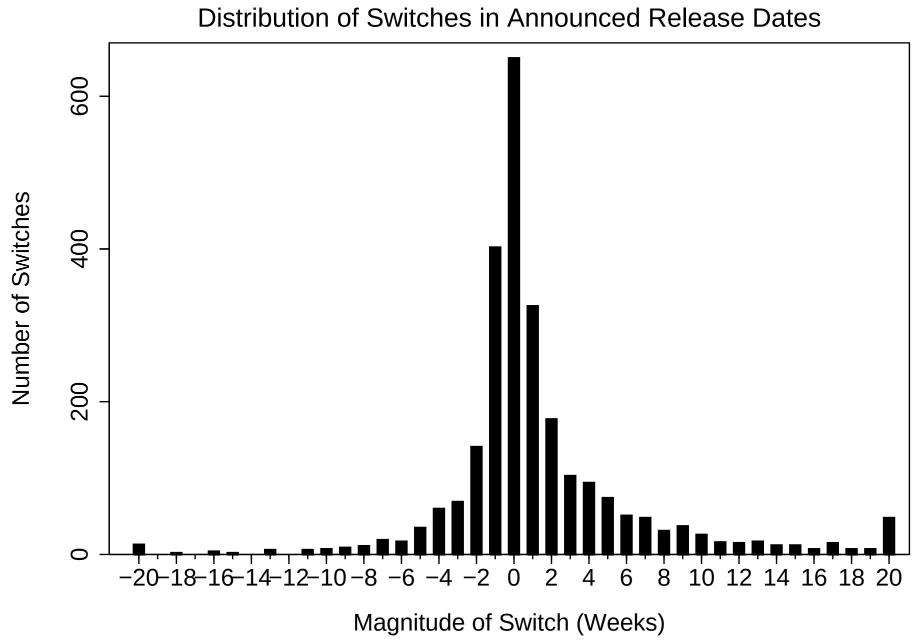

Figure 4: Distribution of the magnitude of release date switches.

different release dates simply by looking at the industry revenues in Figure 1. This approach is imperfect, as the observed seasonality of the industry is a combination of two different effects. First, certain periods of time tend to be more popular among moviegoers. Second, as explained earlier, studios tend to release better movies during high demand periods, which attracts even more consumers to the market. Since the prices are stable over the course of a year, this endogenous composition of movies amplifies a seasonal pattern of the industry market share. As a result, observed seasonality of industry revenues will in general overestimate profitability of periods with high underlying demand.

The model proposed here is a nested logit demand model as in Einav (2007). This model has two attractive features. The first one is that it allows to separately estimate underlying demand and qualities of movies in a simple way. I explain the details of identification strategy later in this section. The other one is that structural parameters of the model can be estimated using standard linear regression techniques. The utility of consumer i going to movie j at week t is assumed to be:

$$u_{ijt} = \tau_t - \lambda(t - r_j) + q_j + \xi_{jt} + \zeta_{it} + \pi\epsilon_{ijt}, \tag{1}$$

where τ_t is a week fixed-effect, r_j is the release week of movie j, and $t - r_j$ is the number of weeks passed since the release of movie j. λ can be interpreted as a rate of decay[4], and ξ_{jt} is a deviation from the common decay pattern. Finally, q_j is the fixed-effect of movie j, ζ_{it} is an idiosyncratic propensity of individual i to go to the movies in week t,

[4]The decay rate helps to capture the decline in weekly revenues depicted in Figure 1. This decline is driven by two effects. One is that consumers prefer to watch new releases rather than movies released in the previous weeks. This can be rationalized by the preference for newness, or by the fact that heavy advertising right before the official release attracts a large mass of consumers in the opening week. Another effect is that in the weeks following release some people have already seen a movie and are not likely to watch it for the second time.

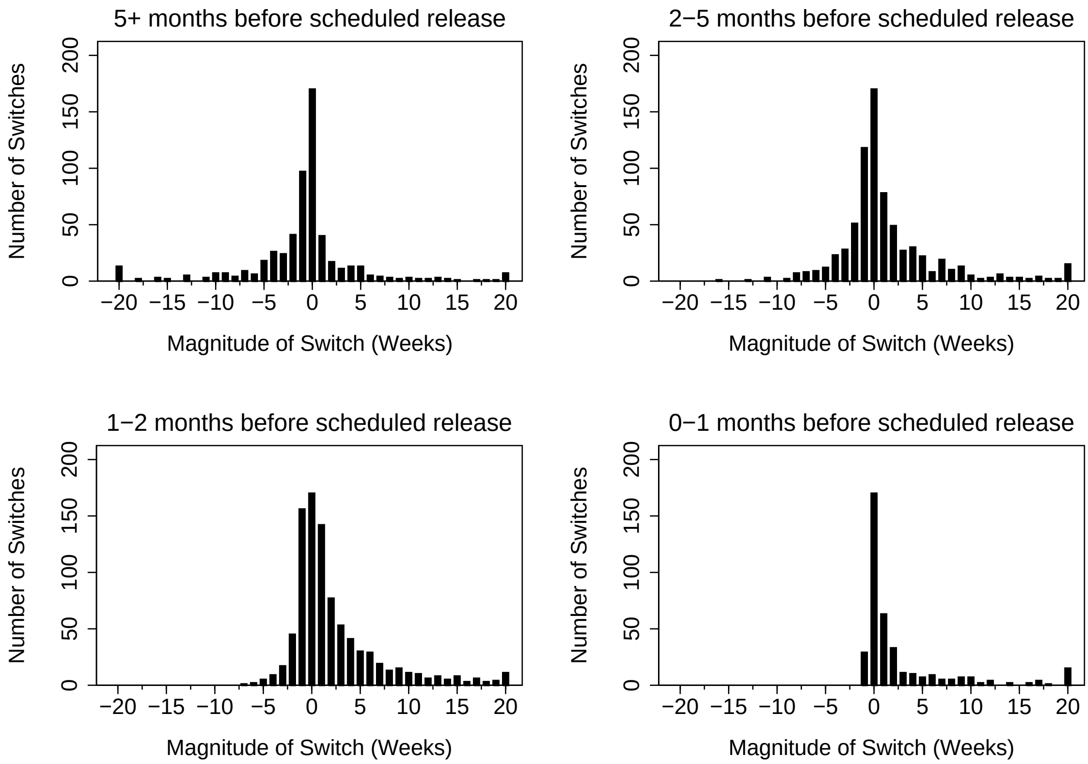

Figure 5: Magnitude of switches in different periods of time.

and ϵ_{ijt} is an unobserved propensity of an individual i to see the movie j in week t. The utility from the outside good $j = 0$ is normalized to:

$$u_{i0t} = \zeta_{it}^{'} + \pi\epsilon_{i0t}. \tag{2}$$

I assume ϵ_{ijt} and ϵ_{i0t} are distributed iid extreme value, whereas ζ_{it} and $\zeta_{it}^{'}$ have distributions that depend on π such that $\pi \in [0, 1]$, and $(\zeta_{it} + \pi\epsilon_{ijt})$ as well as $(\zeta_{it}^{'} + \pi\epsilon_{i0t})$ are distributed extreme value (Cardell, 1997).

The parameter π captures the heterogeneity of tastes across individuals. When π is close to zero, tastes are homogeneous as all individuals agree on which movie is the best. By contrast, as π approaches one, tastes become heterogeneous, and the market can fit larger amount of different movies. In this case the model collapses to a simple multinomial logit. Alternatively, one can interpret π as a degree of market expansion. When π is close to zero, a newly released movie earns a large part of its profits by stealing consumers from the existing movies and market expansion is weak. As π goes to one, market expansion effect becomes stronger, and newly released movies attract a significant mass of new consumers to the market. This parameter defines to which extend seasonality of the industry is amplified by endogenous release decisions of studios.

The model predicts that the market share of movie j at week t is:

$$s_{jt} = \frac{\exp\left(\frac{\tau_t - \lambda(t - r_j) + q_j + \xi_{jt}}{\pi}\right)}{D_t + D_t^{(1-\pi)}}, \tag{3}$$

where

$$D_t = \sum_{k \in J_t} \exp\Big(\frac{\tau_t - \lambda(t - r_k) + q_k + \xi_{kt}}{\pi}\Big) \quad (4)$$

and J_t is a set of all movies run in the theaters in week t. I invert the expression for market shares to get the mean utility:[5]

$$\log(s_{jt}) - \log(s_{0t}) = \tau_t - \lambda(t - r_j) + q_j + (1 - \pi) \log s_{j|IN} + \xi_{jt}. \quad (5)$$

This expression suggests that the share of individuals who watch the movie j in week t depends on the seasonal demand component τ_t, the number of weeks passed since the release of the movie $(t - r_j)$, and the quality of this movie. The within-industry market share, $s_{j|IN} \equiv s_{jt}/(1 - s_{0t})$, is endogenous. Following Berry (1994), I instrument this variable using the characteristics of other movies shown in the same week. Two instruments I use are the total number of competing movies and their average "newness", with the latter measured by the amount of weeks passed since the release. The main identifying assumption is that the instruments are not correlated with the idiosyncratic decay pattern of movie j captured by the error term ξ_{jt}. Under this assumption the model can be estimated by 2SLS using the weekly data on the market shares.

The identification strategy deserves a short discussion. In general, identification is difficult because of endogenous composition of movies. Better movies are released in weeks with high demand, which makes it hard to disentangle underlying demand from the qualities of movies. But even though movies of different quality are released in different weeks, later we still observe them run in the theaters at the same time. We can therefore exploit the panel dimension of the data and infer relative qualities of movies by comparing their relative market shares within the same week. Of course, movies shown in the same week will be characterized by different amount of time passed since their official release dates. Under constant decay rate this is not a problem, and the main identifying assumption we need to infer relative qualities of movies is that decay rate does not vary depending on when the movie is released.

Underlying demand in different weeks is identified using cross-year variation in the data. In particular, time-effect for a particular week is estimated by averaging market shares of movies run in the same week but in different years. Long time span of the data guarantees that estimates constructed in this way will be relatively precise. Finally, the total amount of movies shown in a certain week is different in different years. A part of this variation is exogenous, because production delays affect the final amount of movies released in different periods of time. The cross-year variation in the amount of movies within the same week allows to identify the market expansion effect.

B. Estimation Results from the Benchmark Model

The results from the benchmark model are presented in Table 3. All coefficients are precisely estimated and statistically significant at 1% level. The instruments have the expected effects on the endogenous variable. Higher total amount of competing films reduces the market share of a movie. Similarly, when competing films are comparatively new, the market share of a movie is substantially lower. The estimation of the model with only one of the two instruments does not have a large effect on the results.

The estimated linear and quadratic decay coefficients in the benchmark model are -0.16 and 0.003, with very small standard errors, while the market expansion parameter,

[5] The linear representation of the model is derived in the Appendix 1.

Table 3: Estimation Results of the Benchmark Model with Movie Fixed-Effects

	Model 1 2SLS	Model 1 1st stage	Model 2 2SLS	Model 2 1st stage	Model 3 2SLS	Model 3 1st stage
Decay	-0.172*	-0.563*	-0.143*	-0.572*	-0.155*	-0.571*
	(0.018)	(0.008)	(0.011)	(0.008)	(0.009)	(0.008)
Decay^2	0.003*	0.010*	0.003*	0.010*	0.003*	0.010*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
$\ln(s_{j\|IN})$	0.703*		0.755*		0.733*	
	(0.032)		(0.019)		(0.016)	
Instruments for $\ln(s_{j\|IN})$:						
Number same week		-0.030*				-0.034*
		(0.003)				(0.003)
Age same week				0.230*		0.248*
				(0.017)		(0.016)
Implied π	0.297*		0.245*		0.267*	
Movie FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,001	37,001	37,001	37,001	37,001	37,001
Number of titles	5,117	5,117	5,117	5,117	5,117	5,117
R^2	0.974	0.751	0.980	0.752	0.978	0.755
F excluded		96.4		185.9		169.6

Standard errors are clustered at the movie level. The estimation method is a two-step instrumental variable within-group regression. * p<0.01

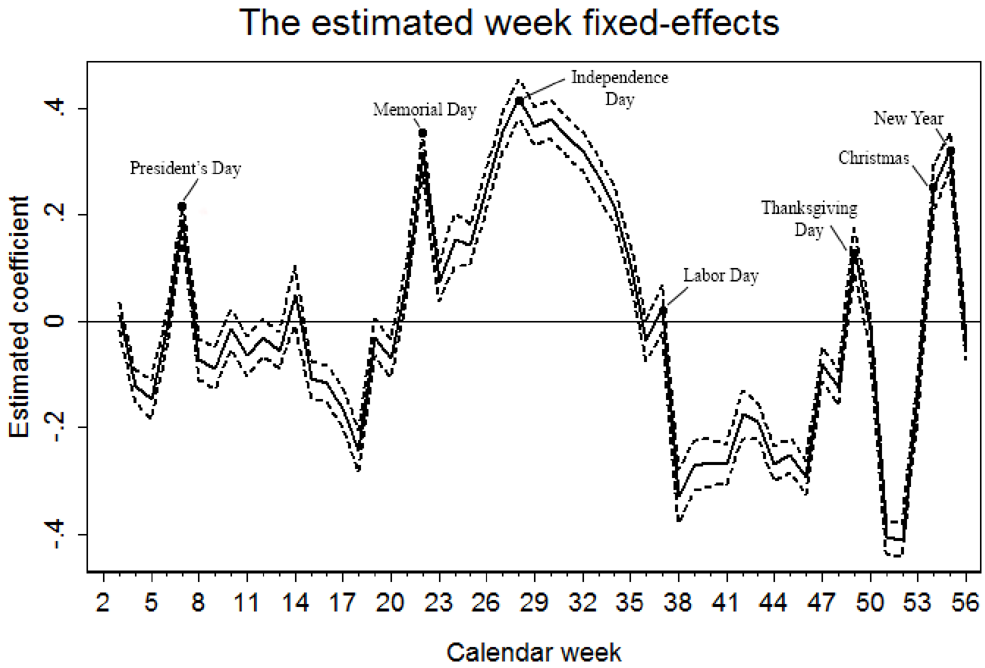

Figure 6: Estimated time effects from the benchmark model with movie fixed-effects. Dashed lines represent lower and upper bounds of the 95% confidence interval.

π, is 0.27. The two coefficients imply an estimated weekly decay of revenues of 39%, close to the observed revenue decline 41.5% in the data. The quadratic assumption on the decay pattern is not important. In one of the robustness checks I allowed decay to be fully flexible by including dummy variables for each of 10 weeks. The estimated decay pattern turned out to be almost identical to the one estimated in the benchmark model.

The market expansion parameter is estimated to be a number between 0 and 1, so the value of π is consistent with the random utility model. Estimated value of π implies that business-stealing effect is strong among movies. For example, in the week when only one movie is shown, the entrant of comparable quality would earn 65% of its profits by stealing consumers from the existing movie, and only 35% by attracting new consumers to the market.

The estimates of underlying demand in different weeks are presented in Figure 6. The seasonal pattern should be compared with the observed seasonality presented in Figure 2. Both underlying demand and industry revenues are high during summer and winter holidays, and low in spring and fall periods. But there are differences between the seasonal patterns of the two series. Industry revenues are high during release weeks with Thanksgiving and Christmas. These weeks are estimated to have high underlying demand, but their relative demand with respect to adjacent weeks and to summer period is not as high. By contrast, underlying demand in the week with President's Day is higher than industry revenues would imply. Finally, industry revenues are high in the week with Independence Day, and substantially lower in the adjacent weeks. Estimated underlying seasonality suggests that demand for movies during the summer period is more flat than industry revenues suggest.

C. Extended Model

Movies of the same genre can be better substitutes for each other than movies from different genre categories. For example, when families with children go to movies, they typically choose a movie from currently run animation films and do not consider thrillers and horrors. Similarly, a dating couple would most likely ignore children movies and documentaries, and choose among available romantic comedies and dramas. To capture such non-trivial patterns I extend the benchmark model to include nests for movie genres. The resulting specification is a three-level nested logit model with all movies grouped into an inside nest, and then partitioned into comprehensive and mutually exclusive sets by movie genre. As in the benchmark model, I use the market share inversion to express a movie j's market share as:

$$\log(s_{jt}) - \log(s_{0t}) = \tau_t - \lambda(t - r_j) + q_j + (1 - \pi_1\pi_2)\log s_{j|g} + (1 - \pi_2)\log s_{g|IN} + \xi_{jt}. \quad (6)$$

where $s_{j|g}$ is a market share of movie j as a fraction of market shares of all movies in genre group g, and $s_{g|IN}$ is a market share of group g as a fraction of the market share of the inside nest. Both variables $\log s_{j|g}$ and $\log s_{g|IN}$ are endogenous. The variable $\log s_{g|IN}$ is instrumented with the same variables as $\log s_{j|IN}$ was instrumented in the benchmark model. To instrument the within-group share $\log s_{j|g}$ I use the total number of movies from the genre group g shown in the same week, as well as the average time since release for the same set of competing movies.

The parameters π_1 and π_2 represent the degree of substitution among alternatives within genre groups and in the pool of all exhibited movies. For instance, when π_1 equals one, there is no correlation between tastes for alternatives that belong to the same genre. As the coefficient approaches to zero, movies of the same genre become much better substitutes than movies from different genre groups. If π_1 and π_2 are both equal to one, the model reduces to a standard logit. The nested logit model is consistent with random utility maximization concept as long as π_1 and π_2 both lie in the interval between 0 and 1 (McFadden, 1980). An additional requirement in the models with more than two levels of nesting is that π at higher levels of the nest structure do not exceed π at lower levels of nesting. In our case, this requirement implies that π_1 and π_2 should satisfy $\pi_1 > \pi_2$ (Börsch-Supan, 1987).

D. Estimation Results from the Extended Model

For the purpose of estimation all movies were grouped into seven genre categories: Action, Animation, Comedy, Drama, Documentary, Horror/Thriller, Romantic.[6] The biggest genre categories are Action (30% of movies) and Comedy (24%), and the smallest is Documentary (only 2%). As an alternative to grouping movies by genre, I also tried to group them by MPAA age rating. This was achieved by splitting all movies into five age rating categories: G (general audiences), PG (parental guidance suggested), PG–13 (parents strongly cautioned), R (under 17 with parent), and NC–17 (adults only). Most of the movies are rated with G or R (35 and 30% relatively), and only a small proportion of movies is rated as NC–17 (1%). I use these two categorizations to estimate the above specified demand model.

The results from the extended model are presented in Table 4. As before, all coefficients are precisely estimated and have small standard errors. Instruments have expected

[6]This grouping is based on the information about genres in IMDb Database. Whenever IMDb assigns a movie to multiple genres, I take the first genre to be a true genre of a movie. The results are not sensitive to using the second or the third genres assigned by IMDb categorization.

Table 4: Estimation Results of the Extended Model with Movie Fixed-Effects

	Genre 2SLS	1st stage $\ln(s_{j\|g})$	1st stage $\ln(s_{g\|IN})$	Rating 2SLS	1st stage $\ln(s_{j\|g})$	1st stage $\ln(s_{g\|IN})$
Decay	-0.166*	-0.538*	-0.073*	-0.157*	-0.530*	-0.044*
	(0.009)	(0.010)	(0.006)	(0.009)	(0.009)	(0.004)
Decay^2	0.003*	0.004*	0.007*	0.003*	0.006*	0.004*
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
$\ln(s_{j\|g})$	0.734*			0.732*		
	(0.014)			(0.016)		
$\ln(s_{g\|IN})$	0.691*			0.712*		
	(0.018)			(0.019)		
Instruments for $\ln(s_{j\|g})$:						
Number same group		-0.213*	0.208*		-0.123*	0.111*
		(0.008)	(0.006)		(0.006)	(0.003)
Age same group		0.443*	-0.347*		0.367*	-0.342*
		(0.009)	(0.008)		(0.012)	(0.008)
Instruments for $\ln(s_{g\|IN})$:						
Number same week		0.011*	-0.044*		0.003	-0.033*
		(0.004)	(0.003)		(0.004)	(0.002)
Age same week		-0.083*	0.288*		-0.084*	0.309*
		(0.019)	(0.013)		(0.020)	(0.011)
Implied π_1	0.861*			0.931*		
Implied π_2	0.309*			0.288*		
Movie FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,196	33,196	33,196	37,001	37,001	37,001
Number of titles	4,545	4,545	4,545	5,117	5,117	5,117
R^2	0.978	0.676	0.402	0.978	0.684	0.327
F excluded		915.2	818.1		474.1	1015.2

Standard errors are clustered at the movie level. The estimation method is a two-step instrumental variable within-group regression. * $p<0.01$

effects on the endogenous variables. Total number of competing movies as well as their newness have a negative effect on the market share of a genre group. Similarly, total number and newness of competing movies from the same genre category reduces the within-group market share of a movie. The same holds for the model with age rating groups.

Estimated coefficients of decay and market expansion are virtually the same as in the benchmark model. Implied nesting coefficients, π_1 and π_2, are both estimated to be between zero and one. In addition, π_1 is estimated to be larger than π_2, so estimated parameters satisfy all requirements of the random utility model. An interesting result is that the estimate of π_1 is well below one, which implies that nesting by genre is important. When a new movie is released, it leads to a proportionately larger decline in the share of movies of the same genre than the share of movies from other genre categories. The same result holds when movies are grouped by MPAA rating. However, the estimate of π_1 is much closer to one, so nesting by age rating plays almost no role.

Nontrivial substitution patterns may have important implications for release decisions of studios. When the market is segmented, similar movies cannibalize each other's profits more than movies from different genre categories. As a result, a distributor that wants to release an animation movie will pay more attention to the release dates of other animation movies rather than those of horrors and thrillers. Unfortunately, estimation of the model where movies differ in both horizontal and vertical dimensions requires more data than I have. Thus, in what follows I use estimation results from the benchmark model to specify payoffs of a release timing game.

5 Release Timing Game

A. Description

The strategic choice of release dates could probably be best described by a repeated game of announcements as in Caruana & Einav (2008b). Studios make consecutive rounds of announcements. In each round a studio can either duplicate its previous announcement or switch to a different release date. As players approach the planned release dates, switching becomes costly as it is hard to alter the marketing campaign of a movie shortly before the scheduled release. When adjustment costs become large enough, distributors commit to certain release dates and do not change them later on. In the model with such structure, final configuration of release dates would be a result of gradual commitment of studios. Estimation of this sequential model is well beyond the scope of this paper, as it is computationally intensive and requires more data.

In this section I propose a simplified version of the release timing game. I assume that studios simultaneously decide on release dates for their movies taking the history of prerelease announcements as given. The version of the model proposed here completely ignores announcements, but later I propose the extended version that explicitly incorporates announced release dates into the picture. The game has a structure of a discrete choice model. Modeling release timing decision as a discrete choice is natural, because studios effectively choose release week-ends instead of particular dates. Another feature of the game is the presence of private information. A studio knows its own week-specific costs associated with release of a movie, but does not observe the costs of its competitors. Given that in reality studios tend to keep the structure of their costs in secret, I believe that this is a realistic assumption.[7]

Finally, I abstract from the choice of movie characteristics e.g. the choice of budget. In practice, by the time studios have to decide on release dates of movies, the main characteristics of a movie such as budget, genre, plot, and actors are already determined. Any changes made to a movie shortly before the release have only a marginal effect on its consumer appeal. Thus, in the model studios make release decisions conditioning on the qualities of their movies.

B. The Setup

Consider a game between N distributors $j = 1, \dots, N$ each holding one movie. Distributors simultaneously decide on a release week of their movies. That is, each of them chooses an action $a_j \in A = \{1, \dots, W\}$, where $a_j = w$ means that the distributor j releases his movie in week w. The qualities of movies $q = (q_1, \dots, q_N)$, underlying demand $\tau = (\tau_1, \dots, \tau_W)$, and demand parameters $\theta = (\lambda_1, \lambda_2, \pi)$ are assumed to be a common knowledge. Let s be a vector of exogenous variables such that $s = (q, \tau)$. The utility of the distributor j from releasing his movie in week $a \in A$ is assumed to be

$$u_j(a) = \pi_j(a_j = a, a_{-j}, s) + \epsilon_j(a), \tag{7}$$

where $a_{-j} = (a_1, \dots, a_{j-1}, a_{j+1}, \dots, a_N) \in A^{N-1}$ describes actions of all distributors except j. In the expression above π_j is a payoff function I will specify later, and $\epsilon_j(a)$ is a choice-specific shock that is a private information of distributor j. This shock is not observed by competitors of j and is unknown to the econometrician. I assume that $\epsilon_j(a)$ is distributed extreme value and independent across distributors and actions. The values of these shocks are drawn before the distributor j makes a choice. I interpret $\epsilon_j(a)$ as private information of the distributor j about his week-specific costs e.g. advertising costs or costs of negotiating screens with theaters.

The expected payoff of distributor j from releasing in week a is then

$$\begin{aligned} \Pi_j(a, s) &= \mathbb{E}\left[\pi_j(a_j = a, a_{-j}, s) \middle| \, s\right] = \\ &= \sum_{a_{-j}} P_{-j}(a_{-j} \mid s) \pi_j(a_j = a, a_{-j}, s) \\ \text{with} \quad & P_{-j}(a_{-j} \mid s) = \prod_{k \neq j} P_k(a_k \mid s). \end{aligned} \tag{8}$$

The expectation in the first line is taken with respect to the actions of competitors a_{-j}, and the set of probabilities $\{P_k(a_k \mid s), a_k \in A\}$ describes beliefs of j about the actions of its rivals. The optimal choice of the distributor j is then:

$$a_j = a \iff \Pi_j(a, s) + \epsilon_j(a) > \Pi_j(\tilde{a}, s) + \epsilon_j(\tilde{a}) \quad \forall \tilde{a} \neq a \quad a, \tilde{a} \in A. \tag{9}$$

Since the value of shocks $\epsilon_j(a)$ is private information of studio j, from the perspective of j's competitors (and from the econometrician's perspective) the choice of j is probabilistic. Given that $\epsilon_j(a)$ are distributed extreme value, the choice of j can be characterized by the conditional choice probabilities:

[7] See, for example, the passage in Los Angeles Times on how studios often misreport their production costs (Los Angeles Times, 5 January 2009).

$$P_j(a \mid s) = \frac{\exp(\eta \Pi_j(a, s))}{\sum_{m \in A} \exp(\eta \Pi_j(m, s))} \tag{10}$$

The parameter η is a scale parameter that is related one-to-one to the variance of the choice-specific shocks ϵ.[8] When η is close to zero, a fit of the model is poor as the variance of unobserved shocks is very large compared to the difference in specified payoffs. By contrast, positive and large η indicates that the model performs good and that the difference in demand-based payoffs allows to explain substantial part of the variation in observed choices. Normally in discrete choice models it is impossible identify the variance of random shocks separately from other structural parameters. However, in the present application I use outside data to estimate the expected payoffs $\Pi_j(a, s)$. By this reason scale parameter will be well-identified from the data on the observed actions of studios.

To close the model we need to define what is an equilibrium in the above-specified game. Let $P_j(s)$ denote a stacked vector of choice probabilities for studio j so that $P_j(s) = (P_j(1 \mid s), \ldots, P_j(W \mid s))$, and let $P(s)$ be a composition of such vectors for all studios, that is $P(s) = (P_1(s), \ldots, P_N(s))$. Finally, I use $P_{-j}(s)$ to denote a vector similar to $P(s)$ but which excludes conditional choice probabilities of distributor j. The Bayesian Nash Equilibrium (BNE) in the game can be characterized by the optimal choice rule (9) and the set of probabilities $P(s)$ that satisfy the following system of $N \times W$ equations:

$$P_1(a \mid s) = \frac{\exp[\eta \Pi_1(a, s, P_{-1}(s))]}{\sum_{m \in A} \exp[\eta \Pi_1(m, s, P_{-1}(s))]} \qquad a = 1, \ldots, W$$

$$P_N(a \mid s) = \frac{\exp[\eta \Pi_N(a, s, P_{-N}(s))]}{\sum_{m \in A} \exp[\eta \Pi_N(m, s, P_{-N}(s))]} \qquad a = 1, \ldots, W \tag{11}$$

Each studio j chooses the most profitable release week given the realization of ϵ_j's, beliefs about the actions of competitors P_{-j}, and the value of s. Competitors of j do not observe ϵ_j's, and for them the strategy of studio j is characterized by the probability distribution $P_j(s)$. In BNE equilibrium choice probabilities $P_1(s), \ldots, P_N(s)$ should coincide with the beliefs of studios. Notice that there are only $N \times (W - 1)$ independent equations in (11) as one of the probabilities for each j can be expressed as a linear combination of others.

The system (11) can be compactly written in the form of a fixed point mapping: $P(s) = \Gamma(P(s))$. To emphasize the dependence on the scale parameter η, we can also write: $P(s; \eta) = \Gamma(s, \eta; P(s; \eta))$. It can easily be shown using Brouwer's fixed point theorem that an equilibrium to this model exists for any finite s. However, nothing in the model guarantees that the solution to the fixed-point problem is unique. Superficial analysis of the game reveals that for a wide range of values of s the game may have multiple equilibria. This presents a challenge for an estimation as the model delivers ambiguous predictions with respect to the equilibrium probabilities $P(s)$.

The issue of multiplicity is typical in the estimation of entry games. When the model has many potential equilibria, a researcher has to make some additional, potentially ad hoc assumptions about the equilibrium selection mechanism. I propose two different ways to proceed with the estimation of the model. In the first, I assume that only one equilibrium is played in the data, even though there may be multiple equilibria in the

[8] To be precise, $\epsilon_j(a)$ is iid across firms and choices and has the CDF $F(\epsilon) = \exp(-\exp(-\eta\epsilon))$. It has mean γ/η (where $\gamma = 0.577$ is the Euler's constant), and variance $\pi^2/6\eta^2$. For details see Ben-Akiva & Lerman (1985).

model. I let the data decide which equilibrium is being played in reality and approximate the main characteristics of that equilibrium from the data on observed choices of studios. Structural parameters are then estimated by maximizing a pseudo maximum likelihood of the data. In the second method, I explicitly solve for all possible equilibria in every market and impose an ad hoc equilibrium selection mechanism. I then use the nested fixed-point maximum likelihood routine to recover key structural parameters of the model. Detailed description of both estimation strategies is presented below.

6 Estimation

Method 1: Two-Step Estimation

The estimation strategy proposed in this section is based on the recent literature on two-step estimation (Aguirregabiria & Mira, 2007; Pakes et al., 2007). The empirical model resembles the one discussed in the survey of Bajari, Hong, & Nekipelov (2010). Suppose we have access to data on $m = 1, \ldots, M$ repetitions of the game. For each repetition we observe the value of the state variables s_m as well as actions of players $a_{1m}, \ldots, a_{Nm}$. By observing choices of release dates in a large number of markets, we can form consistent estimates $\hat{P}_j(a \mid s)$ for $P_j(a \mid s)$ for $j = 1, \ldots, N$. In practice, this simply boils down to flexibly estimating the probability that studio releases in a week $a \in A$ conditional on a given set of covariates. Given first-stage estimates $\hat{P}_j(a \mid s)$ we could then estimate η by maximizing a pseudo-likelihood function using $\Gamma_j(\eta, s, \hat{P}_{-1}(s))$ for $\forall j$.

Several assumptions are necessary to proceed with this estimation strategy. Let $a_m = (a_{1m}, \ldots, a_{Nm}) \in A^N$ be a vector of observed actions in market m. The first assumption states that in spite of potential multiplicity of equilibria in the system (11), there is only one equilibrium played in the data:

Assumption 1 (Unique equilibrium in DGP)
Let $P_m^0 = \{Prob(a_m = a \mid s_m = s) : (a, s) \in A^N \times \mathbb{R}^{|s|}\}$ be the distribution of a_m conditional on the value of exogenous variables s_m in market m.
(A) Observations $\{a_m, s_m\}$ are independent across markets
(B) For $\forall m$ we have $P_m^0 = P^0$

This assumption implies that in two markets characterized by the same values of the exogenous variables s_m, studios will always play the same equilibrium. An underlying idea is that there is some random mechanism which is used by market participants to coordinate on the equilibrium being played. We need this assumption to ensure that first stage estimates $\hat{P}_j(a \mid s)$ are consistent $P_j(a \mid s)$. The second assumption ensures that small changes in the value of exogenous variables s_m affect equilibrium only marginally:

Assumption 2 (Smoothness)
$Prob(a_m = a \mid s_m = s)$ is a smooth function of s for $\forall a \in A^N$.

The smoothness assumption ensures that choice probabilities in the data are well-behaved and thus be approximated by standard nonparametric techniques.

First stage. The purpose of the first stage is to obtain rough approximation of equilibrium choice probabilities $P_j(a \mid s)$ $(j = 1, \ldots, N)$ from the data on the observed actions of players. In this stage I form estimates $\hat{P}_j(a \mid s)$ for $P_j(a \mid s)$ using two alternative methods. The first is based on sieve series expansions (see Newey 1997, Ai & Chen 2003), whereas the second is a version of local linear regression (Hastie & Tibshirani 1990).

Let $\{z_l(s) \ \ l = 1, 2, \dots\}$ denote a set of basis functions having the property that linear combination can approximate some unknown real valued measurable function $g(s)$. The usual approach in nonparametric estimation is to form a sieve expansion for $g(s)$ using polynomials as basis functions $z_l(s)$. While polynomials are widely used in sieve estimation techniques, I form the bases from B-splines as they typically allow to achieve better approximation. I let the basis of splines to become increasingly flexible as the number of game repetitions M increases. Let $\kappa(M)$ denote the total number of basis functions to be used when sample size is M. I assume $\kappa(M) \to \infty$, but $\kappa(M)$ does not increase too fast, that is $\kappa(M)/M \to 0$ (e.g. $\kappa(M) \approx \sqrt{M}$).

Denote $\kappa(M) \times 1$ vector of basis functions as $z^{\kappa(M)}(s) = (z_1(s), \dots, z_{\kappa(M)}(s))'$, and let Z_M be a collection of these vectors such that $Z_M = (z^{\kappa(M)}(s_1), \dots, z^{\kappa(M)}(s_M))'$. The first estimator I use is based on a linear probability model, where regressors are splines from $z^{\kappa(M)}(s)$. The estimator can be written in a compact way as:

$$\hat{P}_j(a \mid s) = \sum_{m=1}^{M} 1\{a_{jm} = a\} z^{\kappa(M)}(s_m)^T (Z_M^T Z_M)^{-1} z^{\kappa(M)}(s) \qquad \text{for} \qquad j = 1, 2 \tag{12}$$

Note that when s contains continuous variables, the sieve estimator $\hat{P}_j(a \mid s)$ will converge to the $P_j(a \mid s)$ at a nonparametric rate slower than $\sqrt{M}$ (Cox 1988, Newey 1997). As a close alternative to a linear probability model, I also try a multinomial logit specification. That is, I model conditional choice probabilities as:

$$\hat{P}_j(a \mid s) = \frac{\exp(z^{\kappa(M)}(s)^T \hat{\theta}_a)}{\sum_{k \in A} \exp(z^{\kappa(M)}(s)^T \hat{\theta}_k)} \tag{13}$$

This is a multinomial logit model with basis functions $z^{\kappa(M)}(s)$ as regressors. The model can be estimated using standard maximum likelihood routine.

The second estimator I propose is a locally weighted linear regression. This is a version of local linear regression with variable bandwidth, tricubic kernel function, and built-in mechanism of downweighting outliers proposed in Cleveland (1979). In practice, I find that the results of two-step estimation are not very sensitive to the choice of specification in the first stage. This is consistent with the finding in Bajari, Hong, Krainer, & Nekipelov (2010) that as long as the first stage model is flexibly specified, asymptotic properties of two stage estimator do not depend on the choice of a particular nonparametric method.

Second stage. The goal of this stage is to take estimated reduced form of the game as given and derive likelihood function of the sample. Suppose we substitute estimates $\hat{P}_j(a \mid s)$ obtained from the first stage in place of $P_j(a \mid s)$ in (8). Then the expected payoff of studio j can be expressed as:

$$\hat{\Pi}_j(a, s, \hat{P}_{-j}(s)) = \sum_{a_{-j}} \hat{P}_{-j}(a_{-j} \mid s) \pi_j(a_j = a, a_{-j}, s) \tag{14}$$

$$\text{with} \quad \hat{P}_{-j}(a_{-j} \mid s) = \prod_{k \neq j} \hat{P}_k(a_k \mid s).$$

Note that in this last expression we treat $\hat{P}_j(a \mid s)$ as consistent estimates of beliefs. In this case, optimization problem of each player turns into a single-agent problem. It can be seen as a game of studio j against "nature" with the latter represented by the distribution $\hat{P}_{-j}(s)$.

The conditional choice probabilities can be then written in the form similar to (10) with the difference that instead of expected payoffs $\Pi_j(a,s)$ the expression now includes approximated values $\hat{\Pi}_j(a,s)$:

$$\tilde{P}_j(a \mid s; \eta, \hat{P}_{-j}(s)) = \frac{\exp(\eta \hat{\Pi}_j(a, s, \hat{P}_{-j}(s)))}{\sum_{m \in A} \exp(\eta \hat{\Pi}_j(m, s, \hat{P}_{-j}(s)))} \qquad \forall a, j \tag{15}$$

Under Assumptions 1 and 2, resulting probabilities $\tilde{P}_j(a \mid s)$ are consistent estimates of $P_j(a \mid s)$ in (10). Finally, let D denote the data on the cross-section of markets. The pseudo log-likelihood function is:

$$\mathscr{L}(D; \eta) = \sum_{m=1}^{M} \sum_{j=1}^{N} \log \tilde{P}_j(a_{jm} \mid s_m; \eta, \hat{P}_{-j}(s_m)) \tag{16}$$

Maximization of this function gives an estimate for the structural parameter η. This estimator falls within the class of semiparametric estimators considered by Newey (1994). Bajari, Hong, Krainer, & Nekipelov (2010) develop the asymptotic theory for this regressor. The key result is that pseudo-MLE is consistent as long as there are no multiple equilibria in the data. A somewhat surprising conclusion is that even though the first stage is estimated nonparametrically and converges slower than $\sqrt{M}$, the structural parameter η will be asymptotically normal and will converge at a rate $\sqrt{M}$. As a practical matter, this result suggests that I can simply bootstrap pseudo-MLE to calculate standard errors for the model.

The pseudo-likelihood estimator has two main advantages. First, numerical burden of estimation is reduced sufficiently, because estimation is broken in two steps. This comes at a cost of lower efficiency compared to the nested fixed-point estimation.[9] Note that the model in (16) is simply a multinomial logit model where regressors are defined using estimated expected payoffs $\hat{\Pi}_j(a,s)$. Computational simplicity of the method allows to run a large number of bootstrap repetitions for a comparatively short period of time. Second advantage is that instead of imposing strong assumptions on the equilibrium selection mechanism, we let the data decide which equilibrium is being played. This is a convenient solution to the problem of multiplicity. Of course, if uniqueness assumption is violated, the two-step estimation is no longer useful as it does not guarantee consistency of estimates.

An assumption that there is a unique equilibrium in the data may seem too strong. However, I believe that in the current application this assumption is natural. Pesendorfer & Schmidt-Dengler (2003) show that the uniqueness of equilibrium in the data is more convincing when the markets are defined across different time periods for a given geographical location than when markets are defined across different geographical locations. This is the case in the current application, where markets are defined as different release seasons. Another important observation is that the movie industry in the United States is stationary in a sense that the same studios interact with each other throughout

[9] Efficiency of the two step estimator can potentially be improved by iterating the second step as in Aguirregabiria & Mira (2007). However, in my application this iteration trick did not have any substantial effect on the standard errors of estimates.

decades. This makes it more likely that there exists an established mechanism used by market participants to coordinate on the equilibrium being played.

Method 2: Nested Fixed-Point Estimation

An alternative method to the two step estimation is the Nested Fixed-Point Estimation (NFXP). NFXP requires solving for equilibrium strategies in many markets and for many values of parameters. The main idea behind this method is to solve for all possible equilibria in each market m and impose a particular equilibrium selection mechanism. The structural parameters can be then estimated by maximizing a mixture likelihood function of the sample.

Estimation starts with computing all solutions to the system (11). Let Ψ_m denote the set of all possible equilibria that can arise in market m, that is:

$$\Psi_m = \{U_m^e : U_m^e = P_m^e(s) \quad e = 1, \dots, E_m\} \tag{17}$$

where each $P_m^e(s)$ is a set of probabilities $\{P_{mj}^e(a \mid s) \quad \forall a, j\}$ that characterizes one of the equilibria. The fact that E_m may be larger than one requires the specification of an equilibrium selection mechanism to calculate the likelihood of a particular outcome. Specifically, I assume that U_m^e is played in market m with probability $P(U_m^e \mid s_m) = f(U_m^e; \lambda)$, where λ is a vector of parameters. One interesting way to parameterize the equilibrium selection would be to assume that:

$$f(U_m^e; \lambda) = \frac{\exp\Big(\sum_{j=1}^N \lambda_j \Pi_{jm}^*(U_m^e)\Big)}{\sum_{r=1}^E \exp\Big(\sum_{j=1}^N \lambda_j \Pi_{jm}^*(U_m^r)\Big)} \tag{18}$$

where $\Pi_{jm}^*(U_m^e)$ is the expected payoff of player j in equilibrium U_m^e. By construction, this is a proper probability distribution as $\sum_{e=1}^{E_m} f(U_m^e; \lambda) = 1$. This equilibrium selection mechanism puts more weight on equilibria where players with large λ_j's earn higher profits.[10] One can estimate the parameters λ together with payoff-related parameters. Resulting estimates can be used to decide whether equilibrium selection favors certain players.[11]

The selection mechanism has a natural interpretation in the context of commitment. If there are many possible equilibria, which one of them is played can be determined by the studio with the highest commitment power. For example, that studio can make an early announcement and force the equilibrium which maximizes its expected profits. In this case, parameters λ reflect the relative commitment power of players, and $f(U_m^e; \lambda)$ can be interpreted as the reduced form outcome of their prerelease strategic interactions.

Finally, we can specify the mixture log-likelihood of the sample as:

$$\mathscr{L}(D; \eta, \lambda) = \sum_{m=1}^{M} \log\Big(\sum_{e=1}^{E_m} f(U_m^e; \lambda) \prod_{j=1}^{N} P_{mj}^e(a_{mj} \mid s_m; \eta)\Big) \tag{19}$$

[10] A similar approach is chosen in Bajari, Hong, & Ryan (2010), where equilibrium selection depends on the properties of the equilibrium itself (e.g. joint payoff-maximizing in the model of collusion).

[11] Even though expected payoffs in (18) are marked with player indices j, one can index those values with a studio index. One can then estimate parameter λ for each studio in the sample.

In taking the model to data I make the additional assumption that only stable equilibria are played, so $f(U_m^e; \lambda) = 0$ for nonstable equilibria. Identification of equilibrium selection parameters λ depends on the presence of multiple equilibria in sufficient amount of markets. If λ are introduced as studio-specific and not player-specific parameters, the additional requirement for identification is that there is a sufficient amount of observations for each studio. The details of NFXP estimation are provided in the Appendix.

The procedure described above has an advantage of being more efficient than the two step estimation. It is also more flexible in the way payoffs can be specified. Two step estimation imposes strict limitations on the dimensionality of the model, as nonparametric estimation in the first stage can only be done with comparatively few exogenous variables. By contrast, NFXP is not sensitive to the dimensionality of s and allows to estimate richer models. I will later use this property of NFXP to estimate the extended version of release timing game with adjustment costs.

The main downside of the procedure is its heavy computational burden. Low computation speed does not allow to estimate a large amount of parameters using this method. In addition, there exists no reliable way to solve for all equilibria of the model. Because of this reason, I use two step estimation and NFXP as complementary ways of inference.

Specification

The general setup for the estimation is as follows. I single out several time periods ("seasons") within the year and take the set of movies that were released in a specified period as given. I then analyze the choice of the week within a season, in which the movie was released. The motivation for this setup comes from the announcement patterns described in one of the previous sections. Ahead of time studios decide that a certain movie is scheduled for a particular month or, say, around Christmas. Only later they start to choose specific release dates and decide on a particular week of release within the narrow period of time.

All seasons are centered around national holidays. Such location of seasons is reasonable, because the best movies are typically released in weeks adjacent to big holidays (see Figure 3 and Figure 7). Studios holding these movies are likely to be more strategic with respect to release dates as opposed to the owners of smaller movies released in low demand periods. In addition, chosen location of seasons makes the pattern of underlying demand comparable across seasons, which simplifies two step estimation.

To take the model to the data, I still need to specify parameters of the game and a particular payoff function. In what follows I describe a simplified setup of the game that reduces dimensionality of the model and decreases computational burden. First, the set of players is restricted to the 4 highest quality movies released in each season, where qualities are approximated by the estimated movie fixed-effects. These movies are high budget blockbusters, which are likely to be the most strategic players in the industry. In estimation I use only markets, in which all N movies belong to different studios. The resulting game is then effectively a game among studios that decide on release dates for their best movies. Restricting attention to one best movie per studio is reasonable, as all other movies of a studio earn on average only 20% of the revenues earned by a movie with the highest quality.

Each season is assumed to be an independent release timing game. In each game 4 movies play against each other, conditioning on release dates of all other movies. This means that studios not only condition on the observed release dates of smaller movies

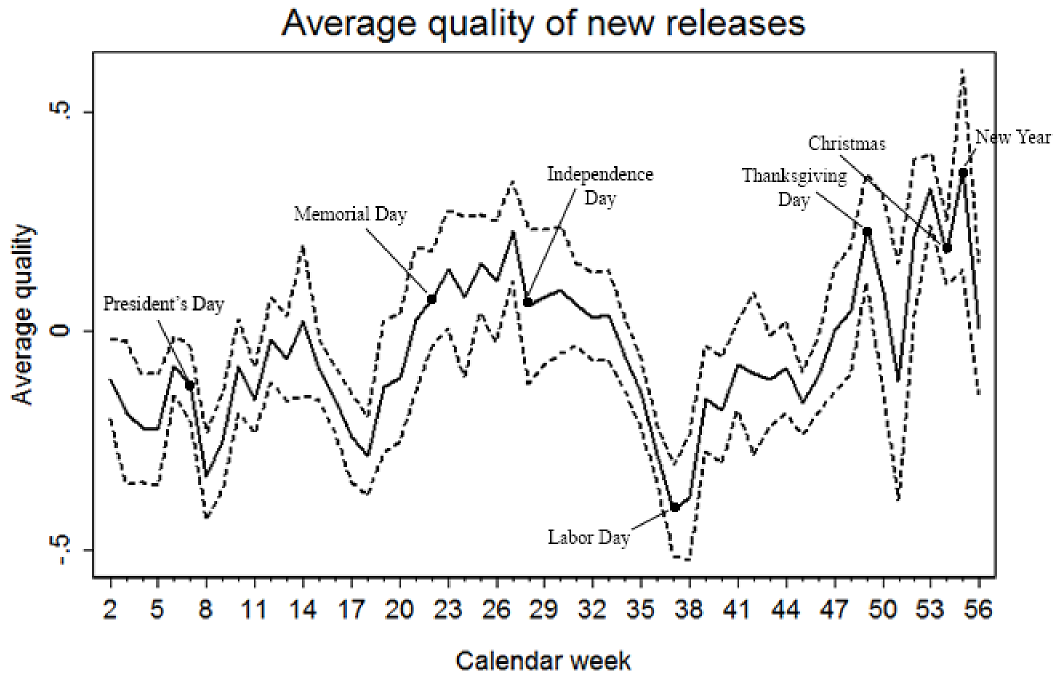

Figure 7: Average value of the estimated fixed-effects for new releases. Dashed lines represent lower and upper bounds of the 95% confidence interval.

released in the same season, but also take as given all movies released in weeks adjacent to the season. Conditioning on movies released in the past is innocuous, because release dates of those movies are known by the time strategic players make their final decisions. Conditioning on movies released after the end of the season is more subtle. This implies perfect foresight of players with respect to the future releases, an assumption that seems quiet strong. However, demand estimation suggests that revenues are decaying very fast. Thus, movies released after the end of the season have only a minor effect on the payoffs of strategic players, and the way future releases are incorporated in the model should not affect estimation results.

Seasons are centered around five major national U.S. holidays: President's Day, Memorial Day, Independence Day, Thanksgiving, and Christmas. As depicted in Figure 8, the length of each season is 3 weeks, and the third week is always a high demand holiday week. This setup is motivated by the observation that studios often release high quality movies in the weeks right before holiday, but rarely schedule releases of big budget films during the after-holiday period (see Figure 3).

The sample consists of 160 seasons (5 seasons for each of 32 years). In selected seasons the average number of releases per season is 10. The quality of an average movie released within one of the seasons is 0.05 with standard deviation 0.51. As explained above, in each season I consider only 4 movies as strategic, and treat release dates of all other movies as exogenous. Average quality of strategic movies is 0.42, whereas an average nonstrategic movie has quality of only -0.19. Around 75% of total box-office revenues within a season is earned by strategic movies, and only 25% is earned by all other films.

Table 5 reports summary statistics for the final samples of games constructed for $N = 2$, $N = 3$, and $N = 4$. A number of games in each of three samples is lower than 160,

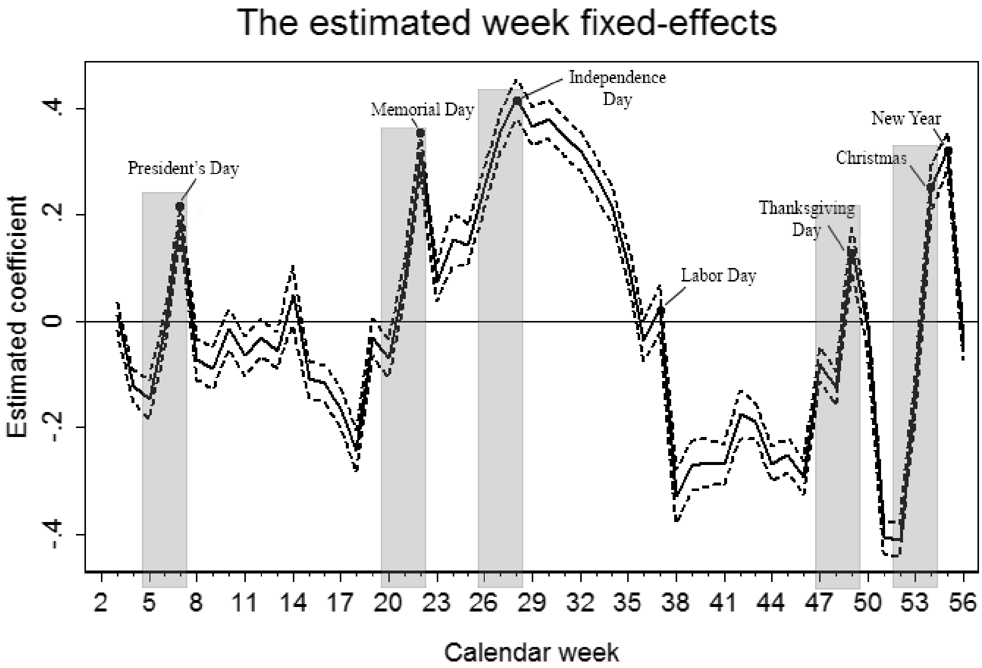

Figure 8: Definition of release seasons.

because in many seasons some of top-quality movies are owned by the same distributors. These markets are excluded from the sample to avoid solving joint maximization problem of players.[12] According to the relative frequencies in Table 5, higher quality movies are released in peak-demand week 3 more often. Movies with lower quality are released mainly in week 2, and less often in week 3. If high quality of a movie gives studio competitive advantage in choosing release dates, this observation indicates that studios perceive week 3 as the most profitable week, and week 2 is viewed to be the second-best release option. Of course, the exact ordering of weeks by profitability is case specific and depends, *inter alia*, on the underlying demand, decay rate of revenues, and intensity of competition. The particular payoff function specified below allows to construct accurate estimates of counterfactual revenues.

Payoff function

I use the nested logit specification of demand to formulate payoffs. Specifically, I assume that the known portion of distributors' profits takes the following form:

$$\hat{\pi}_j(a_j, a_{-j}) = \sum_{t=t(a_j)}^{t(a_j)+T} \hat{s}_{jt}(a_j, a_{-j})$$

$$= \sum_{t=t(a_j)}^{t(a_j)+T} \Big(\hat{D}_t + \hat{D}_t^{(1-\pi)}\Big)^{-1} \exp\Big(\frac{\tau_t - \lambda(t - t(a_j)) + q_j}{\pi}\Big) \tag{20}$$

where $\hat{D}_t$ is defined as:

[12]Estimation of a complete model, in which studios simultaneously decide on release dates for all their movies, is not only hard computationally but would also require much more data.

Table 5: Summary Statistics for the Sample of Games

Rank	Average Quality	Released in Week 1	Released in Week 2	Released in Week 3
Sample 1 (N=2, 151 Observations)				
1	0.642	23.1%	34.4%	42.3%
2	0.457	21.1%	39.0%	39.7%
Sample 2 (N=3, 127 Observations)				
1	0.653	21.2%	35.4%	43.3%
2	0.475	19.6%	40.1%	40.1%
3	0.338	28.3%	36.2%	35.4%
Sample 3 (N=4, 97 Observations)				
1	0.647	22.8%	31.9%	45.3%
2	0.475	18.6%	41.2%	40.2%
3	0.344	24.8%	40.2%	35.0%
4	0.208	21.7%	43.3%	35.0%

Rank indicates a position in the list of new releases ordered by quality. Quality is approximated by the estimated fixed-effect of a movie.

$$\hat{D}_t = \sum_{k \in J_t(a_j, a_{-j})} \exp\Big(\frac{\tau_t - \lambda(t - t(a_k)) + q_k}{\pi}\Big) \quad (21)$$

In these expressions $t(a_j)$ is the endogenous release week chosen by studio j, τ_t is the estimated week-effect, q_j is the estimated movie-effect of movie j, λ and π are the estimated decay and market expansion parameters. I assume that every movie is shown in theaters for $T + 1$ weeks independent of its quality, so T represents the length of the planning horizon. To simplify construction of the payoff matrix I assume $T = 3$[13]. $J_t(a_j, a_{-j})$ is the set of movies that play in week t. This set is endogenous and depends on the release dates chosen by strategic studios, as well as on the observed release dates of the nonstrategic movies.

Expression (20) is a modified version of the market share specified in (3). There are two differences. First, I assume that studios make their release decision under the assumption that $\xi_{jt} = 0$. Since ξ_{jt} is the idiosyncratic decay pattern unknown to a studio ex ante, this is a reasonable assumption.[14] Second, true values of structural parameters are replaced by the estimated values. A proper estimation procedure should account for the uncertainty in these estimates.

It is convenient to decompose $\hat{D}_t$ into two parts, strategic and nonstrategic:

$$\hat{D}_t = \sum_{l \in G_t(a_j, a_{-j})} \exp\Big(\frac{\tau_t - \lambda(t - t(a_l)) + q_l}{\pi}\Big) + \sum_{k \in F_t} \exp\Big(\frac{\tau_t - \lambda(t - t(a_k)) + q_k}{\pi}\Big) =$$
$$= \hat{H}_t(a_j, a_{-j}) + \hat{C}_t \quad (22)$$

where $G_t(a_j, a_{-j})$ is the set of strategic movies that play in week t, F_t is the set of nonstrategic movies shown in that week. $\hat{H}_t(a_j, a_{-j})$ and $\hat{C}_t$ are two statistics that summarize

[13]In practice, I find that the model performs much worse under $T > 3$ than under $T \leq 3$. Later I discuss why this can be the case.

[14]In one of the robustness checks I impute ξ_{jt} from estimated demand system. By doing so, I assume that realized idiosyncratic pattern does not depend on the release date of a movie. This exercise have a negligibly small effect on the results, because the variance of residuals is very small.

overall strength of strategic and nonstrategic movies relatively. This decomposition tells us that all exogenous competition from nonstrategic movies in week t can be summarized by a sufficient statistic $\hat{C}_t$. To see why it is useful, consider the following representation of the payoffs $\hat{\pi}_j(a_j, a_{-j})$:

$$\hat{\pi}_j(a_j, a_{-j}, q, \tau, \hat{C}) = \sum_{t=t(a_j)}^{t(a_j)+T} \hat{s}_{jt}(a_j, a_{-j}, q, \tau, \hat{C})$$

$$= \sum_{t=t(a_j)}^{t(a_j)+T} \Big(\hat{H}_t + \hat{C}_t + (\hat{H}_t + \hat{C}_t)^{(1-\pi)}\Big)^{-1} \exp\Big(\frac{\tau_t - \lambda(t - t(a_j)) + q_j}{\pi}\Big) \tag{23}$$

where C is a vector of sufficient statistics that summarize competition from non-strategic movies, so that $C = (\hat{C}_{t(a_j)}, \dots, \hat{C}_{t(a_j)+T})$. Thus, the environment of the game can be fully described by qualities q, week-effects τ, and competition statistics C. This is especially useful in two step estimation, where the first step requires regression the observed release dates on all exogenous variables. The representation above reduces dimensionality of the exogenous vector s and therefore improves the quality of the first stage approximation.

Estimation results

Table 6 presents the two step estimation results for different choices of N and T. The first stage estimation method is a linear probability regression described above. Overall, the results are quite stable across different choices of parameters. In all specifications with $T \leq 2$, the estimate of η is positive and significant at a 10% confidence level[15]. Recall that η is the scale parameter of the model. An insignificant η would imply that the modeled payoffs do not help in explaining observed release dates, and a negative η would imply that the modeled payoffs are negatively associated with release timing decisions of studios. Therefore, the positive and significant estimate of η suggests that specified payoffs, together with the estimated parameters, are indeed useful in explaining the release date decisions.

The magnitude of the estimated η can be interpreted in an intuitive way. In the empirical model η is inversely related to the variance of a shock $\epsilon_j(a)$. High value of the estimated η implies that unobserved week-specific costs account for only a small part of the variation in the variables that are relevant for release timing decisions. The statistic R^2_{MZ} reported in Table 6 reflects the relative importance of the modeled payoffs.[16] Depending on specification, the specified payoffs account for up to 25% of the variation in all decision-relevant variables. Thus, the trade-off between seasonality and competition is indeed an important determinant of release timing decisions.

The results are robust to the various choices of the first stage estimation method. Table 12 presents the estimation results with local polynomial regression run in the first stage. The estimates of η as well as p-values are virtually the same. I also tried other estimation methods such a linear probability model with polynomials, multinomial

[15]The standard errors in Table 6 were obtained by running two-step estimation on the bootstrapped samples of games. That is, I ignore the uncertainty in the demand parameters and compute standard errors as if these parameters are known. In practice, bootstrapping all three steps of estimation (instrumental regression, nonparametric estimation, and maximum likelihood) changes standard errors only marginally and does not affect significance of coefficients.

[16]The idea behind this statistic is described in McKelvey & Zavoina (1975). In the current application, R^2_{MZ} is defined as $R^2_{MZ} = \widehat{VAR}(\hat{\Pi}_j(a, s))/(\widehat{VAR}(\hat{\Pi}_j(a, s)) + \widehat{VAR}(\epsilon_j(a)))$.

Table 6: Two-Step Estimation Results. First Stage: Sieve Regression with Splines

		$T=1$	
	$N=2$	$N=3$	$N=4$
$\hat{\eta}$	20.31**	17.64*	29.33**
	(9.37)	(10.66)	(12.70)
$\log L^*$	-329.94	-417.04	-422.19
LR	3.69	3.07	8.14
R^2_{first}	0.155	0.201	0.281
R^2_{MZ}	0.100	0.089	0.129
R^2_{pseudo}	41.1%	37.0%	42.3%
		$T=2$	
	$N=2$	$N=3$	$N=4$
$\hat{\eta}$	18.92**	17.99**	25.59**
	(9.45)	(9.17)	(11.92)
$\log L^*$	-329.50	-416.27	-422.27
LR	4.57	4.60	7.98
R^2_{first}	0.166	0.228	0.281
R^2_{MZ}	0.182	0.212	0.246
R^2_{pseudo}	38.1%	36.6%	36.6%
		$T=3$	
	$N=2$	$N=3$	$N=4$
$\hat{\eta}$	10.11	9.67	16.68
	(11.09)	(12.63)	(14.38)
$\log L^*$	-331.20	-418.03	-425.01
LR	1.15	1.08	2.51
R^2_{first}	0.203	0.228	0.332
R^2_{MZ}	0.078	0.101	0.179
R^2_{pseudo}	39.7%	37.8%	41.2%
Markets	151	127	97
Observations	302	381	388

Table 7: Nested Fixed-Point Estimation Results

		$T = 1$	
	$N = 2$	$N = 3$	$N = 4$
$\hat{\eta}$	22.36***	26.08**	35.52***
	(7.07)	(10.42)	(12.00)
$\log L^*$	-329.39	-415.04	-420.95
LR	4.84	7.14	10.71
R^2_{MZ}	0.086	0.137	0.173
		$T = 2$	
	$N = 2$	$N = 3$	$N = 4$
$\hat{\eta}$	19.28**	25.77***	30.33***
	(8.98)	(9.38)	(10.68)
$\log L^*$	-329.20	-414.02	-421.07
LR	5.22	9.19	10.46
R^2_{MZ}	0.174	0.253	0.297
		$T = 3$	
	$N = 2$	$N = 3$	$N = 4$
$\hat{\eta}$	12.14	20.70*	27.54**
	(9.46)	(10.73)	(13.14)
$\log L^*$	-330.90	-416.40	-423.50
LR	1.82	4.42	5.61
R^2_{MZ}	0.117	0.258	0.349
Markets	151	127	97
Observations	302	381	388

regression with splines, and Nadaraya–Watson frequency estimator with kernel weighting. In all cases the estimation results changed only marginally, and coefficients in all specifications with $T \leq 2$ remained significant at a 10% confidence level.

Empirical model performs better in some seasons than in others. Table 13 presents the estimation results obtained separately for two subsamples of games. The model performs comparatively better in case of spring and summer seasons, but the estimated η for Christmas and Thanksgiving seasons is small and not significant. This poor fit suggests that in the end of a year studios face different incentives with respect to release timing decisions. Specifically, studios may want to release movies early in order to qualify for the Academy Awards. They may also want to avoid competition of their best movies with the Oscar candidates of other distributors. However, sample size is too small and the estimates of η in Table 13 are less reliable than those obtained for the whole sample.

Table 7 presents estimation results from the Nested Fixed-Point algorithm. The estimates of η are comparable in magnitude and have smaller standard errors, which reflects higher efficiency of the estimator. On top of that, estimates of η under $T = 3$ are now significant at a 10% confidence level. Overall, the estimated model does a better job in explaining release decisions of studios. Modeled payoffs now account for up to 30–35% of the variation in all decision-relevant variables. A somewhat surprising finding is that under $\eta < 100$ I always find only one equilibrium, and it seems that for those

Table 8: Summary Statistics of the Announcement Data

Studio	Number of movies	Reports per movie	Percent of Switches	Commitment Time
Fox	196	11,2	21,6%	70,6
Warner Bros.	296	10,7	20,2%	80,7
Paramount	212	11,6	18,5%	97,6
Columbia	408	10,7	18,3%	79,3
Universal	267	9,7	17,1%	93,6
Disney	400	10,2	21,1%	85,7
Others	945	9,3	22,5%	62,9
All Studios	2724	10,1	20,3%	76,9

values of η multiplicity is not an issue.[17] This has two implications. First, equilibrium selection plays a very limited role in the estimated model. The experimentation with different selection mechanisms showed that the estimate of η is not sensitive to the way equilibrium is selected. It is therefore impossible to identify parameters of the equilibrium selection mechanism e.g. to estimate λ_j's in (18). Second, in the model without multiplicity two step estimation and NFXP should deliver similar results by construction. The results presented in this section show that the results from these two different estimation procedures are indeed very similar.

The absence of multiple equilibria can be the consequence of high importance of private information. According to the estimation results, over 60% of the variation in variables relevant to release decisions are unobserved week specific costs. Strategic part of payoffs plays only a limited role in the model. Thus, very often the final configuration of release dates is determined by realization of choice-specific shocks, and not by the trade-off between seasonality and competition. One possible remedy to this limitation of the model would be to combine estimation of η and all demand parameters in one efficient procedure.[18] This would insure higher relevance of the strategic part of payoffs and reduce the importance of private information. The resulting model would be likely to have multiple equilibria, a feature that can be used to identify the components of equilibrium selection mechanism.[19]

[17] In the Appendix 2 I describe the details of NFXP procedure. I tried to increase the amount of initial points for the fixed-point iteration procedure from 100 to 100,000. I also tried to update best response probabilities at a slower pace, sometimes as slow as by 0.1% of the difference between the current guess and the best response probabilities. None of these tricks helped to find any additional equilibria.

[18] A simple but computationally intensive way to implement joint estimation would be to combine the set of conditional moments coming from the IV within-group regression (5) with the set of moments based on choice probabilities (10). Structural parameters could be then estimated by the means of optimally-weighted GMM with the nested fixed-point algorithm.

[19] It may seem at first that we are trying to introduce multiplicity artificially in the model. This is not fully correct, as the model with efficiently estimated parameters would be closer to the true model, and thus it is a "more correct" model to analyze.

7 Announcements

I. Analysis of Correlations

The main goal of this section is to check whether observed announcement patterns are consistent with the commitment story. As discussed before, studios may be able to use prerelease announcements as a commitment mechanism. One potential strategy a studio could use is to announce its future release plans early and hope that it will deter competitors from choosing the same release date. I now check whether the observed behavior of distributors resembles this kind of commitment strategy.

Assume a studio makes consecutive announcements with respect to one of its movies. Let $a_{T-K}, a_{T-K+1}, \ldots, a_{T-1}, a_T$ denote these announcements, where each a_t is a tentative release week, indices $T-K, \ldots, T$ mark successive rounds of announcements, and a_T is the last announcement that corresponds to the official release date of a movie. I define the statistic "commitment time" in the following way:

$$Commitment\ Time = T - t_{min}$$

$$t_{min} = \inf\{t : a_t = a_T \quad \text{and} \quad a_s = a_T \quad \text{for} \quad \forall s \in (t; T)\}$$

This statistic reflects how long before the official release a studio decided to stick to the final release date without changing it later on. In the data on prerelease announcements commitment time has a mean of 77 days and standard deviation of 70 days. Table 8 presents average commitment time for different studios. Paramount Pictures and Universal Pictures have the highest average commitment time that exceeds 90 days, whereas minor studios commit to the final release date only 60 days in advance. The value of commitment time is correlated with the size of a movie, when the latter is approximated by the budget, maximum amount of screens, or total realized box-office revenues (See Figures 15, 16, and 17). This correlation is especially strong among the largest movies in the sample.

Table 9 presents the results of regression of commitment time on the characteristics of a movie. Conditional on movie's budget, Paramount Pictures and Universal Pictures commit on average 20 days earlier than independent studios from the baseline category. 20th Century Fox commits 10 days later than independent studios, although coefficient is significant only marginally. This result survives when other movie characteristics are controlled for e.g. genre, age rating, and best picture winner status. At the same time, ex ante bigger movies tend to commit earlier. When the budget of a movie is doubled, commitment time is 16 days shorter. Similarly, when the peak amount of screens is increased by 1000, a movie commits 25 days earlier. Overall, the results suggest that certain studios tend to commit earlier, especially when they hold ex ante successful movies.

The results in Table 9 should be interpreted with caution. Ideally, we would like to allocate movies randomly to the studios and then check whether commitment time depends on the identity of a studio or on the observed movie characteristics. In reality composition of movies held by each studio is endogenous, so it is difficult to disentangle studio-effect from movie-effects. Paramount Pictures and Universal Pictures may be committing earlier because movies they own have higher quality, a competitive advantage that is not fully captured by the production cost or maximum amount of screens. Thus,

Table 9: Commitment Time and Movie Characteristics

	Model 1	Model 2	Model 3	Model 4	Model 5
Fox	9.036*	-9.836*	-9.400	-10.75**	-10.42**
	(5.327)	(5.336)	(5.985)	(5.262)	(5.251)
Warner Bros.	20.04***	2.977	1.693	0.0309	-1.128
	(4.557)	(4.584)	(5.497)	(4.557)	(4.546)
Paramount	36.72***	16.82***	19.59***	14.99***	14.71***
	(5.227)	(5.265)	(5.979)	(5.204)	(5.205)
Columbia/Sony	14.62***	4.133	5.229	3.715	3.862
	(4.122)	(4.058)	(4.998)	(4.009)	(4.014)
Universal	30.11***	15.10***	21.31***	14.35***	14.46***
	(4.823)	(4.792)	(5.615)	(4.730)	(4.712)
Walt Disney	21.08***	6.435	0.770	8.337**	5.592
	(4.200)	(4.203)	(5.189)	(4.105)	(4.191)
Log of Total BO Revenues		11.10***			
		(0.837)			
Log of Production Cost			16.63***		
			(1.689)		
Max Screens				2.527***	2.330***
				(0.168)	(0.193)
MPAA G/PG					10.62
					(8.830)
MPAA PG-13					9.367
					(8.676)
MPAA R					2.421
					(8.327)
Comedy					-2.058
					(3.637)
Drama					7.784**
					(3.712)
Children					19.68***
					(5.536)
Sequel					21.84***
					(4.853)
Best Picture					-1.213
					(6.275)
Observations	1,203	1,203	510	1,203	1,203
Adjusted R-squared	0.054	0.138	0.148	0.158	0.178
Year FE	Yes	Yes	Yes	Yes	Yes

Table 10: Profitability of the Observed Release Week Related to Commitment Time

	Monopoly Revenues	Oligopoly Revenues	Total Market Revenues	Individual Revenues
Commitment time (months)	0.009***	0.021**	0.019***	0.048***
	(0.002)	(0.008)	(0.004)	(0.011)
Log(Production Cost)	0.065***	0.226***	0.151***	0.683***
	(0.008)	(0.028)	(0.014)	(0.037)
Year FE	Yes	Yes	Yes	Yes
Number of movies	1,320	1,320	1,320	1,320
Adjusted R^2	0.081	0.115	0.214	0.245

Robust standard errors are reported in parentheses. All dependent variables are proxies for profitability of the week, when a movie was officially released. Monopoly revenues are total box-office revenues that a movie would earn, if did not face any competition from other movies. Oligopoly revenues are total box-office revenues that a movie would earn, given the observed configuration of release dates in the data. Total market revenues are observed total box-office revenues earned by all movies. Individual revenues are observed cumulative box-office revenues earned by a movie. *** p<0.01, ** p<0.05, * p<0.1

the fact that both studio and movie effects appear to be significant should be seen as a suggestive, but not conclusive evidence.

A studio that has a chance to make a binding announcement will use it to release a movie in the most profitable time period. I now check if movies that commit earlier also tend to be released in more profitable weeks. In doing so, I construct three different profitability measures. The first one, monopoly revenues, is defined as:

$$\widehat{MR}(w) = \sum_{t=w}^{w+T} \frac{1}{1 - \exp(-\hat{\tau}_t)}$$

These are the expected revenues that a movie would get, if none of other movies were shown in the theaters at the same time. Monopoly revenues exhibit similar seasonal patterns to the ones of underlying demand, as it is shown in Figure 9. According to this measure, releasing a movie one week before the holiday can be almost as profitable as releasing in the holiday week itself. This explains why so many high quality movies in the data were released just before the peak demand week of the season.

Monopoly revenues tend to move in the same direction with the average commitment time (See Figure 10). The weeks with higher average commitment time also tend to bring higher expected revenues. This co-movement is especially vivid in the weeks adjacent to the national holidays. Raw correlation between two series is 0.16 and is significant at a 1% confidence level. But average commitment time varies largely from year to year, and within–year correlation between commitment time and monopoly revenues is often as high as 0.30–0.35. Table 10 presents the results from regression of profitability measure on commitment time, budget, and year dummies. Conditional on production cost, a movie that commits 60 days earlier has a tendency to be released in the weeks with 2% higher monopoly revenues.

The second profitability measure, oligopoly revenues, takes into account the intensity of competition in different weeks. This measure is defined in the following way:

$$\widehat{OR}(w) = \sum_{t=w}^{w+T} \Big(\hat{D}_t + \hat{D}_t^{(1-\hat{\pi})}\Big)^{-1} \exp\Big(\frac{\hat{\tau}_t - \hat{\lambda}(t-w)}{\hat{\pi}}\Big)$$

It reflects the expected revenues that a movie would get conditional on the official release dates of all movies in the sample. As it is clear from Figure 11, seasonality of oligopoly revenues differs from the one of underlying demand. Competition among movies is more intense during summertime and near holidays, which results in low values of expected revenues in these periods. By contrast, the end of Spring and the time between Thanksgiving and Christmas are associated with high oligopoly revenues, because these are non-popular release weeks characterized by low competition. There is a clear co-movement between oligopoly revenues and commitment time (See Figure 12). Raw correlation of two series is 0.22, and within–year correlation achieves 0.40 in certain years. The results in Table 10 show that when a movie commits 60 days earlier, it is also released in the weeks that have, on average, 4% higher values of oligopoly revenues.

The third measure of profitability, total market revenues, is simply total box-office revenues earned by all movies in a particular week (and during the weeks right after that):

$$\widehat{TMR}(w) = \sum_{t=w}^{w+T} Market\ Revenues(t)$$

In a sense, this is a naive measure of profitability that ignores the structure of the model and relies on raw data on revenues. Seasonal dynamics of total market revenues closely follows the seasonality of underlying demand (Figure 13). According to the results in Table 10, a movie that commits 60 days earlier is typically released in the weeks with 3.8% higher market revenues. The last column of the table also suggests that movies with 60 days lower commitment time also have a tendency to earn 9.6% higher individual revenues, with the latter defined as:

$$\widehat{IR}_j = \sum_{t=w}^{w+T} BO\ Revenues_j(t)$$

Strong robust correlation between commitment time and various profitability measures of a release week suggests that there is indeed a prominent relation between announcement behavior of a studio and its release timing decisions.

II. Estimation of Adjustment Costs

Announcements can serve as a commitment tool only if they are binding. Perhaps, the best way to test whether shifting release dates is indeed costly would be to setup a strategic game of announcements and estimate switching costs from the data. Estimation in that case would rely on the revealed preference argument. If changing an announced release date is costly, announcements of studios will be characterized by certain degree of rigidity. Once an announcement is made, a studio will be reluctant to shift a release date even if it may increase expected revenues. We could then infer the magnitude of switching costs from the amount of revenues studios are ready to give up. As discussed above, estimation of the dynamic game of announcements is beyond the scope of this paper. Fortunately, there is a simple way to estimate switching costs within the static setup developed in the previous section. It relies on exact same identification strategy. Below I propose an extension of the release timing game that allows to recover the magnitude of switching costs from the observed release dates.

Consider the following version of release timing game. The setup is exactly like in the previous section but with the different payoff function. Let $z_1, \ldots, z_N$ ($z_j \in A \;\; \forall j$) denote prerelease announcements that studios have made with respect to their movies. The deterministic part of payoffs is now defined as:

$$\hat{\pi}_j(a_j, a_{-j}, q, \tau, \hat{C}, z_j) = \sum_{t=t(a_j)}^{t(a_j)+T} \hat{s}_{jt}(a_j, a_{-j}, q, \tau, \hat{C}) - \gamma \mathbb{1}\{a_j \neq z_j\}$$

where the first summand is specified in (23). The parameter γ in the second summand represents adjustment costs, and indicator function $\mathbb{1}\{a_j \neq z_j\}$ captures the fact that a studio only incurs adjustment costs if a chosen release week does not coincide with the previously announced one. The structural parameter γ is interpreted as a combination of all costs associated with reoptimization of an advertising campaign and renegotiation of screens with theaters.[20] If the game of releases has a repeated nature, γ may also include implicit reputational costs.

It is convenient to normalize the variance of private information shock $\epsilon_j(a)$ to $\pi^2/6$, so that payoffs can be re-written in the following way:

$$\begin{aligned}\hat{\pi}_j(a_j, a_{-j}, q, \tau, \hat{C}, z_j) &= \eta \sum_{t=t(a_j)}^{t(a_j)+T} \hat{s}_{jt}(a_j, a_{-j}, q, \tau, \hat{C}) - \eta\gamma \mathbb{1}\{a_j \neq z_j\} = \\ &= \eta \sum_{t=t(a_j)}^{t(a_j)+T} \hat{s}_{jt}(a_j, a_{-j}, q, \tau, \hat{C}) - \theta \mathbb{1}\{a_j \neq z_j\} \qquad (24)\end{aligned}$$

where $\theta = \eta\gamma$. The goal of estimation is to recover parameters η and θ from the data on observed choices of release dates. Identification relies on the assumption that announcements $z_1, \ldots, z_N$ are exogenous. Under this assumption the presence of announcements in the model generates useful exclusion restrictions. When z_j changes, this has a direct effect only on the payoffs of studio j, and affects the expected payoffs of all other studios only indirectly through the strategic channel. This helps to disentangle strategic effect from the effect of adjustment costs, and as a result both η and θ are well identified.

Exogeneity of announcements is a strong assumption. In reality, studios may choose announced release dates strategically. To see why this is a problem for identification, imagine that announcements $z_1, \ldots, z_N$ are determined as an outcome of some strategic game. When z_j changes, the expected payoffs of competitors are affected not only through the strategic channel, but also through the channel of adjustment costs. This is a classic multicollinearity problem, which makes it hard to disentangle the effect of two different channels on release timing decisions of studios. As a result, without exogeneity assumption identification is weak and relies only on a nonlinear functional form of the model. One solution to this problem would be to endogenize $z_1, \ldots, z_N$ and estimate a

[20] In principle, it is possible to introduce different adjustment costs for different studios, e.g. γ_j for $j = 1, \ldots, N$. I believe that estimation of such asymmetric model would require much more data than I currently have.

Table 11: Estimation Results for the Model with Adjustment Costs

	30 days		60 days	
	Model 1	Model 2	Model 1	Model 2
$\hat{\eta}$	45.70**	47.30	41.63*	43.61*
	(22.64)	(32.66)	(23.21)	(23.17)
$\hat{\theta}$		3.02***		1.93***
		(0.44)		(0.33)
$\log L^*$	-79.204	-30.08	-70.447	-43.885
N obs.	75	75	66	66
R^2_{MZ}	0.55	0.67	0.48	0.60
	90 days		120 days	
	Model 1	Model 2	Model 1	Model 2
$\hat{\eta}$	39.91	44.65*	43.91	42.90
	(24.74)	(26.63)	(26.77)	(28.44)
$\hat{\theta}$		1.35***		1.36***
		(0.33)		(0.35)
$\log L^*$	-57.554	-47.866	-50.836	-42.21
N obs.	54	54	48	48
R^2_{MZ}	0.42	0.55	0.46	0.55

full scale dynamic game of announcements. An alternative way to proceed is to search for the data on exogenous cost shifters and use that data to generate additional exclusion restrictions. I leave implementation of these remedies for the future research.

Table 11 presents estimation results for the model with adjustment costs. The model was estimated with the NFXP algorithm. In estimated models z_j correspond to announcements made by studios 30, 60, 90, or 120 days before the official release date of a movie. Early announcements (120 days before release) have a large amount of missing values and some of them do not contain specific release dates. Late announcements (30 days before release) mostly coincide with the official release dates, so there are no switches in the data.[21] Hence, my preferred specifications are the ones, in which announcements are made 60 and 90 days before release.

Estimated η is larger than in the models considered earlier, and significant at a 10% confidence level. When adjustment costs are introduced in the model, estimates of η do not change much. At the same time, estimated θ's are positive and have very small standard errors. Joint significance of both estimated η and θ suggests that prerelease announcements have additional effect on release decisions that is unrelated to the trade-off between seasonality and competition. Note, however, that the number of observations used in estimation is small because of missing data on the announcements. Thus, all results in Table 11 should be interpreted with caution.

To understand the magnitude of estimated switching costs, consider the following interpretation of results. Estimated coefficients imply that paying adjustment cost γ is equivalent to a reduction of the market share by 0.03–0.04. Simple back-of-the-envelope calculations suggest that, given the average U.S. population of 250 million and the average

[21]Non-trivial proportion of both switching movies and those movies that do not switch helps to identify the magnitude of adjustment costs.

ticket price of \$4, estimated switching costs have a magnitude of around \$30–40 million. This figure may seem out of scale considering that an average movie in the sample earns total revenues of \$70 million and spends only \$15 million on advertising. But if γ is interpreted as reputational costs, this result does not sound very extreme. Consider a stylized example. Assume that whenever a studio changes a previously announced release date, it looses reputation of being a "tough" player for one next game. Imagine that, as a result, in the next game a studio is forced to release a movie in the least profitable week. If this is the case, then based on the constructed matrix of payoffs the loss of reputation can be equivalent to a reduction of the market share by 0.01–0.02, a number that is comparable to the estimated adjustment costs.

8 Discussion and Limitations

The main conclusion from the empirical analysis of this paper is that studios seem to be using prerelease announcements as a way to commit to certain release strategies. The results presented in the paper closely relate to the main ideas of the recent theoretical work. According to the theory, three conditions are necessary for commitment strategies to arise endogenously within a particular environment. First, commitment should have a considerable value for market participants. This is indeed the case in the movie industry, as an ability to make binding promises can help a studio to fight for the most profitable release dates.

Second, there should exist a commitment device that players can use to make their promises credible. As discussed above, prerelease announcements may play a role of such device. Estimation results suggest that the announcements made by studios have a considerable effect on their final release timing decisions, and therefore are not likely to be cheap talk. Third, players should be different in their ability to use an existing commitment device. Based on the observed announcement patterns, I argue that such asymmetries exist in the industry both because adjusting release dates is more costly for high budget movies, and because for some studios switching is associated with higher reputational costs. By and large, presented empirical evidence suggests that behavior of movie distributors is largely consistent with the main predictions of the endogenous commitment theory.

The empirical strategy in this paper has several limitations. Some of them are obvious e.g. the empirical model restricts the amount of weeks in one season and the total number of strategic players. Others are more subtle, for example, the commitment story is only one of many possible ways to explain the observed behavior patterns of studios. A very different way to rationalize the observed behavior would be to argue that studios use announcements to coordinate their release dates. A potentially optimal collusion scheme would be to set release dates of high budget blockbusters further apart in order to minimize business-stealing effect and achieve maximum market expansion. Studios may also try to coordinate release dates of films sharing the same genre, as these movies tend to be the closest competitors.[22] Whether studios are indeed using announcements as a coordination device is an empirical question. Under collusion the observed release schedule will be designed to maximize total expected profits of studios. This is a testable hypothesis that could potentially be explored within the static model proposed in this

[22] See Corts (2001) for more detailed discussion of the incentives of studios to coordinate release dates of movies.

paper.

There are reasons to believe that commitment story is much more plausible in the context of the movie industry than the hypothesis of collusion. The conventional wisdom about release date competition in the U.S. movie market is that competition seems so intense that it often leads to overcrowding of releases in peak demand periods, and a dearth of films in off-peak weeks. Industry practitioners often characterize this clustering of films as "self-destructive" and "a nightmare for all parties".[23] This conventional image suggests that movie industry is highly competitive and does not resemble a cooperative environment.

9 Conclusion

This paper studies the release timing game played by movie distributors. The timing game is formulated as a static game with private information, with distributors choosing among a fixed set of release weeks. Studios face a trade-off between seasonality and competition: some weeks have higher demand but are also characterized by more intense competition among movies. Presented empirical findings show that, when incorporated into a release timing game, this trade-off proves useful in explaining observed release dates of movies.

The main empirical finding of this paper is that prerelease announcements play an important role in the game of releases. Announced release plans tend to have substantial effect on final release decisions of studios, and are not likely to be cheap talk. In addition, observed behavior of market players is consistent with the idea that certain studios are using announcements as a way to pre-commit to particular release dates. As a whole, the results suggest that behavior of movie distributors is largely consistent with the main predictions of the endogenous commitment theory.

The motion picture industry is not the only market, in which public announcements can play an important role. Release timing of new products is central in many industries including the markets for laptops, tablets, cellphones, and videogames. Manufacturers typically inform the public about the forthcoming launch of new products long before the start of the sales. To the extent that such promises are binding, they may play a role similar to prerelease announcements in the movie industry.

Another example is strategic scheduling of broadcast media products (Internet, television, radio, etc.). Modern broadcasters regularly change the scheduling of their programs in order to build an audience for a new show and to compete effectively with the shows of other broadcasters.[24] Printing a preliminary schedule in newspapers and magazines and conveying it to the wide audience could be used by broadcasters as a way to pre-commit to a certain programming strategy. To find out whether firms in these markets indeed use public announcements as a commitment mechanism could be an interesting direction for future research.

[23] For example, see the discussion of movie overcrowding in *Variety, 22 July 2013.*

[24] There are only a few papers that analyze strategic scheduling. Goettler & Shachar (2001) construct a strategic scheduling game between television networks, but do not use it for estimation. Sweeting (2009) models the timing of radio commercials as an outcome of the strategic game played by radio stations.

Table 12: Two-Step Estimation Results. First Stage: Local Linear Regression

		$T = 1$	
	$N = 2$	$N = 3$	$N = 4$
$\hat{\eta}$	20.28**	18.16*	31.20**
	(9.66)	(10.10)	(14.09)
$\log L^*$	-330.03	-416.57	-421.38
LR	3.50	3.99	9.77
R^2_{first}	0.163	0.241	0.302
		$T = 2$	
	$N = 2$	$N = 3$	$N = 4$
$\hat{\eta}$	18.71**	17.94**	25.79**
	(9.27)	(7.99)	(12.36)
$\log L^*$	-329.63	-416.03	-422.19
LR	4.30	5.09	8.14
R^2_{first}	0.179	0.261	0.327
		$T = 3$	
	$N = 2$	$N = 3$	$N = 4$
$\hat{\eta}$	9.13	11.39	18.00
	(10.63)	(12.33)	(15.65)
$\log L^*$	-331.31	-417.77	-424.81
LR	0.94	1.60	2.91
R^2_{first}	0.192	0.285	0.340
Markets	151	127	97
Observations	302	381	388

Table 13: Two-Step Estimation Results Season by Season

	Seasons 1-3 (President's Day, Memorial Day, Independence Day)	Seasons 4-5 (Thanksgiving Day, Christmas)
	$N = 2$	
$\hat{\eta}$	33.29***	-5,91
	(12.32)	(14.44)
$\log L^*$	-200.78	-127.32
LR	7.12	0.24
Markets	93	58
Observations	186	116
	$N = 3$	
$\hat{\eta}$	37.89***	6.78
	(13.31)	(12.43)
$\log L^*$	-261.94	-151.43
LR	10.04	0.36
Markets	81	46
Observations	243	138
	$N = 4$	
$\hat{\eta}$	50.76***	7.28
	(15.18)	(16.50)
$\log L^*$	-274.18	-144.86
LR	14.13	0.31
Markets	64	33
Observations	256	132

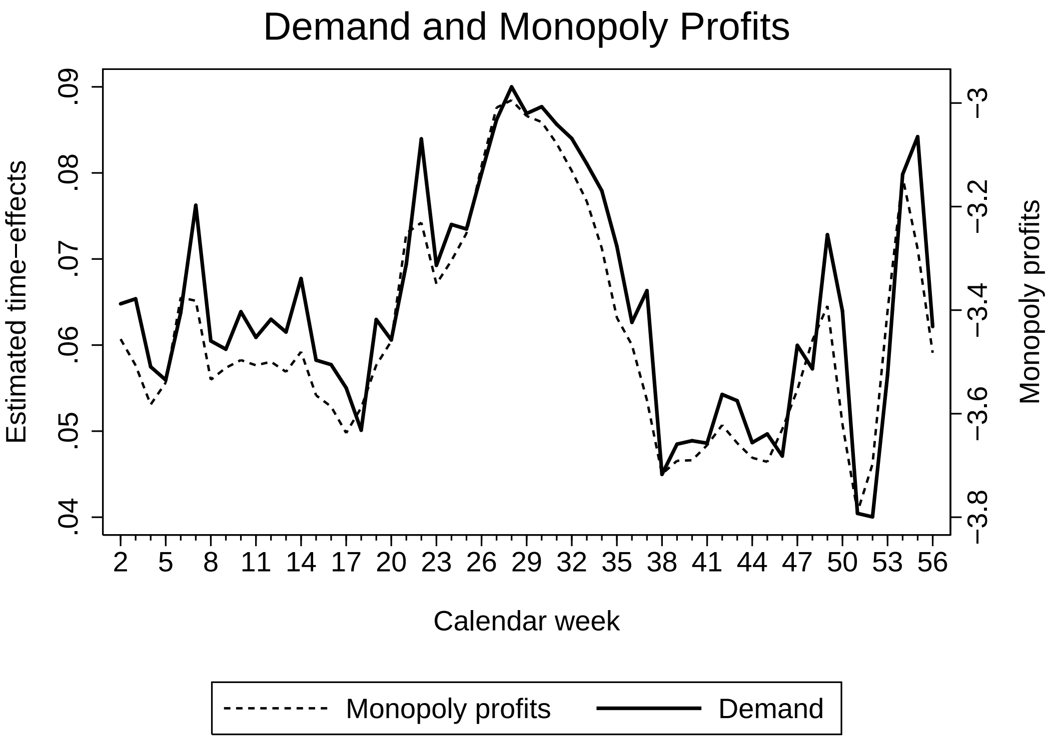

Figure 9: Monopoly revenues and underlying demand.

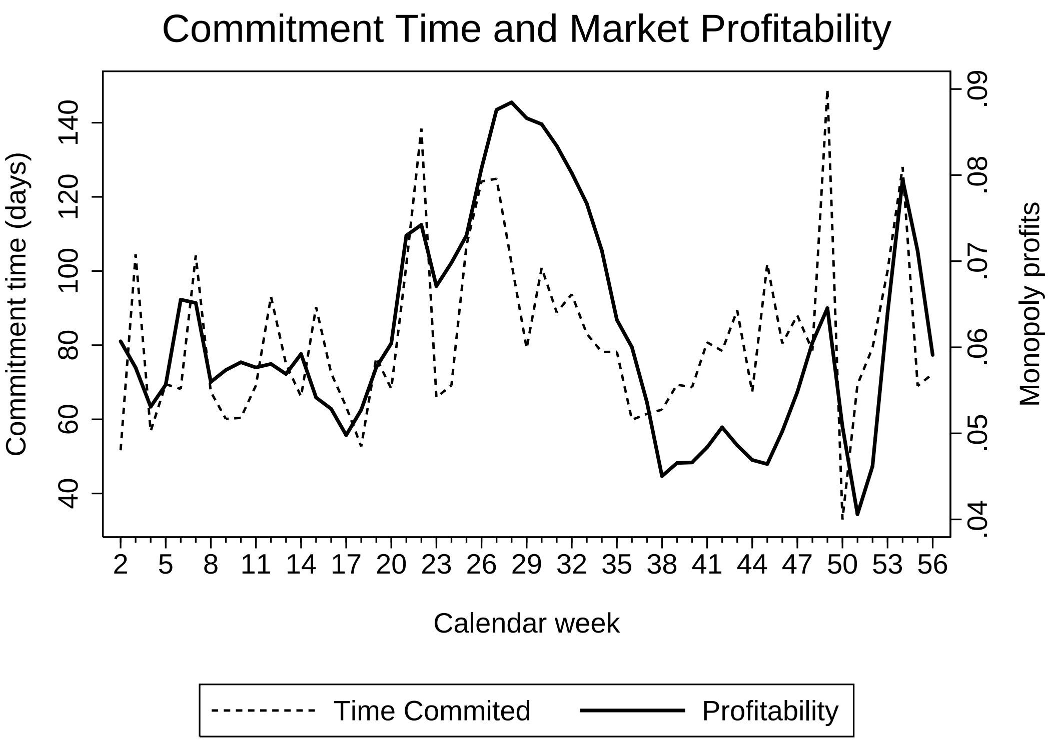

Figure 10: Monopoly revenues and commitment time.

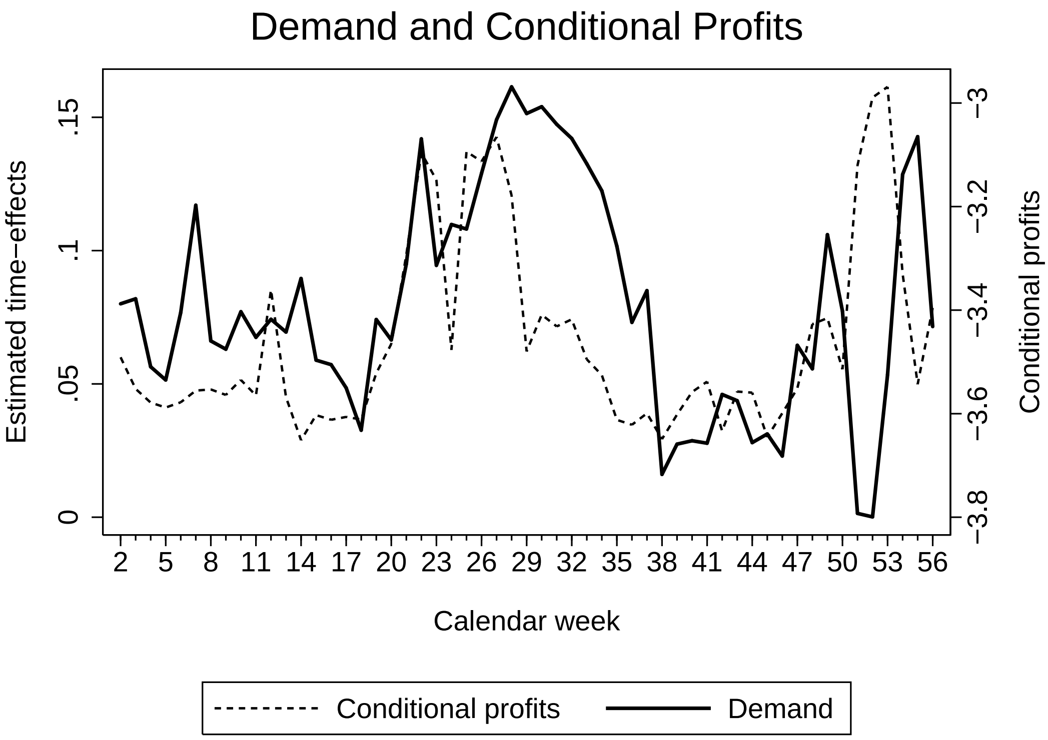

Figure 11: Oligopoly revenues and underlying demand.

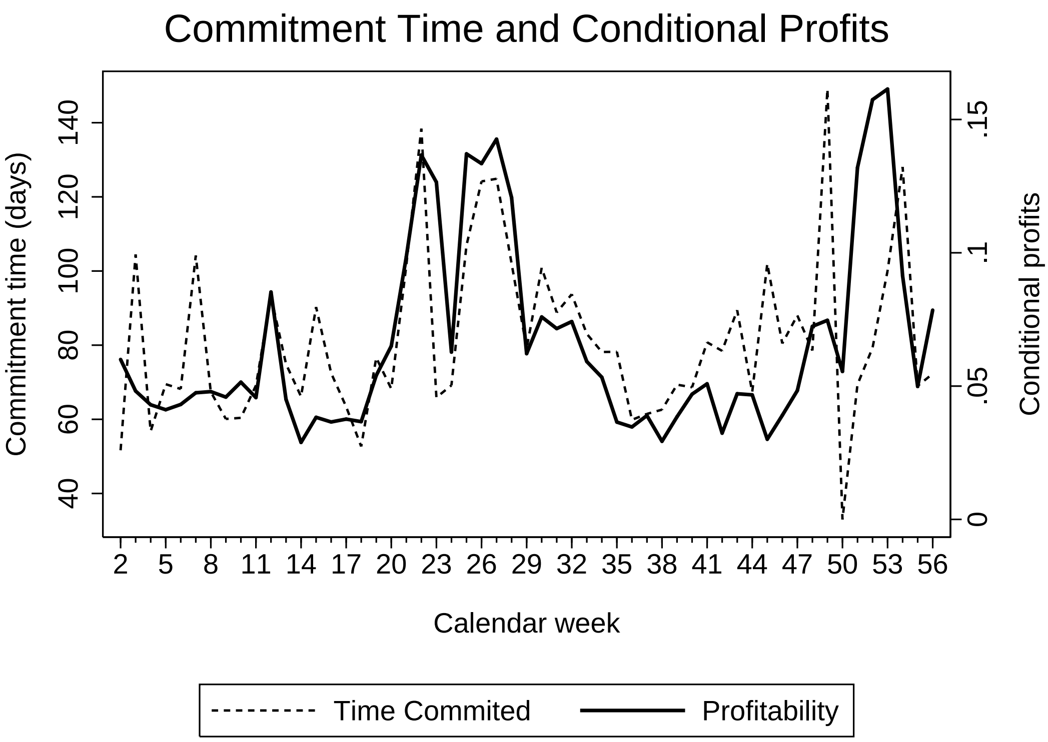

Figure 12: Oligopoly revenues and commitment time.

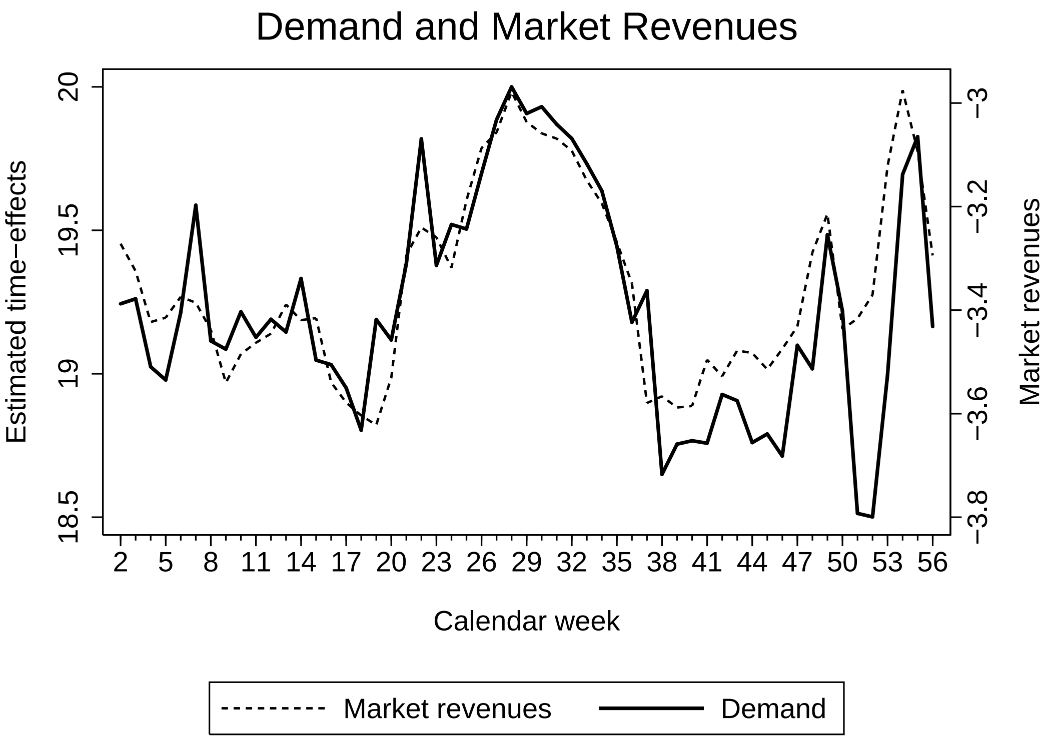

Figure 13: Total market revenues and underlying demand.

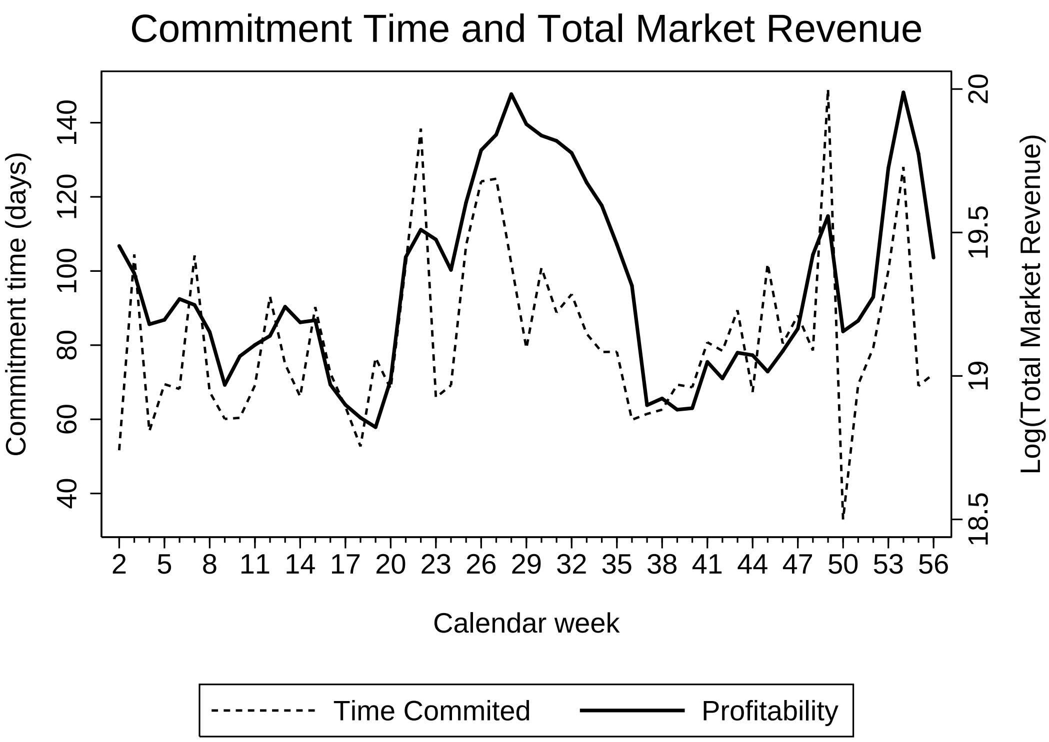

Figure 14: Total market revenues and commitment time.

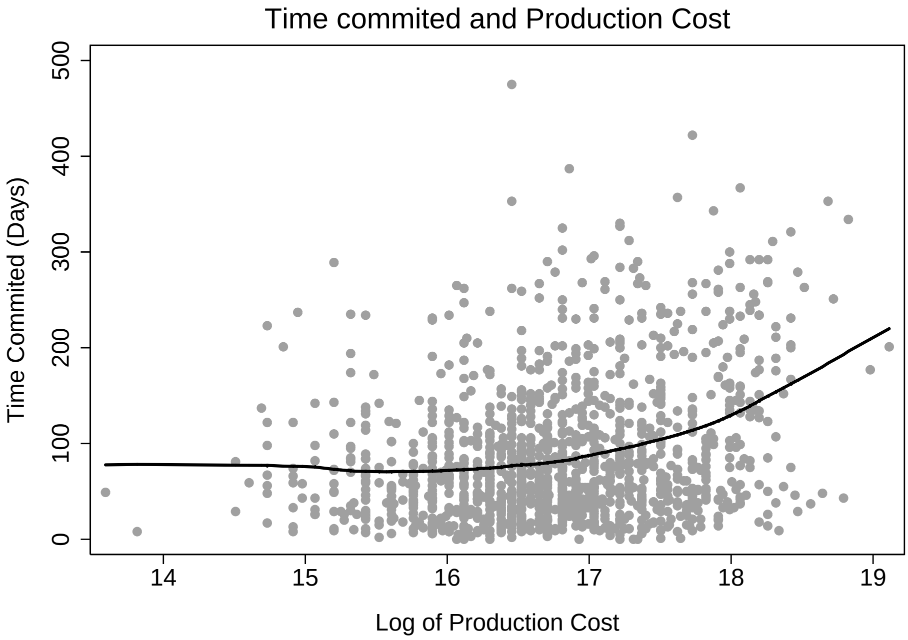

Figure 15: Correlation of commitment time with production cost.

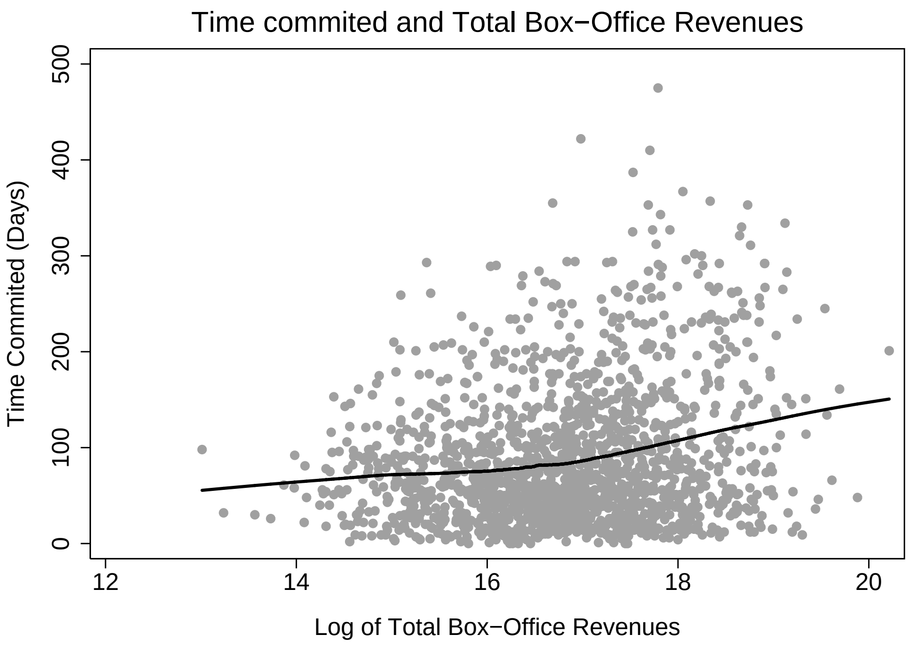

Figure 16: Correlation of commitment time with total realized box-office revenues.

Figure 17: Correlation of commitment time with maximum number of screens.

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